Intergenerational Mobility in Sweden: a Regional Perspective

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Abstract

I employ high quality register data and present new facts about income mobility in Sweden. The focus of the paper is regional mobility using a novel estimation approach based on a multilevel model. The maximum likelihood estimates are substantially more precise than those obtained by running separate OLS regressions. I find small regional differences in income mobility when measured in relative terms. Regional differences are large when adopting an absolute measure and focusing on upward mobility. On the national level I find that the association between parent and child income ranks has decreased over time, implying increased mobility.

Keywords: intergenerational income mobility, regional analysis, multilevel model

JEL Classification: D31, J62, R0

1 Introduction

The academic and public interest in the shape and changing patterns of income distributions has been growing steadily over the past decades. The rising top income share in the US, for example, has inspired many discussions on everyone's equal opportunity to prosperity through

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hard work in the formerly known "land of opportunity". In a recent paper, Chetty et al. (2014a) emphasize the importance of regional differences in income mobility and describe the US as being, instead of a *land of opportunity*, a collection of *societies* some of which are *lands of opportunity* with high rates of mobility across generations, and others in which few children escape poverty.[1]

This paper employs high quality register data to present new facts about the state of income mobility in Sweden with a focus on regional differences in income mobility. My data set allows me to analyze national and regional mobility measures very precisely for the Swedish population born between 1968 and 1976.

Income mobility refers broadly to the extent child income can be predicted using parent income. The by far most commonly employed mobility measure in the literature is the intergenerational elasticity (IGE). This is simply the slope parameter of a regression of log lifetime income of generation t on log lifetime income of generation $t-1$. A small IGE means that it is harder to predict child income using parent income, and thus more income mobility. Estimates of the IGE in the literature center around 0.4 with higher estimates for the US, and usually smaller estimates for the European and especially the Nordic countries (see Björklund and Jäntti, 1997; Solon, 1992; Solon, 1999; Solon, 2004; or Mazumder, 2005). Recent summaries of economic research in intergenerational mobility are provided by Björklund and Jäntti (2009) and Black and Devereux (2011). Recent extensions include the study of more than two generations such as Lindahl et al. (2015).

The IGE has, however, some well-known drawbacks. One limitation is that zeroes have to be dropped from the regression which can lead to biased estimates. There is also evidence that a linear model does not fit very well the relationship between the logged incomes of two generations (see, i.e., Couch and Lillard, 2004 and Bratsberg et al., 2007).

More recently, scholars have directed attention to an alternative measure of mobility based on income ranks. This measure, called the rank-rank slope, is obtained by regressing the

[1]Chetty et al. (2014a; 2014b) find large differences in mobility across the 741 commuting zones in the US, and that economic mobility in the US has not changed significantly over time for cohorts born 1971 to 1993 (even though the consequences of this same mobility have increased due to the growth in income inequalities).

position in the income distribution (expressed in percentiles) of each member of the child generation on the position in the income distribution of their parents. In this paper I compute, in addition to traditional IGE measures, regional and national measures of mobility based on income ranks. For the regional analysis I employ two different mobility measures based on income ranks. The first one is "relative mobility" which describes the mean difference in outcomes between children with parents in the top and bottom of the income distribution, respectively. The second one is "upward mobility" which measures the mean absolute outcome of children from families with below-median income levels and, importantly, focuses exclusively on the regional differences in outcomes of children in the poorer half of the population.

It is important to keep in mind that both the IGE and relative mobility (as defined above) are *relative* measures and therefore do not reveal if an improvement in mobility is driven by better outcomes of some poorer families, or solely by worse outcomes of richer families. Therefore, upward mobility, and other measures based on absolute outcomes, are necessary to obtain a more comprehensive picture of income mobility.

The geographical unit that I focus on in the regional analysis is 'local labor market' which is an aggregation of municipalities defined by commuting patterns. The local labor market unit is similar to the commuting zone used by Chetty et al. (2014a). However, in comparison to the commuting zones in the US, there is much more variation between different Swedish local labor markets in terms of population size (and thereby the number of observations). As I show below, this aspect of the data results in imprecise estimates. To remedy this problem I propose a joint estimation technique using maximum likelihood, referred to as a multilevel (or hierarchical) model. In contrast to the approach taken in Chetty et al. (2014a), where they essentially run a set of distinct regressions, the multilevel model allows me to make a comparison between the different regional mobility measures in a statistically rigorous way. For example, I can test if the mobility estimate of one particular region is statistically significantly different from the national average. For completeness however, I also report and discuss results based on separate OLS regressions by region.

My results can be summarized as follows. I find that relative mobility is relatively homogeneous across Sweden. The difference of mean son income rank between families at the very top and the very bottom of the income distribution, respectively, is 22.2 percentile ranks in most local labor markets. Only 9 areas out of 112 show significantly lower or higher relative mobility, i.e. a larger or smaller difference between sons from families with highest and lowest incomes, respectively. Stockholm ranks in the bottom with the lowest relative mobility, and the Umeå region in northern Sweden shows the highest relative mobility.

Upward mobility, the expected outcome for sons from below-median income families, varies considerably more across Swedish local labor market areas, from 36.32 percentile ranks in Torsby to 50.77 in Hylte. This corresponds to an income difference of 32.842 SEK per year ($\approx$3.839 USD). In addition, children who spend a significant part of their childhood in very rural areas of Sweden have in general significantly worse outcomes compared to children growing up in urban areas. This result can be explained in part by the large fraction of rural kids that do not move into cities when adults: those who do move, do on average even better than city kids.

For Sweden as a whole, the association between parent and son income measured by the relationship between income ranks has declined between 1968 and 1976. The IGE shows the opposite development and is misleading: the IGE reflects, in addition to the parent-child income association, also the considerable increase in the ratio of the standard deviations of son over parent income.

The remainder of the paper is organized as follows. In section 2, the theoretical background of the IGE, mobility measures based on income ranks, and a description of the multilevel model is given. The data and variables used are described in section 3. In section 4, non-parametric and parametric results for intergenerational mobility on the national level and over time are reported. The regional results are the focus of section 5 and section 6 concludes.

2 Measuring Intergenerational Mobility

This first part of this section comprises a rather short review of the estimation of the intergenerational income elasticity. Further details can be found in the cited references. In the second part, I explain the concepts relative- and upward mobility used later on to compare the Swedish local labor markets in terms of mobility. A brief introduction to multilevel modelling and the exact model used in this study is given in the last part of this section.

2.1 The Intergenerational Income Elasticity

The IGE is typically estimated using the following benchmark equation:

$$y_f^C = \alpha + \beta y_f^P + \varepsilon_f^C \tag{1}$$

where y_f^C and y_f^P are a the log of child and parent lifetime earnings in family f, respectively, and ε_f^C is assumed to be an iid error term representing all other influences on child earnings not correlated with parental income. I will use the terms income and earnings interchangeably in this section due to the range of different income/ earning concepts used in this literature. Traditionally, this relationship has been estimated for sons and fathers only. In Sweden, female labor market participation has been close to male participation for more than three decades. This makes it particularly interesting to study also the association between the child income and combined parent income, in addition to father or mother income only.

β is the parameter of interest, the elasticity between parent and child income. Equation (1) is a simple Markov model and a lower IGE corresponds to a greater regression toward the mean of income from one generation to the next. Black and Devereux (chapter 1.2 in 2011) review the results obtained for the IGE in different studies over the past decades.

What makes the estimation of the IGE difficult is the need for lifetime income data for the two generations. Approximations made in lack of sufficient data lead to at least two known measurement problems: attenuation bias and life-cycle bias. Attenuation bias occurs due to measurement error of the regressor, most clearly seen when single year income observations are used to estimate the IGE. This was typical in early studies such as Solon (1992). Assuming a classic error-in-variables-model, measured income y_f then equals the true income $y_f^\star$, plus an error:

$$y_f = y_f^\star + v_f \ . \tag{2}$$

The known implication (Hausman, 2001) is a downward inconsistent IGE estimate.[2] The bias can be reduced using an average of T income observations to approximate the average of true lifetime income:

$$y_f^P = \frac{1}{T}\sum_{t=1}^{T}\left(y_{f,t}^{P\star} + \nu_{f,t}^P\right). \tag{3}$$

Björklund and Jäntti (1997) showed that in this case the inconsistency is diminishing in the number of observed years T (assuming the measurement errors/ transitory fluctuations are not serially correlated).[3] Mazumder (2005) used simulations to show that using a five year average (a number of typical magnitude in the literature) to measure father lifetime income still results in a downward bias of around 30 percent.

Life-cycle bias arises when single-year income observations of the child systematically deviate from the average of annual lifetime income (left hand-side measurement error). One can think of a parameter in front of $y_t^\star$ in equation (2) that is time variable. In this case, the inconsistency of the OLS coefficient varies as a function of the age at which annual income is measured. Simply adding age controls as done in earlier literature will not prevent this inconsistency. Life-cycle bias is a serious concern in the Swedish context where sons' individual income trajectories have been shown to be correlated with family characteristics (Nybom and Stuhler, 2011). Using the "correct" age as suggested for example by Haider and Solon (2006) to measure son's income can therefore only diminish, but never totally eliminate life cycle bias.

I address attenuation bias by averaging over a very large number of annual income observations where T is 17 for most parents in the sample (see section 3.1 for more details). Importantly, income is observed for all individuals during the same age span, in the middle of their working lives. Life-cycle bias is handled by measuring child income at the approximate

[2]This can be seen from the probability limit of β in equation (1) after substituting (2) for y_f^P: $\underset{N\to\infty}{\text{plim}}\,\hat{\beta} = \frac{Cov(y_f^C, y_f^P)}{Var(y_f^P)} = \frac{\sigma^2_{y_f^{P\star}}}{\sigma^2_{y_f^{P\star}} + \sigma^2_{\nu_f^P}}\beta < \beta$, assuming $Cov\left(y_f^{P\star}, \nu_f^P\right) = 0$ and $\sigma^2_{\nu_f^P} \neq 0$, where $\sigma^2_{\nu_f^P}$ denotes the variance of the measurement error.

[3]The probability limit of β is here $\underset{N\to\infty}{\text{plim}}\,\hat{\beta}_1 = \frac{Cov(y_f^C, y_f^P)}{Var\left(y_f^P\right) + Var\left(\frac{1}{T}\sum_{t=1}^{T}\nu_{f,t}^P\right)} = \frac{\sigma^2_{y_f^{P\star}}}{\sigma^2_{y_f^{P\star}} + \frac{\sigma^2_{\nu_f^P}}{T}}\beta < \beta$

age where Swedish individuals have been shown to earn just as much as the yearly average over a whole lifetime. [4]

There are two additional problems associated with the IGE measurement, the functional form and the handling of observations with zero income. Chetty et al. (2014a) showed for US data that the relationship between log incomes of children and their parents is not well represented by a simple linear regression model. This point has even been raised by Couch and Lillard (2004) and Bratsberg et al. (2007). One suggested remedy is to use income ranks instead of the log of incomes.

The issue with zero-income observations has long been known and dealt with in different manners such as dropping those observations or recoding zeros to different, usually small values. Dropping individuals with zero income will overstate mobility if children with zero incomes are over-represented in low income families. Those families with low mobility will not be part of the sample. Recoding all zeros, on the other hand, leads to highly variable results depending on the replacement values chosen. A detailed analysis of this issue for my data can be found in appendix A. Income ranks are found to be the preferred choice, and are thus used exclusively in the regional part of this paper.

2.2 The relationship between income ranks

A different approach to measuring intergenerational income mobility is to use income ranks instead of log incomes. Children are ranked based on their average lifetime income relative to other children in the same birth cohort. Parents are ranked similarly, based on their average lifetime incomes relative to other parents with children in the same cohort. Importantly, observations with zero income do not need any special treatment here (Dahl and DeLeire, 2008). The ordered income levels are then transformed into percentile ranks[5] (normalized fractional

[4] Recently, Nybom and Stuhler (2015) studied attenuation- and life-cycle bias for the most common measures of income mobility in the literature. Based on nearly career-long income histories for a sample of two generations of Swedish individuals, they found that measurement bias is much less of a problem when using income ranks (as described in the next section), compared to log incomes.

[5] Fractional ranks are calculated by cohort and then normalized to span from 0 to 100. In case of ties all observations with identical incomes share the mean rank for this group. For example, if 20% of a cohort had zero income, they all would be assigned a percentile rank of 10.

ranks). The following equation is then estimated by OLS:

$$R_f^c = \alpha + \beta R_f^p + \varepsilon_f^c \tag{4}$$

where R_f^c and R_f^p are the rank of the child and parents in family f, respectively. The coefficient β is equal to the correlation coefficient between the ranks since, by construction, the ranks are uniformly distributed. Both the IGE and the rank-rank slope show the degree of dependence between parent and child average lifetime income. The measures differ conceptually when inequality is larger in the child generation compared to the parent generation: with growing inequality, moving one rank down will correspond to a larger income loss in absolute terms since the distance between ranks increases.

When estimating rank-rank relationships on the regional level below, the national ranks assigned to each individual remain the same. If we were to use regional ranks instead, i.e. order individuals within each region, we would have a hard time interpreting the results: what does it mean that sons from low-income families in Stockholm reach on average the 38th percentile rank (within Stockholm), while sons from low-income families in Göteborg reach on average the 35th percentile rank (within Göteborg)? Is the income level at the 38th percentile within Stockholm higher or lower than the 35th percentile within Göteborg? Using national ranks, we create a common unit that makes a regional comparison meaningful.

I analyze two mobility measures on the regional level, relative and absolute mobility. Relative mobility is the difference in mean outcomes of the children from parents at the highest and lowest rank respectively:

$$\bar{R}_{100,r}^c - \bar{R}_{0,r}^c = 100 \times \beta_r \tag{5}$$

where $\bar{R}_{p,r}^c$ is the average child rank at percentile p in region r and β_r is the rank-rank slope parameter in region r. Relative mobility is thus just the re-scaled rank-rank slope coefficient in region r.

