THE EFFECT OF MOVING DURING CHILDHOOD ON LONG RUN INCOME: EVIDENCE FROM SWEDISH REGISTER DATA

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ABSTRACT

In this paper I study the long-term effects of inter-municipal moving during childhood on income using Swedish register data. Due to the richness of the data I am able to control for important sources of selection into moving, such as parent separation, parents' unemployment, education, long run income, and immigration background. I find that children's long run incomes are significantly negatively affected by moving during childhood, and the effect is larger for those who move more often. For children who move once, I also estimate the effect of the timing and the quality of the move. I measure the quality of each neighborhood based on the adult outcomes for individuals who never move; the quality of a move follows as the difference in quality between the origin and the destination. Given that a family moves, I find that the negative effect of childhood moving on adult income is increasing in age at move. Children benefit economically from the quality of the region they move to only if they move before age 12 (sons) and age 16 (daughters).

JEL classification: D31, J17, J24, J62, R23
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1 Introduction

Levelling the playing field and ensuring that individual outcomes depend more on effort than family background is an outspoken goal of many western societies. However, differences in income and wealth have been growing significantly during the past decades (Organisation for Economic Co-operation and Development, 2015). In order to determine the most equitable and efficient form of public policy intervention to cope with this development, it is essential to understand the drivers of an individual's income, i.e. the human capital production function. Childhood is a very important phase during human capital development, since many skills that are capitalized during adulthood are obtained early in life. As Cunha and Heckman (2007) pointed out, skills produced at an earlier point in life will not only augment the skills attained at a later stage, but also increase the returns to later skill investments.

Recent evidence stresses the importance of neighborhood quality for children's long run outcomes (Chetty et al., 2015; Chetty and Hendren, 2015; Heidrich, 2015). However, identifying certain neighborhoods that are better or worse for a child's development leads to another question: what is the effect of moving from one neighborhood to another? If neighborhoods matter, moving to a better area can be thought to be beneficial for a child. However, there might also be disruption costs from moving. Being taken out of the home environment and having to adjust to a new neighborhood and school, finding new friends and leaving the old ones behind can negatively impact the human capital development of the child. Research in sociology for example indicates that moving can have negative effects on academic performance (Hagan et al., 1996). Disruptions during childhood can potentially accumulate to long-term effects, when taking into account the dynamic nature of human capital development. An important question is then whether these effects are economically important.

My contribution to the literature consists of the first estimates of the long run costs incurred by individuals due to childhood moving. I define those costs as the effect of childhood moving on long run adult income. I show not only that such costs exist and that they increase in the number of times a child moves, but also that the timing of the move matters. The results are well in line with predictions from the human capital literature where shocks in the skill formation process can accumulate to large differences in adult outcome (see for instance Cunha and Heckman 2007; Currie and Almond 2011; Heckman 2006; Heckman et al. 2013).

The main difficulty when trying to measure the costs of moving is selection. In observational data, we will suspect differences between families that move a different numbers of times, as well as non-randomness in the type of location that families move to and from. Parent income, for instance, is an important factor to take into consideration since higher income families are able to better compensate for disruption effects suffered by the child. Other transitions in family life that occur at a similar time as the move have the potential to confound the true effect of moving. Parental separation or unemployment are two common reasons to move, and these also affect children's outcomes independent of moving.

Based on earlier studies on child human capital production I estimate the effect of moving on long-term incomes with help of a detailed panel data set of Swedish families. The richness of my data allows me to control for many factors that would otherwise bias the results. The estimated moving costs are robust to the model specification, the covariates included, and the definition of moving used. An additional aspect to consider is that children can be expected to have only a minor say in when or where to move. That is, children are usually tied to their parents which suggests that any selection effect left can reasonably be assumed to be smaller compared to studying the effect of migration on adults (even if

some families move because of their child).

This paper relates to the literature on childhood neighborhood effects by focusing specifically on the cost of transitioning between two regions. Since moving is a form of disruption in a child's development, this study naturally relates to the field of human capital development, an overview of which can be found in Becker (2009). Early childhood development and skill formation in particular have been studied by Cunha et al. (2010), Currie and Almond (2011), Heckman et al. (2013) and others. The common conclusion is that children are highly sensitive to their environment in terms of developing both cognitive and non-cognitive skills.