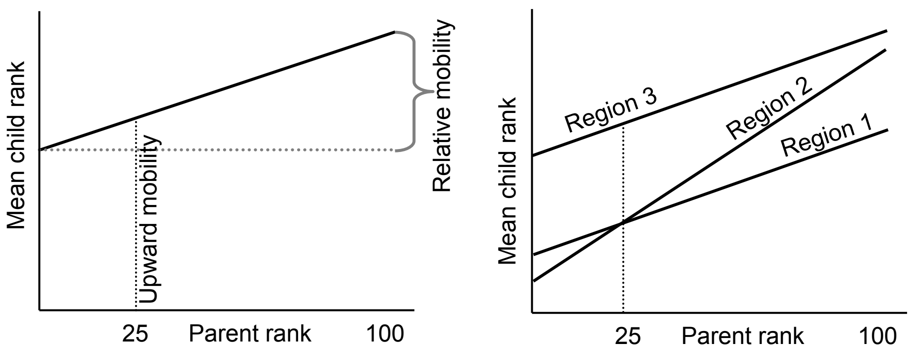
Absolute mobility is defined as the mean rank of children with parents at a certain percentile of the parent distribution (looking thus not only at the slope but also at the intercept). This measure adds no information on the national level since it is mechanically related to the rank-rank slope (Chetty et al., 2014a, p. 1562). Keeping the national income ranks for the regional analysis, however, incomes in one region can be assumed to have no influence on the national income distribution.

This absolute measure can be used to describe upward mobility, defined as the expected income rank of children from families with below-median income. This measure of mobility focuses thus on the absolute outcomes of the poorer half of the population, and is not affected by relative income changes between children in different percentiles. Since we assume that the rank-rank relationship is linear, this equals the mean child rank of children with parents at the 25th percentile, which we can predict using the estimated regional coefficients:

$$\bar{R}^c_{25,r} = \alpha_r + \beta_r \times 25. \tag{6}$$

The left panel in figure 1 illustrates relative and upward mobility. The former is given by the difference in mean child rank (Y-axis) between parents with the highest and lowest income rank (X-axis), while the latter is measured by the mean child rank for parents at the 25th percentile. The right panel shows three example regions. Region 1 and region 3 share the

Figure 1: Relative and Upward Mobility



Note: The left figure illustrates relative- and upward mobility. Relative mobility is the difference between the expected outcome of a child with parents in the top of the income distribution and a child with parents and the bottom of the income distribution. Upward mobility is the expected income rank of a child with below-median parent income. The right figure shows the association between child and parent income for three different regions. Regions 1 and 3 exhibit the same level of relative mobility, and regions 1 and 2 share the same level of upward mobility. Regions 1 and 3 would be indistinguishable from each other when using purely relative measures.

same level of relative mobility, i.e. the mean difference in ranks for children from the top and bottom of the parent income distribution is the same. However, mobility differs in absolute terms: for every parent percentile, the mean child rank is higher in region 3. Region 1 and region 2 have the same level of upward mobility. Children with parents below the median reach, on average, the same national income rank. However, relative mobility is lower in region 2 which can be seen by the steeper rank-rank slope. Note that a steeper rank-rank slope means a lower level of relative mobility. The steeper the slope, the stronger the association between the two generations' incomes, and thus the lower the intergenerational mobility.

It is important to be aware of which aspects the mobility measures above can and cannot capture. The IGE, the slope coefficient of a regression of log incomes, takes into account both the correlation between log incomes and the spread of the child and parent income distribution, since it is equal to

$$\beta = \frac{Cov\left(y_f^C, y_f^P\right)}{Var\left(y_f^P\right)} = \frac{Cov\left(y_f^C, y_f^P\right)}{\sigma_P \sigma_C} \frac{\sigma_C}{\sigma_P} = corr\left(y_f^C, y_f^P\right) \frac{\sigma_C}{\sigma_P}, \tag{7}$$

where $\sigma_{C(P)}$ is the standard deviation of the child (parent) distribution. The rank-rank slope on the other hand is just equal to the correlation coefficient between the income ranks since, after transforming income levels into percentile ranks, incomes in all generations are uniformly distributed between 0 and 100 and the ratio of standard deviations cancels out.

If income inequality had grown more from one generation to the next everything else equal (i.e., an increase in σ_C only), the IGE would be larger while the rank-rank slope would not change. A change in the mean of the income distribution (a shift of the complete distribution to the left or right) will show up in neither the IGE or the rank-rank slope. Yet, any measure based on absolute outcomes such as upward mobility will reflect such a shift, since absolute mobility makes use of the regression's constant to predict outcomes.

2.3 Regional Estimation

The estimation of rank-rank slopes and intercepts by region can be implemented in a variety of ways. The simplest one would be to estimate R different equations as in equation 4 for regions $r = 1, ..., R$ by OLS, resulting in R different slopes and intercepts (as done in Chetty et al. (2014a)). Let us call this the no-pooling case. Ignoring the regional information completely and estimating the equation for the whole sample as one group would give us one slope estimate and one intercept, i.e. the national estimates. We can call this the complete pooling case, for further reference below.

A third and potentially better alternative is to recognize not only the grouped nature of the problem at hand (individuals are sorted into different regions), but to explicitly model this relationship by taking into account both the within- and the between-region variances using a multilevel (or hierarchical) model. Multilevel models are widely used in political sciences (modelling for instance election turnouts or state-level public opinion, see for example Lax and Phillips (2009), Galbraith and Hale (2008), Shor et al. (2007), or Steenbergen and Jones (2002) for an overview) and in the context of education (students are grouped into class rooms and class rooms into schools and school districts, see for example Koth et al. (2008)). The terminology and notation below follow Gelman and Hill (2006).

The multilevel model is characterized by a level-1 equation for the smallest units, in this case relating child income rank to parent income rank for family f, and a set of level-2 equations for the larger units, here the regions. The level-2 equation models explicitly the intercept and slope coefficients by region r:

$$R_f^c = \alpha_r + \beta_r R_f^p + \varepsilon_f^c \tag{8}$$

$$\alpha_r = \gamma^\alpha + \eta_r^\alpha \tag{9}$$

$$\beta_r = \gamma^\beta + \eta_r^\beta \tag{10}$$

where ε_f^c, η_r^α and η_r^β are random errors centered around zero and with variances σ_R^2, σ_α^2, and σ_β^2. Another common and equivalent way to write this model is

$$R_f^c \sim N\left(\alpha_r + \beta_r R_f^p, \sigma_R^2\right), \text{ for } f = 1, ..., F \tag{11}$$

$$\begin{pmatrix} \alpha_r \\ \beta_r \end{pmatrix} \sim N\left(\begin{pmatrix} \gamma^\alpha \\ \gamma^\beta \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\beta \\ \rho\sigma_\alpha\sigma_\beta & \sigma_\beta^2 \end{pmatrix}\right), \text{ for } r = 1, ..., R \tag{12}$$

which emphasizes the fact that the coefficients α_r and β_r are given a probability distribution with means and variances estimated from the data. Substituting equations 9 and 10 into equation 8, the model can be re-expressed as a mixed model

$$R_f^c = \gamma^\alpha + \eta_r^\alpha + \gamma^\beta R_f^p + \eta_r^\beta R_f^p + \varepsilon_f^c \tag{13}$$

where, in multilevel terminology, the γ's are "fixed effects" (= averages across all regions) and the η's are "random effects" (= draws from the estimated distributions).[6]

The multilevel model appears similar to a random- or fixed effects model often used in economics, but there are some important differences. We could for instance estimate a fixed effects model by simply adding $2 \times (R-1)$ regional dummies to equation 4, for regional intercepts and slopes. This approach would basically control away all between-region differences. In a multilevel model, the between-regions variance is explicitly estimated from the data and used to predict the regional effects. Also, if there are only few observations in some regions, the estimates using regional dummies will be inefficient. The multilevel model on the other hand makes use of all observations when estimating the variance components and leads therefore to more precise estimates when there is little within-region variance.

If we were interested in the effect of parent income on child income in general but were worried about regional unobservables, adding standard fixed- or random effects would be a good solution. However, since we are particularly interested in the mobility estimates for each of the regions, the multilevel framework is here the better choice.

[6]Note the important differences in terminology between fixed-effect models in economics and multilevel modelling. While a different intercept per region would be termed a regional-fixed effect in the former, it is a random effect in the latter. Only estimates of the average coefficients across all regions like the γ's are thought of as fixed here.

In a second model, I add five regional types (as described in section 5.1 below) as a regional level predictor in the form of dummies to equations 9 and 10:

$$\begin{aligned} \alpha_r &= \gamma_1^\alpha + \sum_{i=2}^{6} \gamma_i^\alpha T_i + \eta_r^\alpha & (14) \\ \beta_r &= \gamma_1^\beta + \sum_{i=2}^{6} \gamma_i^\beta T_i + \eta_r^\beta . & (15) \end{aligned}$$

This gives the following mixed model:

$$R_f^c = \gamma_1^\alpha + \eta_r^\alpha + \sum_{i=2}^{6} \gamma_i^\alpha T_i + \gamma_1^\beta R_f^p + \sum_{i=2}^{6} \gamma_i^\beta T_i R_f^p + \eta_r^\beta R_f^p + \varepsilon_f^c \tag{16}$$

which allows the type of region during childhood to have an effect on both regional intercepts and slopes via $\sum_{i=2}^{6} \gamma_i^\alpha$ and $\sum_{i=2}^{6} \gamma_i^\beta$.

In the no-pooling case, the α_r's and β_r's in equation 8 are the OLS estimates from separate regressions, varying completely freely from each other. In the complete pooling case, the α_r's and β_r's are constrained to one common α and β. Here in the multilevel model where equations 8 - 10 are fitted simultaneously by (restricted) Maximum Likelihood estimation, the α_r's and β_r's are given a "soft constraint": they are assigned a probability distribution given in 12, with mean and standard deviation estimated from the data, which pulls the coefficient estimates partially towards their mean (termed shrinking).

The amount of pooling depends on the number of observations in each group as well as the between-regions variance of the parameters. For example, an estimate of a regional intercept can be expressed as a weighted average between the mean across regions γ^α (complete pooling), and the average of the R_f^c's within the region $\bar{R}_r^c$ (no-pooling):

$$\begin{aligned} \hat{\alpha}_r^{multilevel} &= \omega_r \hat{\alpha}^{complete-pooling} + (1-\omega_r)\, \hat{\alpha}_r^{no-pooling}. & (17) \\ \hat{\alpha}_r^{multilevel} &= \omega_r \gamma^\alpha + (1-\omega_r)\, \bar{R}_r^c & (18) \end{aligned}$$

where the pooling factor ω_r is calculated according to

$$\omega_r = 1 - \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_R^2/n_r}. \tag{19}$$

Thus, the intercept in a region with few observations is assumed less reliable and pulled towards the average value of all regions. The estimate for a region with many observations on the other hand will usually coincide with the a separate OLS regression.

This is the main argument for using multilevel modelling in this particular study: there are many regions in Sweden with relatively few observations. The large regions have more than 400 times as many observations as the small regions. A separate regression for those small regions leads to extreme mobility estimates with large standard errors. In other words, we would not trust those estimates (even though they might seem appealing since we could report some exceptionally low and high levels of intergenerational mobility). Another useful aspect of multilevel models is that it is possible to include regional-level indicators along with regional-level predictors, which would lead to collinearity in OLS.

The model is built step wise, starting with a random intercept per region and adding then random slopes and predictors. After each step, the model is assessed using a log-likelihood ratio test to assess if the model is a better fit to the data compared to classical regression (first model), or a better fit compared to the previous step.

Maximum likelihood estimation is used to fit the model. The "fixed effects" (regional average) parameters of intercept and slope given by the gammas in equation 12 are analogous to standard regression coefficients and are directly estimated. The regional effects given by the etas are not directly estimated but summarized in terms of their estimated variance and covariances. The best linear unbiased predictors (BLUPs) of the regional effects and their standard errors are computed based upon those estimated variance components as well as the "fixed effects" estimates. [7]

[7] The exact estimation method used in this study is restricted maximum likelihood (REML). The basic idea behind REML estimation in this context is that one can form a set of linear contrasts of the response that do not depend on the estimated "fixed effects" (gammas), but instead depend only on the variance components to be estimated. One can then apply maximum likelihood methods by using the distribution of the linear contrasts to form the likelihood. If estimation is done by REML, the predicted standard errors of the BLUPs account for uncertainty in the estimate of the gammas which leads to slightly larger and more conservative standard errors. See for example Thompson (1962), Bates and Pinheiro (1998), Steenbergen and Jones (2002), and StataCorp (2013) for further technical details of the estimation procedure.

3 Data and Variable Descriptions

The data in this study comes from the SIMSAM database at Umeå University (Swedish Initiative for Research on Microdata in the Social And Medical Sciences). SIMSAM combines several different Swedish micro data registers and the population, geographic and income registers used in this study are provided by Statistics Sweden. A detailed description of the sample, the income variable used, as well as the geographical unit used for the regional analysis is given below.

3.1 Sample Selection and Income

My population sample consists of all individuals born in Sweden between 1968 and 1976, in the following termed children (927,008 observations before applying any restrictions). Due to the Swedish centralized registration system 99.5 percent of those children can be linked to their fathers and mothers. The age of the parents at their child's birth is restricted, 16 to 40 years for fathers and 16 to 36 years for mothers.[8] This makes it possible to observe parental income from their early/mid thirties onward while including 95 percent of the sample.

The income variable used here is the sum of taxable income from employment, self-employment, and transfers from the Swedish Social Insurance Agency.[9] The taxable transfers include parental benefits, pension payments and sick pay, and are labor market and -income related. Using this income variable on the individual level, the focus lies on how the child's ability to earn income is related to parental earned income.

Chetty et al. (2014b) measure instead family income for both children and parents (average income of two adults if married). This is potentially problematic since this measure is more affected by assortative mating. What one might be measuring in this case is the relationship between parental income and a child's ability to find a high income partner.[10]

Annual earned income can in principle be observed for each individual (children and par-

[8] I can choose a slightly smaller age span for mothers without loosing observations since there is less variance in mothers age at birth.

[9] "Sammanräknad förvärvsinkomst"

[10] See Ermisch et al. (2006) for a specific treatment of assortative mating and intergenerational mobility,

ents) over the time period 1968 to 2010. All income observations are expressed in 2010 SEK. Income and earned income are used interchangeably in the following.

I follow the literature discussed in section 2 and approximate average parental lifetime income by averaging over a large number of annual incomes. For 96 percent of the parents, I have 17 consecutive income observations available from when they were 34 to 50 years old. The smallest number of income observations available is 10, for fathers born in 1928 (only 0.1 percent of all fathers). On the mothers' side, 99.6 percent have 17 consecutive years of income observations, from 34 to 50 years. Due to the restriction to 36 years, even the oldest mothers born in 1932 have observable income records for 15 years. Parents missing too many income observations are dropped from the sample.[11] The great advantage here compared to earlier studies is that I measure parental income at approximately the same age for each parent, as well as over a very long time span. Averaging instead over the same calendar years for everyone (i.e. 2010 - 2012) as done in many other studies would give a biased measure: we would underestimate average income for young parents and overestimate average income for old parents, and even include some parents who are already retired.

For the children I have naturally fewer income observations available. Following the results by Bhuller et al. (2011) and Nybom and Stuhler (2011), I choose to approximate sons lifetime income by taking the average over three years when 32 to 34 years old.[12] All children missing more than one observation are deleted from the sample (3.5 percent).[13]

In my sample, around 45 percent of the daughters in each cohort receive maternal leave payments in their early thirties. Due to the flexible ways to take out parental leave days as well as the income cap used to calculate the amount of parent leave payments in Sweden, it is very difficult to impute a reliable "true" income of the daughters in their early thirties based

[11]Parents are allowed to miss at most 4 years of income observations when having 15 - 17 observations (most parent cohorts), and then a decreasing number of years until missing at most 1 observation (for parents having only 10 years of income observations). Depending on the cohort, 97 or more percent of the parents fulfill this requirement.

[12]Bhuller et al. showed with Norwegian register data that annual earnings when 32-33 years old most closely reflect men's lifetime earnings. Nybohm and Stuhler (table 4) showed for Swedish male cohorts 1955-1957 that the correlation between annual and the average of annual incomes over a lifetime is close to one when using a three year average around the age of 33.

[13]Missing observations occur for example when living (temporarily or permanently) abroad or after death,

on the available information in my data set. The observed income is potentially a bad proxy for annual lifetime income for daughters and, as a consequence, I will report only the baseline estimates for them.[14] For those estimates I use the same approximation of average lifetime income as for boys, namely the average income between the age of 32 and 34.

Table A.2 in the appendix summarizes the sample. The average age at child birth is 26 for mothers and 28 for fathers, and has increased slowly but steadily over the observed time horizon. There are roughly between 80,000 and 90,000 children in each cohort and 774,953 children (and their parents) in total.

Table 1: Income Distributions

N = 781,630	Mean	St.dev.	Min	Max	p50	p90/p10
Son income	312,515	(169,699)	0	9,841,421	297,163	3.3
Daughter income	223,147	(104,796)	0	5,361,351	214,724	3.2
Children income	269,171	(148,835)	0	9,841,421	254,923	3.6
Mother income	157,958	(72,146)	0	5,565,328	156,356	3.3
Father income	269,116	(132,778)	0	15,160,164	244,572	2.5
Parent income	427,074	(161,288)	0	15,288,524	404,252	2.2

Note: All incomes are expressed in 2010 SEK.

Table 1 shows an income summary for the individuals in the data (all cohorts pooled). Mothers have on average about 60 percent of fathers incomes (but only 36 percent in terms of the highest income). The daughters distribution has come somewhat closer to their male counterparts compared to the previous generation but a strong difference persists both in level and variance. However, since daughters' incomes are affected heavily by maternal leave taking during the observed income years the numbers are not fully comparable. The last column shows that income inequality has risen from the father to the son generation, dividing the 90th income percentile by the 10th percentile increased from 2.5 to 3.3.

[14] Böhlmark and Lindquist (2006) studied the development of annual versus lifetime income separately for men and women. While their results for sons was similar to the findings in the above studies, the income trajectories for women follow quite a different pattern that, along with the increasing labor market entry, also changes strongly over time.

3.2 Geographic Unit

The geographic unit I choose to work with is the local labor market region, or LLM. An LLM is a self-sufficient area in terms of labor within which individuals live and work, and thus spend most of their time. The aggregation of municipalities into LLMs is taken from Statistics Sweden which measures commuting flows between municipalities. The aggregation into local labor markets corresponds most closely to the commuting zones which are used by Chetty et al. (2014a) for the US.

Studying local labor markets is a first step towards measuring the effect of immediate conditions (family, neighborhood), the local community (school quality, for example), and the larger metro area which is picking up for example labor market conditions. Using smaller geographical units such as municipalities there is a larger risk of selection bias due to residential segregation, i.e. that families sort themselves into certain residential areas and municipalities. A local labor market area contains several municipalities and probably several different residential areas, with different types of families. There are currently 75 LLMs in Sweden (112 in 1990 due to increasing commuting patterns), containing on average 4 municipalities and a population of 90,000. In contrast, there are 741 commuting zones in the US containing on average 4 counties and a population of 380,000.

In addition, I use five different regional types, based upon the "regional families" classification of local labor markets by The Swedish Agency for Economic and Regional Growth. The five regional types (T1-T5) are large cities (such as Stockholm), large regional centers (university cities, for example), small regional centers (small cities employing a large share of the population in the surrounding rural areas), sparsely populated regions (less than 6 people per square kilometer), and other small regions (ranking in between small regional centers and sparsely populated regions). A complete list of local labor market regions and their type classifications can be found in table A.3 the appendix.

Research by Cunha and Heckman (2007), Cunha et al. (2010), and Heckman (2007) indicates that the early environment is important in the human capital formation of children. Early investments generate not only human capital directly but also lead to higher returns to later investments. Other potentially important factors influencing the accumulation of human capital and life time income are the school environment and peers (Lavy et al., 2012), the home and neighborhood environment (Chetty et al., 2015), the availability of adult role models, and guidance when choosing higher education or career paths during teenage years.

I therefore assign children to the local labor market region in which they lived for at least six years between the age of 6 and 15 (ignoring moves within a local labor market), in order to capture both some influences during earlier as well as some teenage years. Using the strict assignment rule of a minimum of 6 years in the same region, we can be sure that a child was actually exposed to this location a significant portion of her childhood and that studying regional differences in mobility is meaningful.[15]

The regional sample now includes 97.5 percent of all sons in the data (393,715 individuals), while 2.5 percent moved too often to determine a childhood region.

4 Mobility on the National Level

In this section, I summarize the national mobility estimates. First, by simply looking at transition matrices, we can see the outcomes in terms of son lifetime income given parent income both for all cohorts pooled and over time, for Sweden as a whole. Next, I present the IGE and rank-rank slope estimates for different family member combinations and discuss how those estimates relate to earlier findings in the literature. Lastly, I decompose the IGE to find that the association between the income of two generations has weakened over the observed time horizon in Sweden.

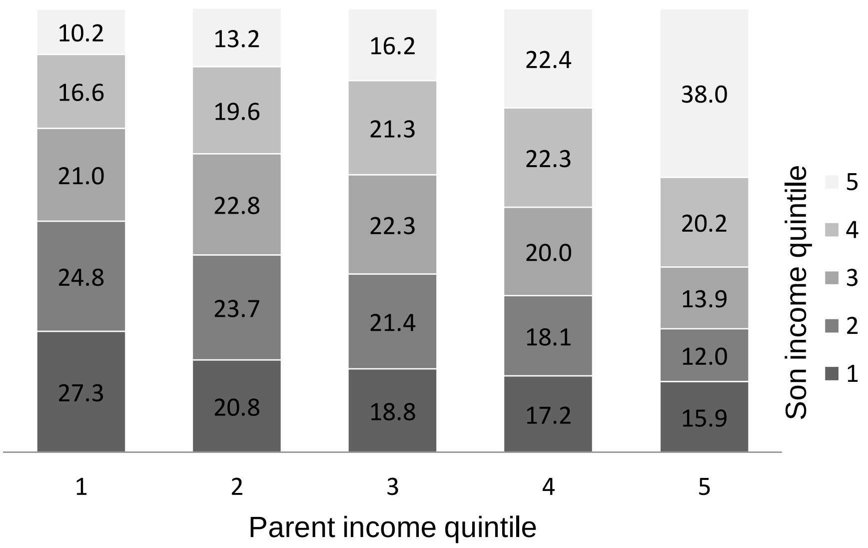
4.1 Non-Parametric Description of Mobility

A non-parametric description of intergenerational mobility is a good starting point for the analysis of joint distributions of incomes (see for example Fields and Ok (1999) and Jäntti and

[15] Sensitivity tests show that, in a country like Sweden with relatively few observations in a large number of regions, the age at which we establish the regional assignment can matter. Assigning children instead to the region where they lived between 0 and 3 years, or at age 15 as done in Chetty et al. (2014), changes the mobility results for the smaller regions. See figure A.3 in the appendix for a sensitivity test of the childhood definition.

Jenkins (2015)). Figure 2 shows a visual transition matrix for sons and their parents. 27.3 percent of the sons with parents in the first quintile are themselves located in the first quintile (of their own income distribution) as adults. Just over 10 percent of sons from the poorest fifth of the parents will reach the top quintile. Mobility of sons with parents in the first quintile is

Figure 2: Quintile Transition Matrix: Parents and Sons



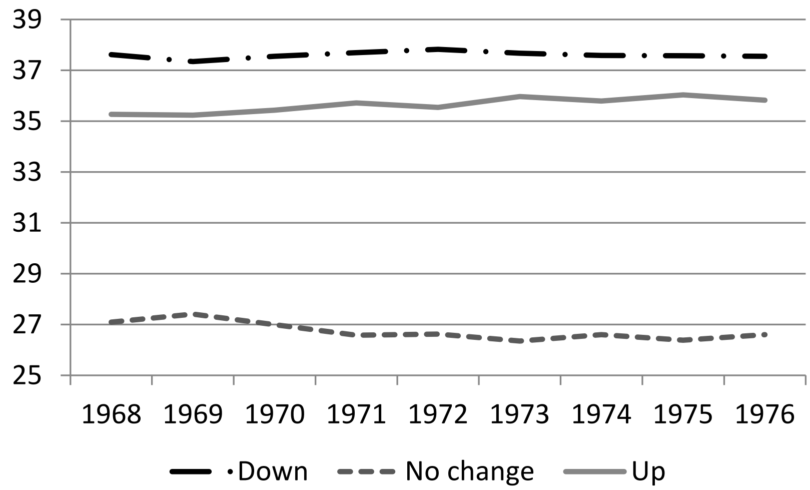
higher than in the US (using the quintile transition matrix given in Chetty et al. (2014a, p.1577)) where 33.7 percent of the children stay in the first quintile and only 7.5 percent of those starting at the bottom reach the top quintile.

Looking at the upper end of the parent distribution, 15.9 percent of their children fall to the first quintile, while 38 percent stay at the very top. This is particularly interesting, again, since the numbers shown here are entirely depicting earned income and not wealth. In the US study, the numbers are 10.9 percent who move down four quantiles, and 36.5 percent who stay in the top, respectively.

Figure 3 shows the fraction of sons who reach the same, a higher, and a lower quintile in their own distribution compared to their parents over time, i.e. for each of the nine cohorts separately. For each year, the three lines add up to 100 percent (for every individual that moves up, another one has to make room and move either also up, or down). The fraction of sons doing worse compared to their parents is the largest group with a very stable 37.5 percent.

There are slightly less sons in the 1976 cohort compared to the older cohorts who do just as well as their parents (from just above 27 down to 26.6 percent). The group of individuals who change places in the income distribution contains in the later years more sons that do relatively better than their parents, which can be seen in the slight upward trend of the “Up”-curve.

Figure 3: Quintile Mobility over Time



4.2 National Mobility Estimates

The base line mobility results for different family member combinations are shown in table 2. Both the IGE and the rank-rank slope show very little dependence between the incomes of mothers and their children. The IGE is largest between sons and parents (and mobility therefore the lowest), while the rank-rank slopes indicate the relation between sons and fathers to be the least mobile. A ten percentile points increase in father’s income rank implies on average a 2.45 percentile increase in the son’s income rank.

The estimated IGE for sons and fathers, 0.253, is in line with previous results. Nybom and Stuhler (2011) got an estimate of 0.27, based on a sample of 3,504 Swedish sons born between 1955 and 1957. Two main differences to their study are that their income measure is total pre-tax income which includes capital realizations, and fathers older than 28 years at their son’s birth are excluded from the sample. The effects of those might however work in opposite directions which could explain the similarity to this study’s result.

Table 2: Mobility Estimates for the Pooled Sample

	IGE			Rank-Rank slope		
	Child	Son	Daughter	Child	Son	Daughter
Parents	0.302	0.326	0.279	0.198	0.238	0.206
	(0.002)	(0.004)	(0.003)	(0.001)	(0.002)	(0.002)
N obs	766,404	394,157	372,247	774,953	399,095	375,858
Father	0.217	0.253	0.180	0.192	0.245	0.180
	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
N obs	766,338	394,122	372,216	774,953	399,095	375,858
Mother	0.071	0.061	0.084	0.101	0.101	0.133
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
N obs	765,327	393,590	371,737	774,953	399,095	375,858

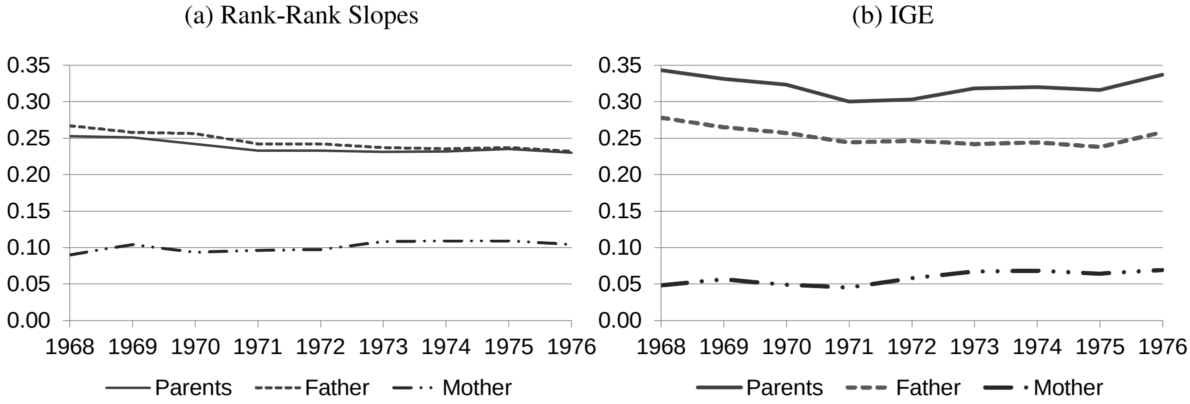
Note: Standard errors are given in parentheses.