This study also relates closely to the literature on migration and the family which goes back to Mincer (1978). While the decision to move usually boils down to a comparison of expected utilities in different locations, many studies have focused on labor market participation effects of married women. If both spouses work in the labor market, the probability of moving tends to be significantly smaller compared to a family with a stay-at-home wife (Rabe, 2011). A few studies specifically focus on moving within in the Nordic countries. Pekkala and Tervo (2002) studied unemployment and migration in Finland and showed there is no causal effect of moving on the probability of finding a job. Axelsson and Westerlund (1998) estimated the effect of moving within Sweden on household disposable income. They found no effect on income and no selection effects, i.e. no significant differences between the families that move and those who do not.

One of the few papers looking at the effects of moving on child outcome is Hanushek et al. (2004). They studied the effects of switching schools, both for the children that move and the externality of the move on classmates who experience others leaving or joining the class during the year. They find significant negative effects on test scores both for the children that move between schools, as well as negative externalities for the class mates.

In the first part of this paper, I study a large sample of children and their parents that move between zero and sixteen times between municipalities during childhood. My results suggest significant negative effects of moving during childhood on long run adult income. The effects differ by gender and parent income. Studying family moves between Swedish counties instead of municipalities, I find that the costs of moving on child long run outcome are very robust to the geographic unit chosen.

The second part of the paper focuses on a reduced sample containing only families that move exactly once during childhood. This way I can control for the type of move, i.e. if families move to areas that are relatively better or relatively worse for the child compared to their region of origin. Taking the type of move into account is important since recent research has shown that neighborhood quality matters for children's long run outcome, as well as what age the child starts living in the new neighborhood (see Chetty et al., 2015; Chetty and Hendren, 2015; Kling et al., 2007). I find that the negative effect of childhood moving on adult income is increasing in the age at the time of the move. I also show that if a family does move, then moving to a higher-quality region increases a child's long run outcome. However, sons have to move before the age of 12 in order to benefit from the better region. From age 12, the quality of the new region has no significant effect. Daughters have to move before the age of 16 in order to benefit from a better region. In general, the effects on daughters' adult income are smaller compared to sons.

The rest of the paper is structured as follows. In Section 2, I present the empirical framework first for the estimation of moving costs and then for the effect of timing and quality of the childhood move.

Section 3.1 contains the description of the data set and the variables used in this study. The family moving pattens in Sweden are described in Section 3.2. In Section 4, I present and discuss the results of the two parts of the empirical analysis as well as some robustness checks. Finally, Section 5 concludes.

2 Empirical approach

The human capital literature offers some guidelines on how to think about the effect of childhood moving on adult incomes. Currie and Almond (2011), for instance, used a model based on Grossman (1972) on the demand for health to study the effect of shocks in early childhood on long run human capital. In their model, adult human capital is a function of the sum of parent investments during childhood. Adult outcomes such as earnings or the health capital stock are determined by the human capital or health capital accumulated during childhood, following the investments and possibly depreciation of the existing stock. The impact of an early-life shock on adult outcomes will then depend on the substitutability of investments in different childhood periods and the share of total investment in the time period of the shock. The possibility to remedy a negative shock in a later period is dependent again on the substitutability of investments between time periods. The effects of a shock can either be reinforced or compensated for by a child's parents, depending on the parent's utility function.

In his work on childhood human capital developmentHeckman (2007) stresses the importance of both cognitive and non-cognitive skills in determining adult outcomes. Cognitive skills can foster non-cognitive skills and vice versa, and different childhood phases can be more or less important for each skill type's development. He also emphasizes the two skill formation characteristics dynamic complementarity and self-productivity, which imply that more skills accumulated in one time period increase the productivity of skill investments well as the size of skill stocks in later time periods.

In light of the existing models, moving during childhood represents a shock to the child's skills formation. The accumulated effect on human capital measured during adulthood will depend on the degree to which parents were able to compensate for this disruption. When the disruption happens at critical ages, however, compensation might hardly be possible. Thus, in the first part I will estimate the effect of moving (the disruption) on long run income. In the next part, I will analyze the effect of the timing at the move in order to learn the critical ages that this particular disruption has on human capital production.

2.1 Estimating the effect of moving on long run income

If long run adult income is assumed to be a function of human capital, we can expect to find lower incomes for individuals that moved during childhood, ceteris paribus. If we had an experimental setup at our disposal where we could pick a random sample of families and move them a random number of times to and from to random locations, we could to estimate

$$y_i^c = \beta_0 + \sum_{m=1}^{M} \beta_m I\left(\text{Moving}_i = m\right) + \varepsilon_i \tag{1}$$

by ordinary least squares, where y_i^c is child long run income as adult in family i, $I\left(\text{Moving}_i = m\right)$ is an indicator equaling one if the child moved m times during childhood, and β_m is the effect of moving m times during childhood on long run income. However, in absence of such an

experiment, I have to make sure to eliminate potential sources of selection that could bias the OLS estimator.