Björklund and Jäntti (1997) estimated the IGE to be 0.216 between fathers and sons. Their sample was quite different from the one used here: no actual father and son pairs were observed but instead two independent samples for both groups were combined. Their income measure was earnings, a five-year average for the fathers and one single observation for the sons.

Österberg (2000) presented also results for daughters and mothers. There are several ways her sample differed from mine. Incomes were observed during three calendar years only where parents are up to 65 years old and thus possibly already retired. Many children in the sample were under 33 years when their income is measured. Her estimate for the IGE between sons/ daughters and fathers (0.13/ 0.071, respectively) as well as for sons/ daughters and mothers (0.022/ 0.036, respectively) are substantially smaller in magnitude than my estimates which might be caused by attenuation and life cycle bias.

The IGE and rank estimates for parents and their children (first row in table 2) are in general larger than the estimates for father and mother separately. This suggests an important role of the parental income combination, or parent income matching, for income transmission between generations, as opposed to just the sum of parent incomes. Investigating this finding further is an interesting direction for future research.

Figure 4: Intergenerational Mobility over Time



Figures 4a and 4b show the development of the IGE and rank-rank slopes for sons and their parents separately by cohort. The association between mother and son income ranks has not changed considerably from the 1968 to the 1976 cohort and fluctuates closely around 0.1. The parents and father associations both show a negative trend, with the father estimates initially being larger than the parents estimates, but converging to the same value as for the parents for the 1976 cohort.

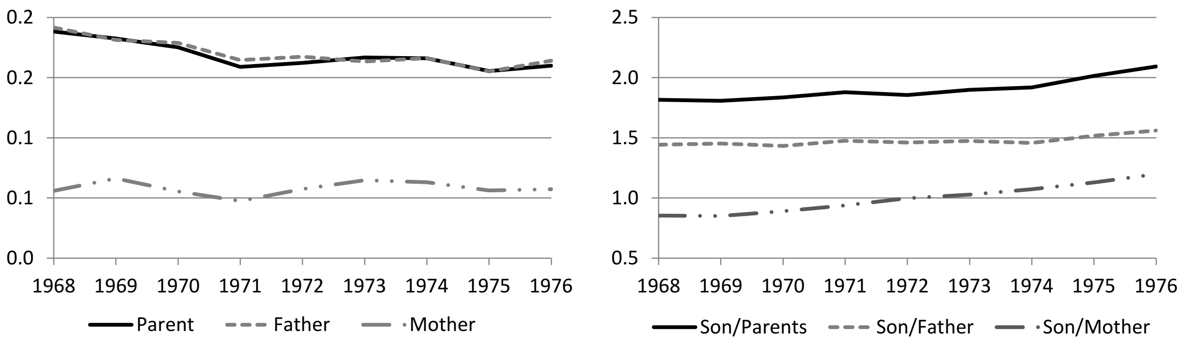
The IGE shows a different development. Both the association between fathers and sons, and parents and sons first declined and then increased again, while the IGE between sons and their mothers increased just slightly over the whole time span. According to the IGE we could thus conclude that the association between son and parent income for the youngest cohorts is just as high as for the oldest cohort, while the rank-rank slope would suggest a decline in the income association.

Equation 7 in section 2.2 can help to explain this apparently contradictory finding: The rank-rank slope is simply the correlation coefficient between the percentile ranks of sons and parents, and the linear dependence between sons and their fathers as well as sons and their parents in terms of income rank has declined over time (and not been subject to a change between sons and their mothers).

The IGE on the other hand is the product of (a) the correlation coefficient between log child income and log parent income and (b) the ratio of their standard deviations. The development of both measures between 1968 and 1976 is shown in figure 5. We can see that the increase in IGE for the later cohorts is driven by an increase in the relative variance of the son income distribution compared to their parents, and not an increase in the linear dependence between the incomes of two generations.

Figure 5: Log Income Distributions

(a) Correlation Coefficients (b) Ratio of Standard Deviations



5 Mobility Across Regions

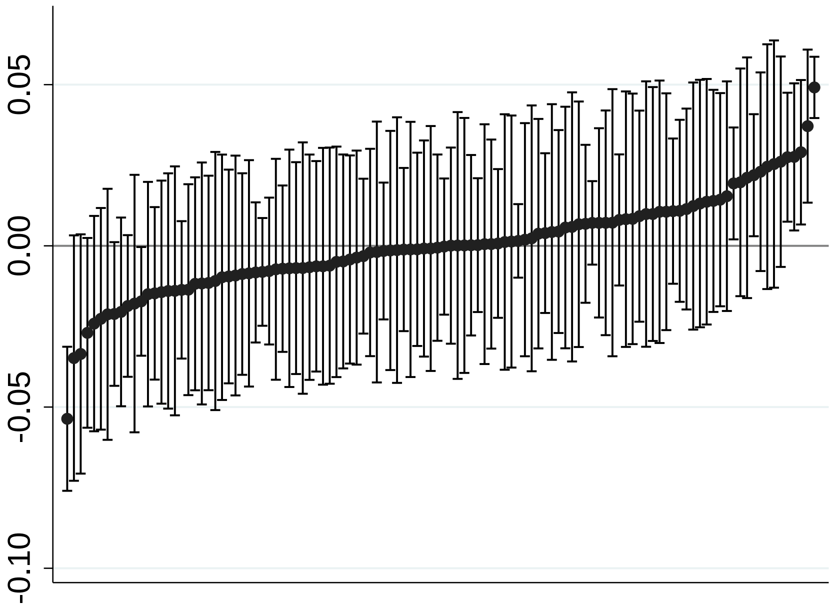
The multilevel analysis reveals some interesting facts about intergenerational mobility across Sweden. The first part in this section discusses the results from the multilevel model and their implications for relative and upward mobility on the regional level. In the second part, I focus on children growing up in very rural areas who are shown to have the lowest expected income ranks as adults.

5.1 Relative- and Upward Mobility on the Regional Level

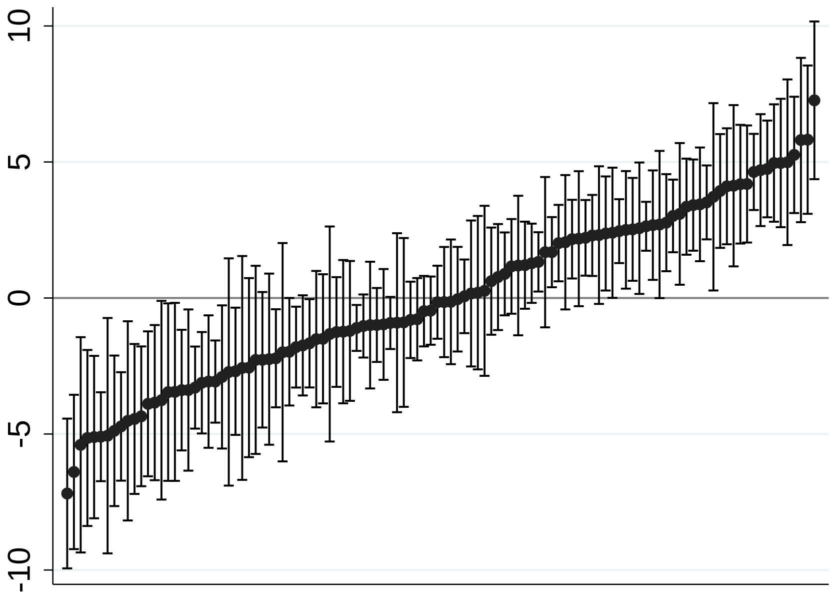
The results of the multilevel model (1) from section 2.3 can be summarized nicely by plotting the predicted slope- and intercept-random effects for each region, relative to the estimated average values across all regions (see table A.4 in the appendix for the detailed estimation output). The slopes and intercepts are used in a later step to compute relative- and upward mobility according to the formulas in section 2.2. As shown in figure 6a, the estimated slope-random effects vary at first glance greatly across Sweden. The regional slopes to the left

Figure 6: Regional Effects

(a) Slopes



(b) Intercepts



Note: The upper panel shows the 112 random intercepts relative to the fixed effect, i.e. the average intercept across all regions (the horizontal line), sorted in ascending order from left to right. The error bars indicate 95% confidence intervals. Regions that include the horizontal line in their confidence interval do not differ statistically from the average. The lower panel shows a similar graph for the estimated random rank-rank slopes relative to the fixed effect slope.

with data points below the horizontal line are smaller than the average, and the regional slopes located above the line to the right are larger. However, most estimates are not significantly different from the average: most of the 95 percent confidence intervals (shown as error bars) include the horizontal line at zero which indicates the average intercept. Of all 112 regions, only 2 show a significantly flatter slope (weaker association between parent and son income rank), and 7 regions show significantly steeper slopes (stronger association). If we had used separate OLS regression for each region, we would probably have overstated the differences in rank-rank slopes over regions since there is no easy way to compare the estimates of many disjoint regressions.

As opposed to the slopes, the regional intercepts (shown in figure 6b), differ significantly from the average in most local labor markets. Thus, we know already that mobility measures based on absolute outcomes will show large differences between regions, while relative measures might not reveal this information.

The fixed-effects (regional average) slope estimate shows that a ten percentile increase of parent income rank implies, on average, an increase of 2.2 percentile ranks for the son (see table A.4 in the appendix for the detailed estimation output). The average slope coefficient across regions is thus slightly smaller than the average slope coefficient across individuals from section 4.2 above (2.38).[16] With a correlation coefficient of -0.54, we also learn that regions with steeper rank-rank slopes on average have lower intercepts.

The relationship between the multilevel model, separate OLS regressions for each region, and the completely-pooled estimates are demonstrated in figure 7. The top panel shows Dorotea, a local labor market region in the north of Sweden with 147 observations. The dotted line shows the mobility estimates from a separate regression: the line is almost completely flat and would indicate extremely high levels of relative income mobility. However, the large spread of the underlying binned scatter plot in gray shows the inefficiency of the estimation and thus how unreliable this result is. The best linear unbiased predictor (BLUP) from the mul-

[16]It is possible that this difference is due to the 2.5 percent of sons who cannot be assigned to a childhood region: if sons with outcomes similar to their parents' are over-represented in the group of dropped observations, average mobility will increase (and the slope coefficient decrease).

tilevel estimation (given by the solid line) deviates from this extreme result and pulls towards the dashed line above, which represents the average mobility level across all regions.

The bottom panel in figure 7 displays a similar figure for Stockholm. According to the gray dots of the binned scatter plot, the observations are located much closer to a line. The multilevel estimates (BLUPs) coincide here completely with the estimates from a regression run exclusively for children grown up in Stockholm (the solid line and the dotted line are indistinguishable from each other). With 67,228 observations there is no shrinkage toward the pooling-result happening at all.

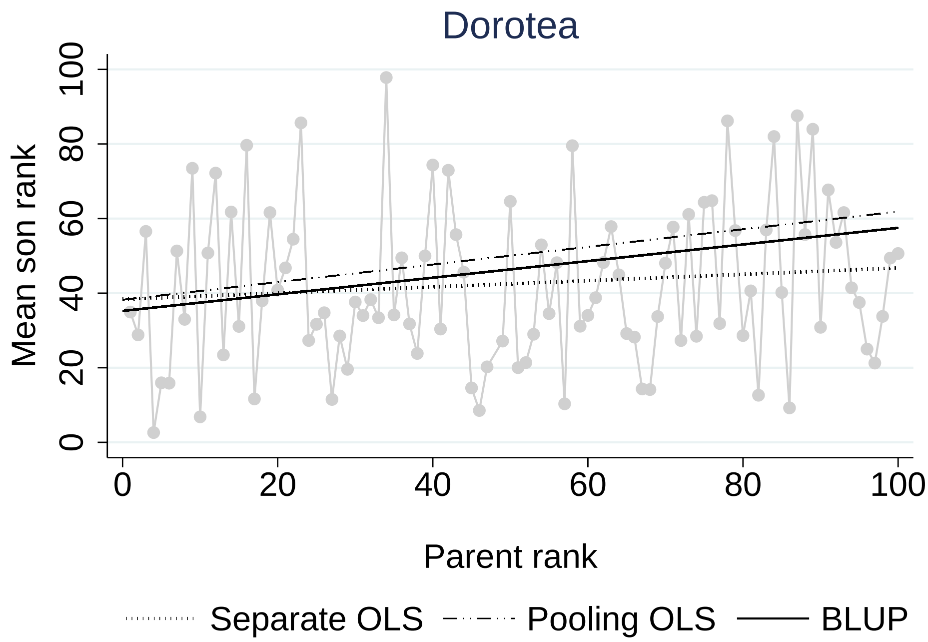
When we add the five regional types (from large city to sparsely populated regions) to the model with large cities as the reference category, we find that only the additional "fixed effect" for sparsely populated regions is significant: growing up in an extremely rural local labor market region reduces the average income rank of sons by 4.4 percentile ranks. The rank-rank slope is significantly different compared to large cities in both small regional centers and other small regions. Here, the association between son and parent income rank is slightly smaller which implies slightly higher relative mobility. Adding the regional types to the model results in a reduction of the variance between regions for the intercepts, but not for the slopes, as can be seen from the lower part of table A.4.

I calculate relative- and upward mobility for each region using the predicted region specific intercept and slope if they are significantly different from zero, and the estimated average value otherwise. The results obtained this way can therefore be interpreted as a lower bound of the existing regional differences in mobility. The complete list of results by local labor market can be found in table A.5 in the appendix.