Any causal interpretation of β_m with observational data relies on the conditional independence assumption, also called selection on observables. That is, moving has to be as good as randomly assigned, conditional on the covariates (Angrist and Pischke, 2008). If the vector X_i includes all relevant controls, the true, "long" regression is

$$y_i^c = \beta_0 + \sum_{m=1}^{M} \beta_m I\left(\text{Moving}_i = m\right) + X'\gamma + \varepsilon_i. \tag{2}$$

The omitted variable formula shows that the regression coefficient for moving in the "short" equation (1) above (where we did not include A') is actually equal to

$$\frac{Cov\left(y_i^c, \beta_m\right)}{V\left(\beta_m\right)} = \beta_m + \gamma\,\delta_{AM}, \tag{3}$$

where δ_{AM} is the regression slope coefficient when regressing the omitted variables on moving. That is, omitting variables that are correlated both with moving and with child long run income will give a regression coefficient that is too large or too small, depending on the signs of the correlations.

There is some guidance in the literature regarding which factors simultaneously affect if and how often a family moves, and the long run income of the child in the family. Starting with the drivers of migration, families will move if the family's net real discounted income gain from moving is positive (Mincer (1978)). Since individuals made a rational choice about their current place of residence, only an unforeseen change in any of the variables determining the family's expected utility of a location will lead to a reevaluation of their choices. It is reasonable to assume that in most cases children follow their parents, and that it is the parents who decide if and where to move. Thus, I focus on the drivers of moving from the parents perspective. One typical reason is job search (see Greenwood (1997) for an overview of research on the causes and effects of internal migration). *Parent unemployment* history is therefore important to explain selection into moving. Young parents are especially likely to move, after completing their education and becoming employed. Thus, *parent age* at child birth should be included. *Parent income* can potentially also affect the moving decision: A better paying job enables a family to move to better regions, and career decisions leading to a steeper income growth might even require the family to relocate regularly. At the same time, low wages might cause a family to relocate to a region with higher relative wages. *Parent education* is an additional reason for moving which is closely related to parent income and unemployment. Highly-educated parents for example might need to move to specific regions in order to find qualified work. A different type of shock which influences a move is a disruption of the family itself. *Divorce* is quite likely to induce a move of one or both parents and the children. Lastly, there might also be a difference in moving patterns between families who live in urban or rural areas *(birth municipality type*).

All of the above reasons that cause families to moving potentially affect a child's long run income. Experiencing unemployment can be a difficult time for a parent both financially and in terms of well being and health. The children can be negatively affected directly by lower investments in their human capital, and indirectly by suffering psychologically. Younger parents that might move after finishing their education will on average also have lower income compared to older parents (who are already higher up on the career ladder), which lowers the investment into their young children and thus children's long run incomes. Studies have shown that children with divorced parents score significantly lower on

measures of academic achievement, conduct, psychological adjustment, self-concept, and social relations (Amato, 2001). Parent education and parent income is usually correlated with child income (see Black and Devereux (2011) or Jäntti and Jenkins (2015) for a survey of the literature on intergenerational income mobility). Parents can also compensate for any negative effects from the move depending on their income, as discussed in the beginning of this section. Growing up in a rural or urban area can also be correlated to child long run income, since individuals from large cities are usually less likely to move to the country side and because individuals in urban areas on average have higher wages than individuals living in the country side.

Even though my sample of children only includes individuals born in Sweden, the parents' country of birth still might impact a child's long run outcome. Children with foreign-born parents have been shown to perform worse academically compared to children with two Swedish parents (Skolverket, 2004). Moreover, we cannot exclude the possibility that immigrant parents differ in their moving patterns from native-Swedish parents. Therefore, I will include *parent immigration* status as a covariate.

The parents' decision to move can be driven by regional characteristics that affect all families in the region similarly. When studying families that move many times, one would have to trace the region-specific incentives that made a family move the fourth, third, second, and first time, and I will use differences between regions in the second part of this study only (where I focus on one-time movers).