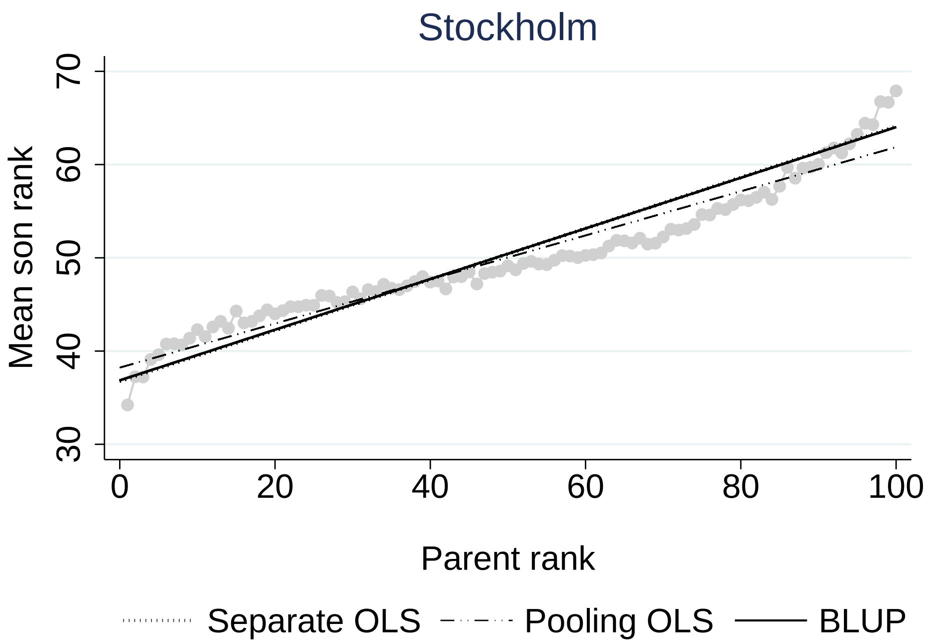
Relative mobility is higher than the average in the two regions Umeå and Uppsala only. The expected outcome difference between top and bottom income families in Umeå is just 16.83 percentile ranks and 20.48 in Uppsala. Seven regions show less than average relative mobility, with Stockholm ranking lowest. Here, the average outcome of sons from the highest and lowest income families differs by 27.11 percentile ranks.

Figure 7: Comparison of Estimation Strategies

(a) Positive shrinkage



(b) No shrinkage



Note: The upper panel shows a binned scatter plot of son and parent income ranks for Dorotea, with three different fitted lines from (1) a separate OLS regression, (2) the national OLS regression, and (3) the Best Linear Unbiased Predictors from the multilevel model. The multilevel estimates are close to the national average and gives less weight on the within-LLM information. The lower panel shows a similar figure for Stockholm. The results from (1) and (3) are here indistinguishable from each other.

Upward mobility varies from 36.32 in Torsby to 50.77 in Hylte[17], with an average of 43.69 across all regions (standard deviation 3). Calculating the percentiles back to income levels, we find that the expected difference in outcome between growing up in Torsby or Hylte for sons from below-median income parents amounts to 32.842 SEK less income per year ($\approx$3.839 USD).

Figure 8 shows relative and upward mobility for all regions. The crossed lines through the center of the plot indicate the average levels of relative and upward mobility, respectively.[18] The arrow-tips indicate the direction in which mobility is increasing (note: high values of relative mobility indicate less mobility due to stronger associations between parent and child income). The quadrant marked with a large plus (minus) sign indicates regions with both above (below) average relative and upward mobility. The data point right in the center represents not one but 45 regions which all have average levels of both mobility measures.

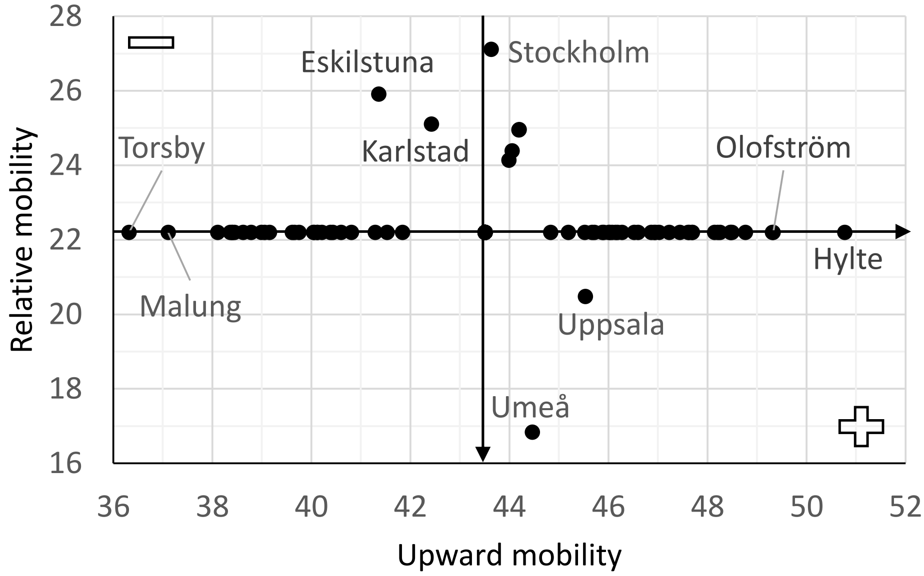
All regions with extremely high- or low levels of upward mobility show just average levels of relative mobility. Thus, even though the relative difference between sons from the highest and lowest income families in, for example, Torsby and Hylte, is the same, sons from below-median income families in those regions will end up with very different levels of income. Using the IGE or the rank-rank slope as the only measure for mobility, this difference would go completely unnoticed.

Stockholm and Malmö have very similar levels of upward mobility, i.e. the same expected outcome for below-median income families. However, due to the much steeper rank-rank slope, sons growing up in Stockholm achieve in general better outcomes than sons growing up in Malmö, and the difference is increasing in parent income rank. Thus, sons from high income families do better when growing up in Stockholm compared to Malmö. Figure A.4 in the appendix shows the expected son outcomes over the whole parent income distribution for some of the local labor markets.

[17] Torsby is located in middle-west Sweden bordering Norway, and Hylte at the west coast south of Göteborg

[18] Assuming average values whenever the 95 percent confidence intervals include zero for the regional random effects.

Figure 8: Relative and Upward Mobility by Region



Note: For each region, relative mobility is plotted against upward mobility. The lines of the crosshair indicate the average levels of the measures. The data point right in the center is actually an overlay of 45 regions, all with average mobility. The quadrant marked with a plus (minus) sign indicates areas with above-average (below-average) mobility levels according to both measures.

The estimates from this study can be compared to the results from Chetty et al. (2014a) for the US. There are some important differences between our studies, besides the obvious issues such as population size. The child cohorts in Chetty et al. are younger (born 1980 - 1982) and life time income for the children is measured at a slightly younger age (during 2010 - 2012 for all cohorts). Importantly, their income variable includes capital income and is calculated per family instead of individually. Parents are age 15 to 40 at child birth and their income is measured between 1996 and 2000. This means that parents are between 29 and 60 when their income is measured (compared to the same age for all parents in this study). The US study includes both sons and daughters.

We can compare the middle 80 percent of the distribution of US commuting zones and Swedish LLMs in terms of upward mobility and relative mobility: upward mobility at the tenth percentile of all regions is 37.4 percentile ranks in the US and 39.1 percentile ranks in Sweden. Commuting zones at the 90th percentile in the US show upward mobility of 52 percentile ranks, Swedish LLMs 47.7. The mean (43.3 in the US and 43.7 in Sweden) and middle 80 percent of the distributions of upward mobility by commuting zone and LLM in the US and Sweden are therefore quite similar, although the tails are thicker in the US with more extreme values at the very top and bottom. Relative mobility on the other hand varies much more in the US, where the outcome difference in percentile ranks for children from families at the top and bottom of the distribution takes on values between 6.8 and 50.8. In Sweden, relative mobility across LLMs varies only between 16.8 and 27.1 percentile ranks.

It is important to keep in mind that Chetty et al. do not discuss how their individual regional estimates relate to each other and in how far they significantly differ from each other (or from the US-average). My results are more conservative both in the sense that my estimation method accounts for the number of observations (which gives less extreme results), and because I choose to compute the mobility measures using the regional predictions solely if they differ significantly from the Swedish average.

Since the income distribution is much more compressed in Sweden compared to the US, the distance between two ranks in terms of income levels is considerably smaller in Sweden. The monetary difference between the top and bottom 10 percent of US commuting zones in terms of upward mobility is 12,600 USD (labor and capital income), while the same difference between Swedish LLMS amounts to just 19,362 SEK (≈2,353 USD) (labor income only).

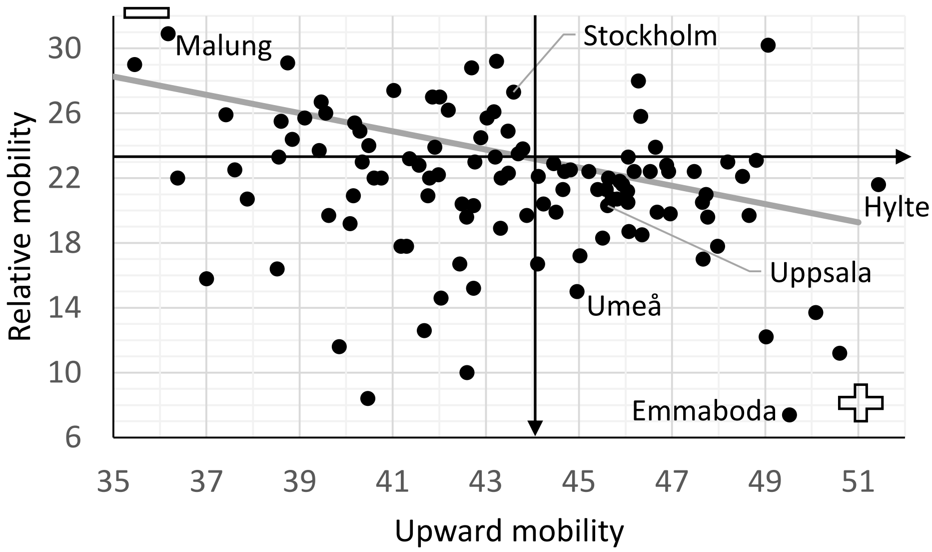
There are four local labor markets that stick out: Eskilstuna and Karlstad with both below average relative- and upward mobility, and Uppsala and Umeå with both above average relative- and upward mobility. Even though an in-depth analysis of the underlying forces driving this result is beyond the scope of this paper, we can look at one known factor correlated with mobility, namely income inequality. Countries with more income inequality have been shown to have less intergenerational income mobility. This relationship has become known as the Great Gatsby Curve, see for instance Corak (2013).

A simple indicator of income inequality is the ratio of median income to mean income level which informs us about the skewness of the income distribution. Across all municipalities in Sweden in 1991, weighted by population size, this measure is 0.9586, i.e. the median income level amounts to 95.86 percent of the mean income and the distribution is thus, as expected, right skewed. Looking at at this indicator separately for the local labor markets Umeå (96.93), Uppsala (95.72), Eskilstuna (96.79) and Karlstad (95.63), we do not find a pattern that could explain the very high/ low combined mobility results. Looking at relative mobility only, however, has some evidence for the relationship between high income inequality and low relative mobility: The Stockholm region has the most right-skewed income distribution (the median income level is just 92.65 percent of the mean income level) and also has the lowest levels of relative mobility among all Swedish LLMs.

5.2 A Comparison to OLS

Figure 9 visualizes relative and upward mobility just as in figure 8 in section 5.1, but here based on 112 separate OLS regressions by region. As expected, the regions differ more in terms of both mobility measures compared to the multilevel approach.

Figure 9: Relative and Upward Mobility by Region using Separate OLS Regressions

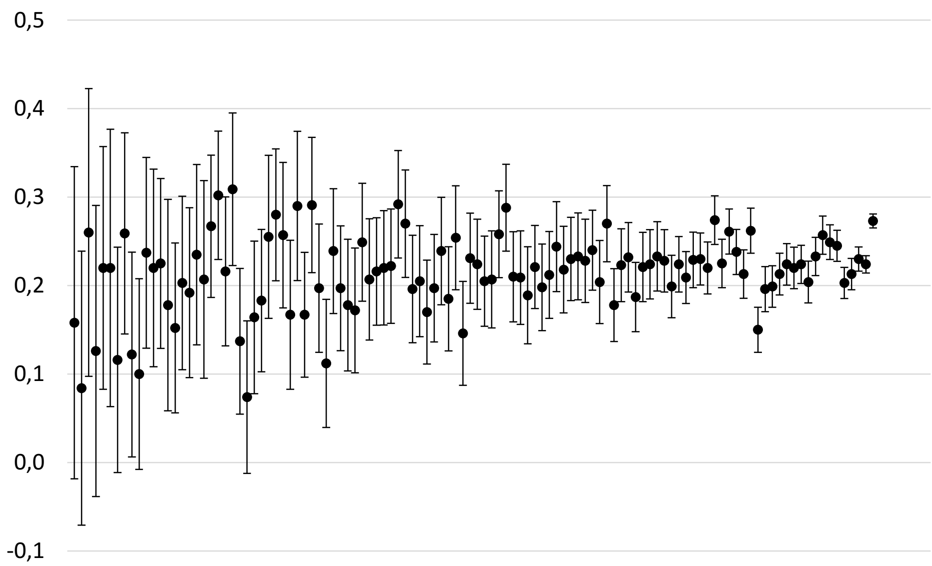


Note: For each region, relative mobility is plotted against upward mobility. The lines of the crosshair indicate the mean of each measure, calculated from the 112 OLS regressions. The gray line shows the fitted values from an OLS regression of the 112 relative mobility results on upward mobility, weighted by the number of observations in each region.

Especially relative mobility (the difference in mean outcome for sons from the families with the highest and lowest income, respectively) varies considerably more: from a 7.4 percentile ranks difference in Emmaboda to 30.9 percentile ranks in Malung. However, as I emphasize in this paper, it is not obvious how to interpret these differences.

Figure 10 illustrates the rank-rank slope estimates underlying the mobility measures obtained by separate OLS regressions in figure 9 above. The regions are sorted in ascending order by number of observation from left to right. It is clear that the lowest and highest slope estimates are found on the left side of the graph, together with the largest standard errors. In addition, most regional slopes are statistically indistinguishable from each other. There is no obvious way to compare the estimates of the 112 regressions. Thus, based solely on those regressions, an interpretation of regional differences in mobility is in the Swedish context not very convincing.

Figure 10: Rank-Rank Slopes and their 95% Confidence Intervals



Note: Every black dot represents a point estimate of the rank-rank slope for one region (112 in total). The regions are sorted in ascending order from left to right. In general, the fewer inhabitants in a region (the more to the left in the graph), the less efficient is the slope estimate.

5.3 The Impact of Regional Types

The model including regional types showed that very rural areas exhibit significantly lower intercepts and thus lower levels of upward mobility than other regional types. This can also be seen from figure 8, where the data points to the very left (lowest upward mobility) all represent very rural local labor markets.

An interesting question is if these lower absolute outcomes of sons growing up in the country side persist independently of location choices later in life. Differently put, are there differences between sons from rural areas who move to the city and those who stay?

Figure 11 shows fitted regression lines for son income rank on parent income rank for the subsample of sons who grew up in a very rural (type 5) area, by type of region those individuals lived in at age 33. It is clear that there are large differences depending on where individuals choose to live as adults: the average outcome of sons, for all parent income ranks, are clearly highest when moving to large cities, and smallest if staying in a very rural area.

Figure 11: Son and Parent Income Associations by Adult Location
(Childhood: Sparsely Populated Regions (T5))

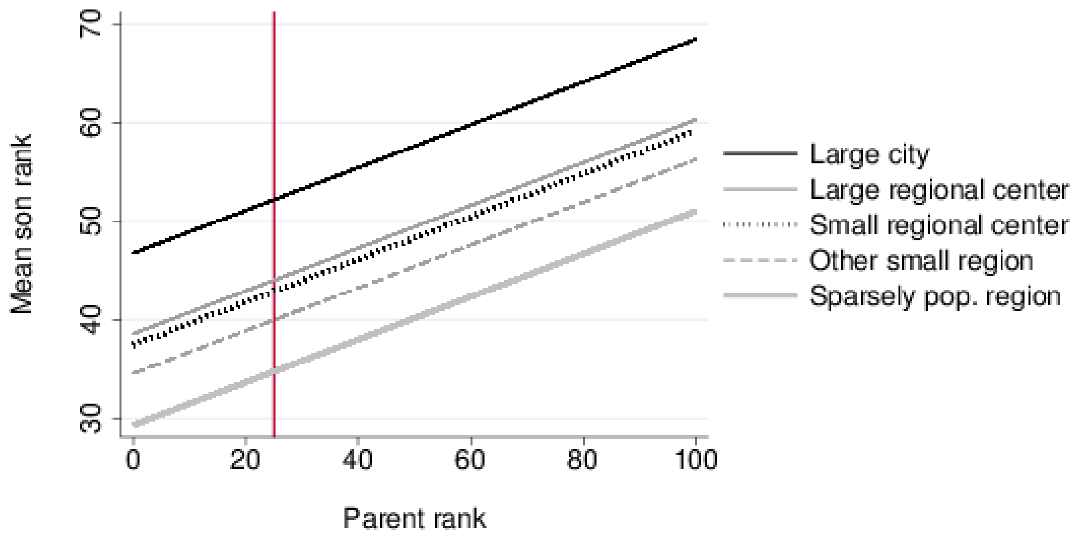


Table 3 shows the moving patterns of the individuals in my sample in percent. The first row, for example, shows that more than 90 percent of the sons who grew up in a large city (type 1) also live there as adults, while less than 1 percent moves to rural areas (type 4 and type 5). The last row shows children from very rural areas. A very large share, 52 percent, lives in a very rural area even as an adult. Going back to the results for local labor markets, we can say that sons from rural areas do well when moving to urban areas. However, since only few do so, the average outcomes for all sons from rural areas is as low as it is. [19]

[19]Note that I am not making a causal statement here: there are possibly very large differences between those sons

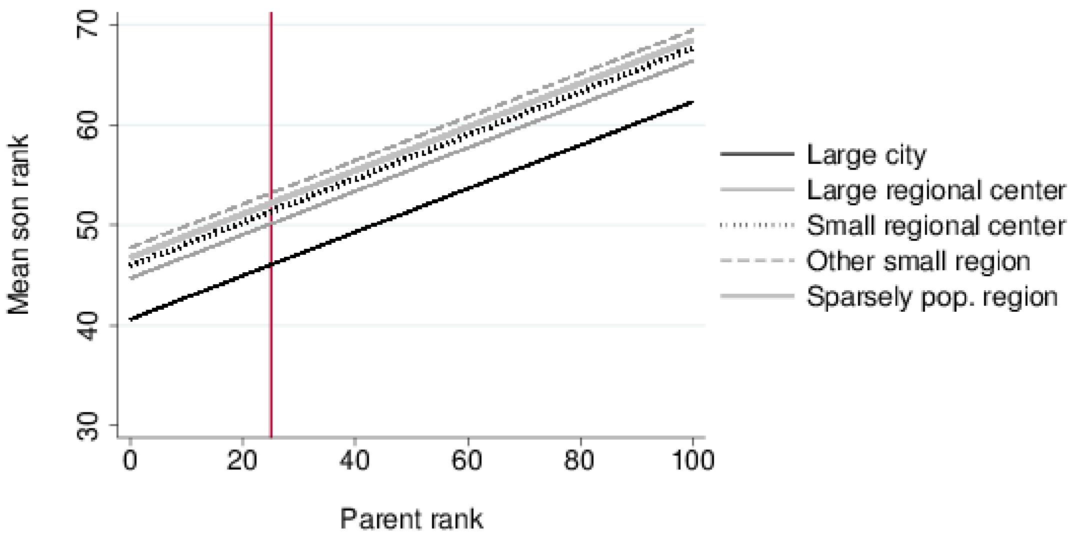
Table 3: Moving Patterns between Regional Types

		Adult					
		T1	T2	T3	T4	T5	Total
Childhood	T1	92.24	5.28	1.92	0.30	0.25	100
	T2	31.87	63.58	3.41	0.67	0.47	100
	T3	24.84	25.42	47.02	2.14	0.57	100
	T4	18.98	28.50	13.88	36.09	2.56	100
	T5	16.38	25.44	5.19	1.39	51.61	100
	Total	49.00	34.59	11.72	2.74	1.95	100

Note: The cells are relative frequencies, by childhood region type. The first row for instance indicates that 92.24% of sons who grew up in a large city stay there as adults.

The local labor markets with the highest levels of upward mobility (the data points to the right in figure 8) are surprisingly also rather rural (type 4), but not as remote as type 5 areas. An analysis for the subsample of sons growing up in type 4 regions by adult location shows a very similar patter as figure 11: the more urban the adult location, the higher the average outcome. Since much fewer type 4-children choose to stay in the country side compared to sons from type 5 areas, however, the overall result of high upward mobility follows.

Figure 12: Son and Parent Income Associations by Childhood Location
(Adult location: Large Cities (T1))



that move to a city and those that stay (ability, education, occupation, etc.).

Interestingly, we see that children who grew up in the country side actually do much better in absolute terms than those who grew up in the city, when comparing all children that live in large cities as adults (see figure 12). This could be a result of sorting behavior: more able individuals growing up in rural areas might choose to get more education and, as a consequence, move to larger cities that offer appropriate jobs and career opportunities. However, less able individuals who grow up in urban areas might just stay there (no active choice of relocation), which results in a different mixture of individuals with an urban childhood, compared to the ones who only moved into the city as adults.

6 Discussion and Concluding Remarks

In this paper I have used detailed population-wide register data on nine Swedish cohorts and their parents to draw a picture of intergenerational mobility in and across Sweden. I have focused on estimating the intergenerational elasticity, as well as the relationship between percentile ranks from one generation to the next.

In line with previous literature, I have focused on income measurements at ages where annual income is most likely to equal average life-time income. These measures were constructed by averaging over 17 consecutive annual income observations for parents (when they were 34 to 50 years old) and three annual income observations for children (when they were 32 to 34 years old). A great advantage of the data is that I am able to measure parental income at approximately the same age for each parent, as well as over a very long time span.

For Sweden as a whole, the estimated IGE between parents and their children is 0.3. This implies that 30 percent of the difference between parent income and the average parent income is inherited by a child. The association between the log incomes of parents and sons is 0.33 and thus even stronger. Using income ranks, I found that a 10 percentile rank increase in parent income implies a 2.38 percentile rank increase of the son's income.

Interestingly, child income is more strongly associated with total parent income than with father income. In the case of the IGE, the child-parent association exceeds the sum of the individual elasticities between child and father and child and mother income. This suggests an important role of parent matching for income transmission, and is an interesting direction for future research.

Focusing on each cohort separately from 1968 to 1976, I found a decrease in the rank-rank association over time (reflecting an increase in mobility over time). This holds true both when considering the association between father income and son income as well as when considering the association between total parent income and son income. The IGE, on the other hand, suggested an *increase* in this association between 1971 and 1976 (and thus a *decrease* in mobility over time). The IGE is here misleading since it mainly reflects the growing variance in the income distribution of sons over time.

In my regional analysis I have estimated mobility measures (relative and upward mobility) for all Swedish local labor markets. This geographical unit is reasonable in the context of intergenerational mobility since it is small enough to account for immediate conditions and the local community, but large enough to capture more general local labor market conditions. The allocation of children to regions was based on the municipality where the child has lived during at least 6 years between age 6 and age 15. I have also tested the robustness to alternative ways of allocating individuals to regions.

My primary measurement vehicle of regional differences has been a multilevel model. However, I have also reported the results from separate regional OLS regressions. The multilevel analysis revealed that relative mobility, the difference in outcomes between two sons with parents in the top and bottom one percent of the national distribution, respectively, is 22.2 percentile ranks in most regions. The strongest association (lowest relative mobility) between son and parent income rank was measured in Stockholm, where the relative outcome difference is more than 27 percentile ranks. On the other end of the spectrum we found Umeå and Uppsala, with the weakest association between income ranks and a relative difference of 16.8 and 20.5 percentile ranks between sons from the highest and lowest income families, respectively.

It is fair to say that upward mobility varies greatly across Swedish local labor markets. The lowest upward mobility (the expected outcome for a son with below-median parent income) is 36.3, measured in Torsby. In Hylte, sons with below-median parent income can expect to reach the 50.8th percentile as adults, more than 14 percentile ranks higher than in Torsby. This difference between growing up in the most and least favorable regions corresponds to 32,842 SEK ($\approx$ 3,898 USD) in yearly income. When using only the IGE or rank-rank slopes to study mobility, these differences in upward mobility would be completely invisible.

Even though the Swedish income distribution is considerably more compressed than the US distribution (measured in terms of percentile locations), the distributions of regional upward mobility estimates for the two countries are similar. Relative mobility on the other hand varies considerably less in Sweden than in the US.

In regions that can be classified as very rural, son outcomes given parent income rank are more than 4 percentiles lower as compared to other, less rural areas. A closer look at the group of sons who grew up in those regions revealed that their outcomes differs greatly depending on where they live as adults. Moving to less rural areas lifts incomes significantly. However, less than half of them choose to move to more urban areas and the low absolute outcomes for this group as a whole remain.

Turning this analysis around and looking at everyone in the sample who lives in a large city as adults, we saw that kids who grew up in rural areas actually do better compared to city kids. This could be a consequence of sorting behavior: highly educated individuals with a rural childhood move to large cities in order to pursue professional careers, while urban kids might stay in the city independently of productivity, education, or occupation (over 90 percent of the sons growing up in large cities live there even as adults).

Sweden is considered to be a country with exemplary high levels of intergenerational income mobility. My results show that there are large differences in terms of mobility across Sweden and that location matters. The evidence provided here indicates that there are particularly large differences in the expected outcomes for children from the lower half of the income distribution, depending on childhood region and moving patterns. A general lesson of this study is that country-wide measures of income mobility might say very little about the state of mobility at a particular location within the country. Cross country comparisons of income mobility, for example, should therefore be interpreted with caution.

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Appendix

A Ranks versus Logged Incomes

In order to judge the use of logged incomes against income ranks, we can look at the fit of the data to a linear model, the distribution of zero income observations, and the sensitivity of the mobility estimates to how zero income observations are treated. Figure A.1a shows a binned scatter plot of logged incomes for parents and sons, as well as the fraction of sons with zero income. The first part of the plot is created by binning the parents into 100 equally sized groups by log income (percentiles), and plotting the mean parent income versus the child mean income for each bin. The vertical lines show the 10th and 90th percentile of parent income, respectively. The reported regression coefficients and standard errors are estimated by OLS using the underlying micro data.

The relationship between log incomes of parents and sons does not appear entirely linear. The slope at the bottom as well as at the top 10 percent of the distribution is less steep than the middle of the distribution. As can be seen in figure A.1b, the non-linearity is even more pronounced in the relationship between log incomes of sons and fathers.

Figure A.2a shows a similar graph using percentile ranks instead of logged incomes, such that the mean son rank is plotted against mean parent percentile rank. For the pooled cohorts of sons and parents, the ends of the distribution diverge again visibly from the fitted regression line. The same is true for the relation between sons and fathers, although the fit in this case appears slightly better, see figure A.2b. The finding by Chetty et al. (2014a) that rank-rank slopes have a better linear fit than the log-log relationship cannot be said to hold in general.[20]

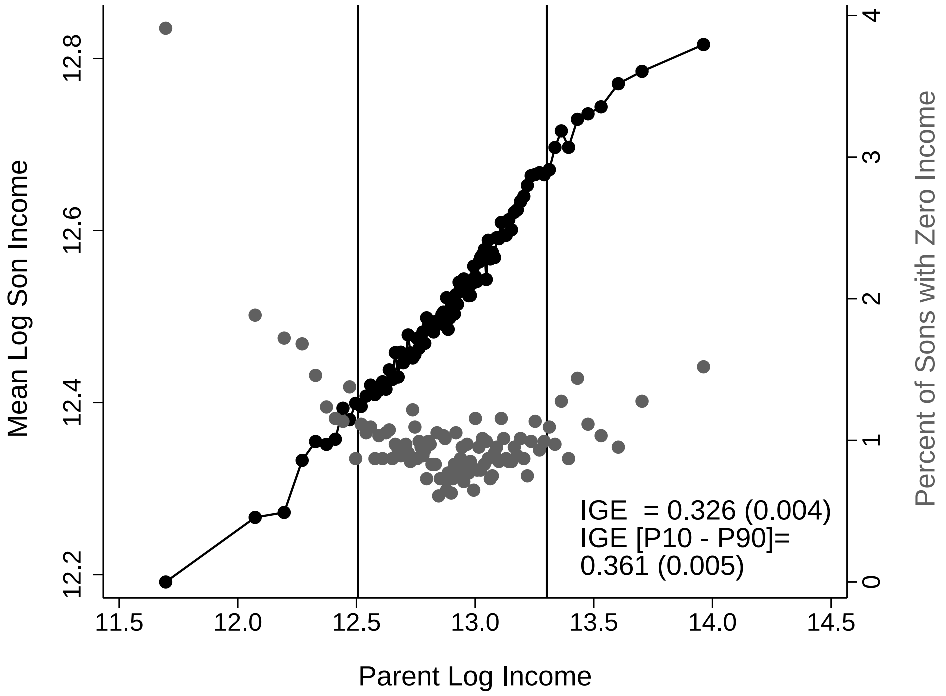
Next, we see also from figure A.1a that the number of children with zero income is clearly highest for parents in the lowest 10 percent of the distribution. Even the top ten percent of parents show a slightly higher number of sons with zero income compared to the middle 80

[20] Interestingly, a similar figure for Denmark shown in Chetty et al. (2014a, p. 1576) in panel B of figure II exhibits equally large deviations from the fitted lines especially at the bottom of the distribution, just as in Sweden. Small differences in low parental income rank result in sizable outcome differences for the children in the two Nordic countries Sweden and Denmark.

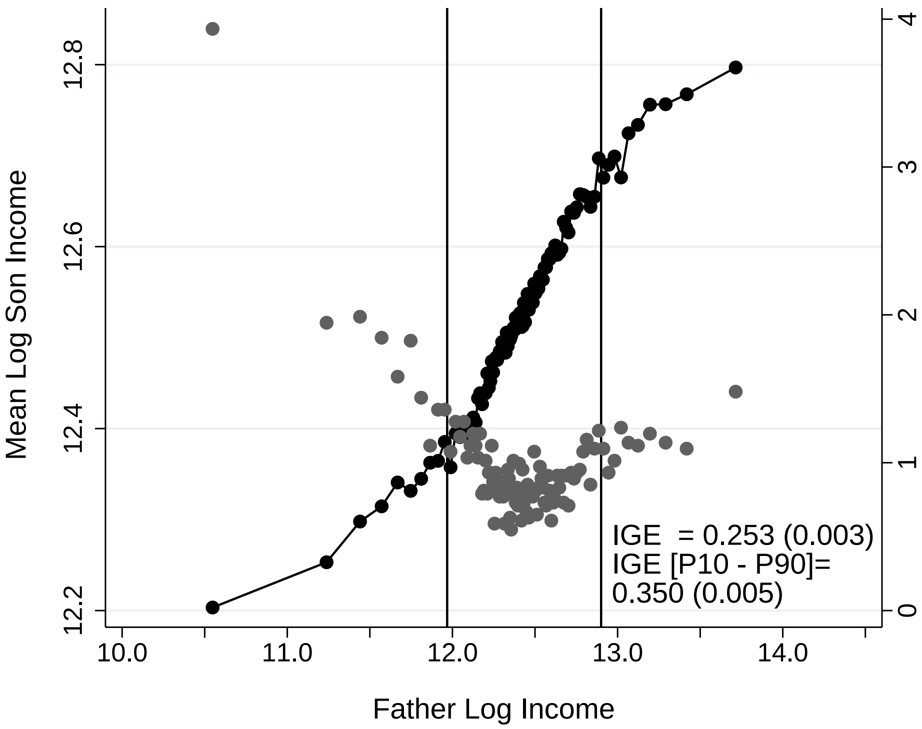
percent. An explanation for this might be the lack of information on capital income. Capital income tends to be concentrated at the top of the income distribution and could be a (here invisible) substitute for earned income. Since zero income children are over represented in the group of low-income parents (i.e., a strong association between parent and child income in the lower part of the distribution), dropping these observations would lead to an upward biased mobility estimate.

Figure A.1: Log Incomes

(a) Log Son Income vs. Log Parent Income



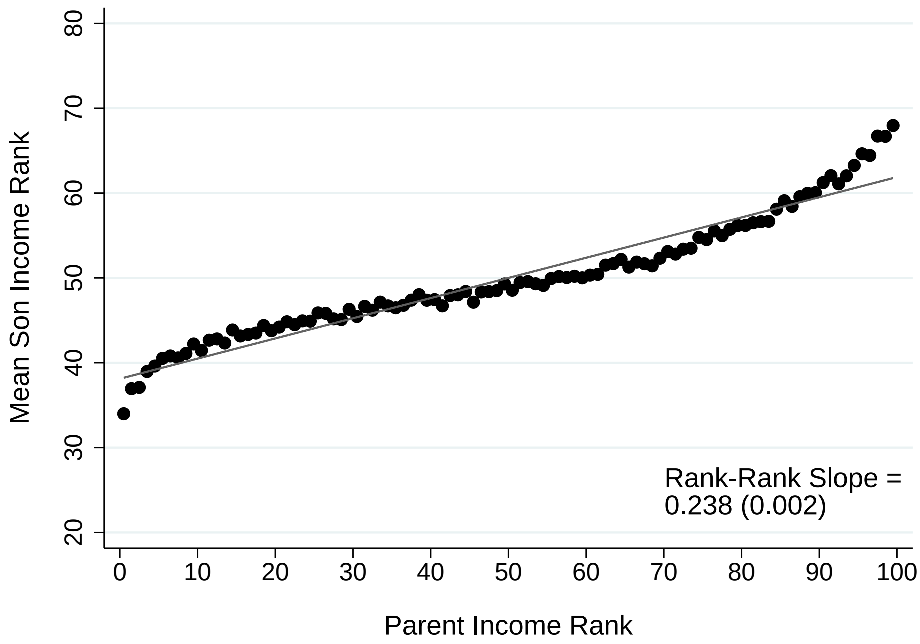
(b) Log Son Income vs. Log Father Income



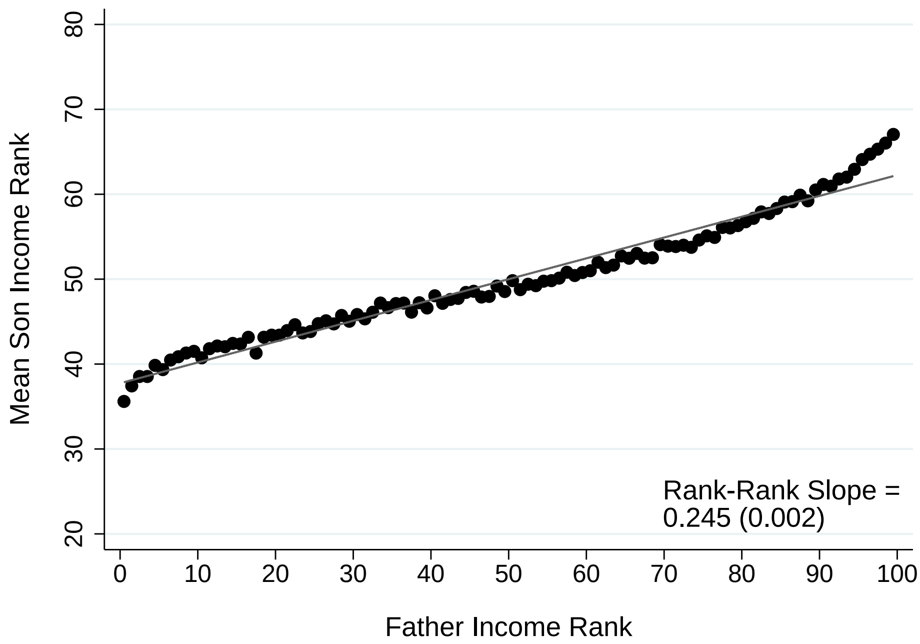
Note: These figures shows a visual regression of log son income on log parent (father) income income. Each black dot shows the mean log son income plotted against the mean log parent (father) income for one percentile of log parent (father) income. The gray dots (measured on the right y-axis) show the share of sons with zero income for each percentile of log parent income. The estimated IGE as well as the IGE between the 10th and 90th percentile are given in the figure.

Figure A.2: Income Ranks

(a) Mean Son Rank vs. Parent Rank



(b) Mean Son Rank vs. Father Rank



Note: These figures shows a visual regression of son income rank on parent (father) income rank. Each dot shows the mean son income rank plotted against the mean parent (father) income rank for one percentile of parent (father) income ranks. The estimated rank-rank slopes are reported in the figure.

Lastly, table A.1 shows the sensitivity of IGE estimates to the way zero incomes are treated. In the first column, all zero incomes are dropped from the data set. In columns two and three, zeros are replaced by 1 and 1000 SEK, respectively. In all specifications (rows), the IGE is very sensitive to how zeros are handled. The largest difference is found in the bottom 10 percent of the father's income distribution (second row) where the IGE almost doubles depending on the treatment. The sensitivity is also present within each cohort separately as shown in the last two rows for cohorts 1968 and 1972 only.

Given the data at hand, using income ranks instead of logged incomes is the preferred option. Importantly, the linear fit of the rank relationship is not found to be superior to logged incomes in general and should be carefully examined on a case by case basis.

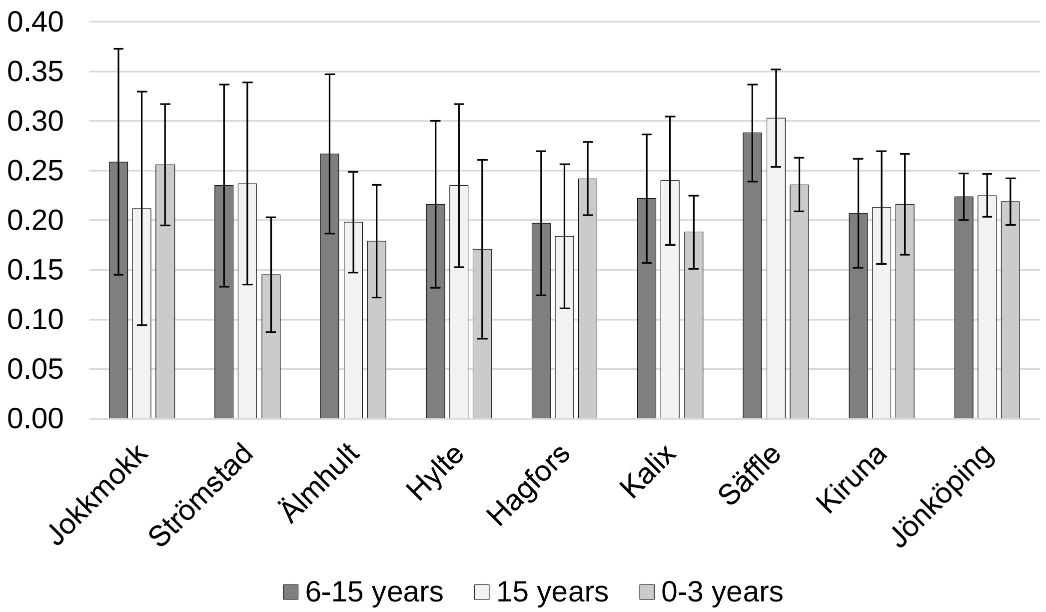
Table A.1: Sensitivity with Respect to the Treatment of Zero Incomes (IGE between Fathers and Sons)

	Exclude zeros	Replace by 1	Replace by 1000
Pooled	0.253	0.311	0.280
	(0.003)	(0.008)	(0.004)
< P10	0.109	0.259	0.201
	(0.011)	(0.03)	(0.016)
P10 - P90	0.350	0.369	0.356
	(0.005)	(0.013)	(0.007)
> P90	0.132	0.040	0.088
	(0.017)	(0.04)	(0.024)
1968	0.278	0.317	0.296
	(0.009)	(0.024)	(0.012)
1972	0.246	0.318	0.280
	(0.008)	(0.02)	(0.012)

Note: Standard errors are given in parentheses.

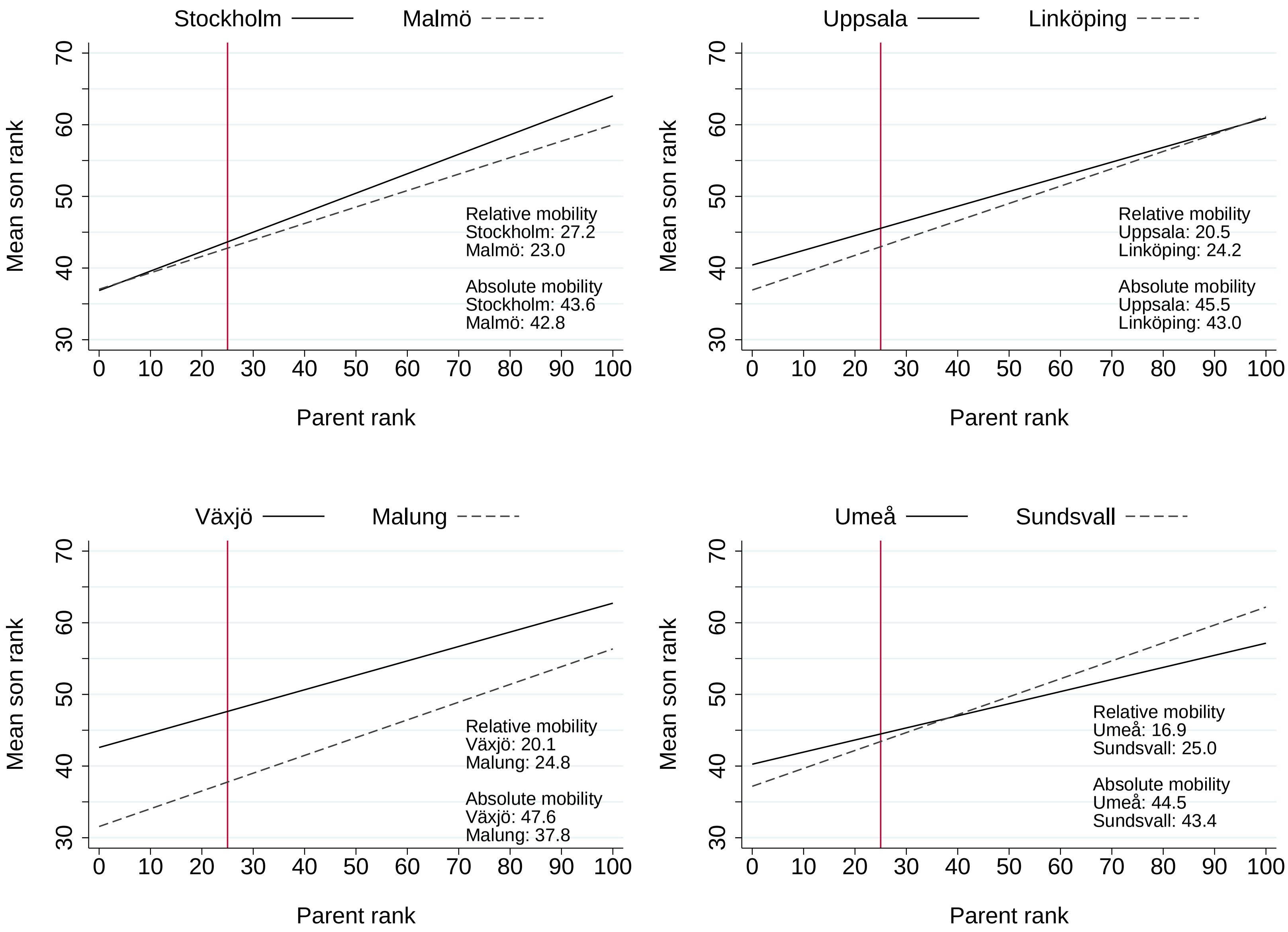
B Figures

Figure A.3: The Effect of Different Childhood Definitions on Mobility Estimates



Note: This figure illustrates the difference in rank-rank slope estimates for some small and medium sized regions when using different childhood definitions. The parameter estimates are obtained by separate OLS regressions by region. The size of the error bars shows 95% confidence intervals. The regions are shown in ascending order from left to right by number of observations. The smaller the region, the larger the differences between the three childhood definitions, and the larger the standard errors.

Figure A.4: Rank-Rank Relationships for some Regions



C Tables

Table A.2: Sample Summary

Child cohort	Fathers age at birth (st.dev.)	Mothers age at birth (st.dev.)	N sons	N daughters	Total
1968	28.0 (4.8)	25.2 (4.1)	43.662	41.573	85.235
1969	28.2 (4.7)	25.5 (4.2)	42.948	40.001	82.949
1970	28.3 (4.7)	25.7 (4.2)	44.003	41.739	85.742
1971	28.3 (4.6)	25.8 (4.2)	46.637	43.633	90.270
1972	28.3 (4.5)	25.8 (4.1)	46.110	43.350	89.460
1973	28.5 (4.4)	26.0 (4.2)	45.534	42.840	88.374
1974	28.5 (4.4)	26.1 (4.2)	45.930	43.284	89.214
1975	28.7 (4.4)	26.3 (4.2)	43.278	40.848	84.126
1976	28.9 (4.4)	26.4 (4.2)	40.993	38.590	79.513
Total	28.4 (4.6)	25.9 (4.2)	399.095	375.858	774.953

Table A.3: Classification of Local Labor Markets

T1 Large cities	T2 Large regional centers	T3 Small regional centers		T4 Other small regions		T5 Sparsely populated regions
Göteborg	Borås	Arboga	Nyköping	Bengtsfors	Sävsjö	Arjeplog
Malmö	Eskilstuna	Arvika	Oskarshamn	Emmaboda	Tidaholm	Arvidsjaur
Stockholm	Falun	Avesta	Simrishamn	Fagersta	Vara	Dorotea
	Gävle	Bollnäs	Skellefteå	Filipstad	Vimmerby	Gällivare
	Halmstad	Eksjö	Strömstad	Gnosjö		Haparanda
	Helsingborg	Falkenberg	Söderhamn	Hagfors		Härjedalen
	Jönköping	Gislaved	Tranås	Hedemora		Jokkmokk
	Kalmar	Gotland	Uddevalla	Hofors		Ljusdal
	Karlstad	Hudiksvall	Varberg	Hultsfred		Lycksele
	Kristianstad	Härnösand	Vetlanda	Hylte		Malung
	Linköping	Hässleholm	Värnamo	Hällefors		Pajala
	Luleå	Höör	Västervik	Kalix		Sollefteå
	Norrköping	Karlshamn	Älmhult	Kramfors		Sorsele
	Skövde	Karlskoga	Örnsköldsvik	Laxå		Storuman
	Sundsvall	Karlskrona		Ludvika		Strömsund
	Trollhättan	Katrineholm		Markaryd		Torsby
	Umeå	Kiruna		Munkfors		Vansbro
	Uppsala	Kristinehamn		Nässjö		Vilhelmina
	Västerås	Köping		Olofström		Ånge
	Växjö	Lidköping		Perstorp		Årjäng
	Örebro	Mariestad		Sunne		Åsele
	Östersund	Mora		Säffle		Övertorneå

Table A.4: Results from the Multilevel Model

N obs: 393,715 N groups: 112	Model 1		Model 2	
Fixed effects (average effects)				
Intercept	37.956***	(0.351)	38.105***	(1.634)
R_f^p: Parent income rank	0.222***	(0.003)	0.243***	(0.013)
T2: Large regional centers			0.444	(1.746)
T3: Small regional centers			0.973	(1.709)
T4: Other small regions			1.545	(1.768)
T5: Sparsely populated regions			-4.411***	(1.816)
T2$\times R_f^p$			-0.018	(0.014)
T3$\times R_f^p$			-0.025*	(0.014)
T4$\times R_f^p$			-0.038***	(0.015)
T5$\times R_f^p$			-0.014	(0.017)
Variance components				
Parent income rank, σ_β^2	0.0005***		0.0005***	
Intercept, σ_α^2	11.5436***		7.9117***	
Cov $\left(\sigma_\alpha^2, \sigma_\beta^2\right)$	-0.0414***		-0.0324***	
Residual, σ_R^2	781.0998***		781.0906***	
LR test M1 vs. linear regression: p = 0.000			LR test M1 vs. M2: p = 0.000	

Table A.5: Relative and Upward Mobility by Local Labor Market

	LLM	Relative Mobility		LLM	Upward Mobility
1	Umeå	16.84	1	Hylte	50.77
2	Uppsala	20.48	2	Olofström	49.33
3	Torsby	22.20	3	Gnosjö	49.31
4	Malung	22.20	4	Ljungby	48.77
5	Överkalix	22.20	5	Hofors	48.50
6	Vilhelmina	22.20	6	Avesta	48.47
7	Årjäng	22.20	7	Värnamo	48.47
8	Gotland	22.20	8	Varberg	48.25
9	Arjeplog	22.20	9	Oskarshamn	48.21
10	Sunne	22.20	10	Växjö	48.14
11	Mora	22.20	11	Vara	47.70
12	Jokkmokk	22.20	12	Gislaved	47.69
13	Härjedalen	22.20	13	Emmaboda	47.63
14	Strömsund	22.20	14	Älmhult	47.61
15	Hagfors	22.20	15	Vetlanda	47.44
16	Filipstad	22.20	16	Perstorp	47.23
17	Övertorneå	22.20	17	Skövde	47.02
18	Hällefors	22.20	18	Nässjö	46.95
19	Storuman	22.20	19	Nyköping	46.92
20	Söderhamn	22.20	20	Örnsköldsvik	46.86
21	Ånge	22.20	21	Hultsfred	46.60
22	Östersund	22.20	22	Jönköping	46.52
23	Bollnäs	22.20	23	Lidköping	46.27
24	Härnösand	22.20	24	Tranås	46.18

Continues on next page

Table A.5: Relative and Upward Mobility by Local Labor Market

	LLM	Relative Mobility		LLM	Upward Mobility
25	Lycksele	22.20	25	Göteborg	46.14
26	Ljusdal	22.20	26	Fagersta	46.07
27	Hudiksvall	22.20	27	Falkenberg	46.03
28	Västervik	22.20	28	Karlshamn	46.01
29	Skellefteå	22.20	29	Lysekil	45.90
30	Arboga	22.20	30	Köping	45.88
31	Arvidsjaur	22.20	31	Kristianstad	45.72
32	Arvika	22.20	32	Halmstad	45.67
33	Bengtsfors	22.20	33	Uppsala	45.53
34	Dorotea	22.20	34	Gävle	45.52
35	Falun	22.20	35	Borås	45.19
36	Gällivare	22.20	36	Helsingborg	44.83
37	Haparanda	22.20	37	Umeå	44.46
38	Hedemora	22.20	38	Sävsjö	44.20
39	Hässleholm	22.20	39	Eksjö	44.19
40	Höör	22.20	40	Vimmerby	44.05
41	Kalix	22.20	41	Kiruna	43.99
42	Kalmar	22.20	42	Stockholm	43.63
43	Karlskoga	22.20	43	Arboga	43.51
44	Karlskrona	22.20	44	Arvidsjaur	43.51
45	Katrineholm	22.20	45	Arvika	43.51
46	Kramfors	22.20	46	Bengtsfors	43.51
47	Kristinehamn	22.20	47	Dorotea	43.51
48	Laxå	22.20	48	Falun	43.51
49	Linköping	22.20	49	Gällivare	43.51

Continues on next page

Table A.5: Relative and Upward Mobility by Local Labor Market

	LLM	Relative Mobility		LLM	Upward Mobility
50	Ludvika	22.20	50	Haparanda	43.51
51	Luleå	22.20	51	Hedemora	43.51
52	Malmö	22.20	52	Hässleholm	43.51
53	Mariestad	22.20	53	Höör	43.51
54	Markaryd	22.20	54	Kalix	43.51
55	Munkfors	22.20	55	Kalmar	43.51
56	Norrköping	22.20	56	Karlskoga	43.51
57	Pajala	22.20	57	Karlskrona	43.51
58	Simrishamn	22.20	58	Katrineholm	43.51
59	Sollefteå	22.20	59	Kramfors	43.51
60	Sorsele	22.20	60	Kristinehamn	43.51
61	Strömstad	22.20	61	Laxå	43.51
62	Sundsvall	22.20	62	Linköping	43.51
63	Säffle	22.20	63	Ludvika	43.51
64	Tidaholm	22.20	64	Luleå	43.51
65	Trollhättan	22.20	65	Malmö	43.51
66	Uddevalla	22.20	66	Mariestad	43.51
67	Vansbro	22.20	67	Markaryd	43.51
68	Västerås	22.20	68	Munkfors	43.51
69	Åsele	22.20	69	Norrköping	43.51
70	Örebro	22.20	70	Pajala	43.51
71	Helsingborg	22.20	71	Simrishamn	43.51
72	Borås	22.20	72	Sollefteå	43.51
73	Gävle	22.20	73	Sorsele	43.51
74	Halmstad	22.20	74	Strömstad	43.51

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Table A.5: Relative and Upward Mobility by Local Labor Market

	LLM	Relative Mobility		LLM	Upward Mobility
75	Kristianstad	22.20	75	Sundsvall	43.51
76	Köping	22.20	76	Säffle	43.51
77	Lysekil	22.20	77	Tidaholm	43.51
78	Karlshamn	22.20	78	Trollhättan	43.51
79	Falkenberg	22.20	79	Uddevalla	43.51
80	Fagersta	22.20	80	Vansbro	43.51
81	Göteborg	22.20	81	Västerås	43.51
82	Tranås	22.20	82	Åsele	43.51
83	Lidköping	22.20	83	Örebro	43.51
84	Jönköping	22.20	84	Karlstad	42.43
85	Hultsfred	22.20	85	Skellefteå	41.84
86	Örnsköldsvik	22.20	86	Västervik	41.53
87	Nyköping	22.20	87	Eskilstuna	41.36
88	Nässjö	22.20	88	Hudiksvall	41.29
89	Skövde	22.20	89	Ljusdal	40.81
90	Perstorp	22.20	90	Lycksele	40.60
91	Vetlanda	22.20	91	Härnösand	40.43
92	Älmhult	22.20	92	Bollnäs	40.39
93	Emmaboda	22.20	93	Östersund	40.21
94	Gislaved	22.20	94	Ånge	40.12
95	Vara	22.20	95	Söderhamn	40.12
96	Växjö	22.20	96	Storuman	40.06
97	Oskarshamn	22.20	97	Hällefors	40.05
98	Varberg	22.20	98	Övertorneå	39.75
99	Värnamo	22.20	99	Filipstad	39.66

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Table A.5: Relative and Upward Mobility by Local Labor Market

	LLM	Relative Mobility		LLM	Upward Mobility
100	Avesta	22.20	100	Hagfors	39.62
101	Hofors	22.20	101	Strömsund	39.16
102	Ljungby	22.20	102	Härjedalen	39.06
103	Gnosjö	22.20	103	Jokkmokk	38.99
104	Olofström	22.20	104	Mora	38.78
105	Hylte	22.20	105	Sunne	38.62
106	Kiruna	24.14	106	Arjeplog	38.44
107	Vimmerby	24.39	107	Gotland	38.41
108	Eksjö	24.95	108	Årjäng	38.39
109	Sävsjö	24.96	109	Vilhelmina	38.36
110	Karlstad	25.10	110	Överkalix	38.11
111	Eskilstuna	25.91	111	Malung	37.11
112	Stockholm	27.11	112	Torsby	36.32

End