Children's individual characteristics such as the highest education level and work experience are important when modelling earnings (Mincer, 1974). However, they cannot reasonably be assumed to cause the family to move during childhood and so are not included here.[1] The birth year of the children on the other hand might be important, since there could be different shocks in the economy making individuals more or less likely to move by a certain child age. There may reasonably also be cohort effects on long run income and birth *cohort* is therefore added as a covariate.

The child's *gender* is also potentially important since the human capital production function might look different for girls than for boys (irrespective of whether those differences are inherent or due to social norms and the way girls and boys are raised). Gender might even play a role in how resilient a child is to shocks and how parents compensated for them. Therefore, I will estimate the effect of moving separately by gender.

2.2 The effect of the quality and the timing of the move

Using a sample of families who move exactly once during a child's upbringing enables me to study the effect of the timing of the move (i.e. the age at which a child moves), as well as the type of move (i.e. does the family move to an area which is relatively better or worse for the child, compared to the region of origin?). If one part of the families moves to better areas and the other part to worse-off areas, the moving costs and age effects might be masked by neighborhood quality effects. Moreover, in a specification with one time movers only it is also possible to include regional fixed- or random effects, which can absorb unobserved regional differences that have an impact on the families' decisions to move.

Chetty et al. (2015) have recently focused on the effect of age at the time of the move. Their study shows that children become similar to the children in the region they move to in terms of adult outcomes. The earlier children move to a certain area, the less differences between permanent residents and the new-comers can be observed as adults. This so called 'exposure effect' implies that the positive effect of

[1] When repeating the analysis below including child education, the results are qualitatively very similar.

a better neighborhood on a mover child will be larger if the child moves at a younger age.

Therefore in order to study the effect of timing and quality of the move, I will construct a variable that proxies for the difference in neighborhood quality between the region of origin and the region of destination. I define the quality of a region by the average adult income achieved for an individual who lived her entire childhood in that region. Using only the sample of stayers, S, who never moved during childhood and thus spent their whole childhood in one region r, I estimate the parameters of the following income equation for each of the R regions by OLS :

$$\begin{aligned} y^c_{s,r} &= \beta_{0,r} + \beta_{1,r} y^p_{s,r} + \beta_{2,r}\text{Educ}_{i,r} + \beta_{3,r}\text{Metro}_{i,r} + \beta_{4,r}\text{Cohort}_{i,r} \\ &\quad + \beta_{5,r}\text{Cont.Family}_{i,r} + \beta_{6,r}\text{Immigr}_{i,r} + \beta_{7,r}\text{Gender}_{i,r} + \varepsilon_{s,r} \; \forall \, r = 1, ...R. \end{aligned} \tag{4}$$

where $y^c_{s,r}$ and $y^p_{s,r}$ are child and parent income of stayer family s in region r, respectively, and the other covariates are child education level, living in a metro area as adult, cohort effects, a dummy for continuous family, parent immigration, and child gender. Next, I use the R sets of estimated regression coefficients obtained from the stayer sample to predict the long run income for all one-time movers, had they grown up completely in their region of origin (denoted by $\hat{y}_{i,o}$). I also use the estimated coefficient to predict the long run income of the mover children had they grown up completely in their region of destination (denoted by $\hat{y}i_{i,d}$). Now, I compute the change in municipal quality for each one-time mover i: $\triangle_i = \hat{y}_{i,d} - \hat{y}_{i,o}$, which is positive if the family moves to an area where children with the same parent income have, on average, higher long run outcomes than in the region they moved away from. The construction of the variable $\triangle_i$ follows Chetty and Hendren (2015). However, these authors use parent income as the only predictor for child income in equation (4).

In a second step, I estimate the parameters of the following equation on the sample of one-time movers by OLS:

$$\begin{aligned} y^c_i &= \alpha_{op} + \sum_{ag=2}^{4} \beta_a I\left(\text{MoveAgeGroup}_i = ag\right) + \gamma_0 \triangle_i \\ &\quad + \sum_{ag=2}^{4} \lambda_a I\left(\text{MoveAge}_m = a\right) \times \triangle_i + X'\eta + \varepsilon_i \end{aligned} \tag{5}$$

where I group the mover children into 4 groups by age at move (age 1-5, age 6-11, age 12-15, and age 16-17). Due to the relatively small number of observations I will focus on the results using age groups. Results using 17 individual age-at-moves can be found in the Appendix. α_{po} indicates parent income quartile by origin fixed- or random effects. I also test using two separate fixed effects but the interaction of region and parent income is significant which is why I focus on the specification as given in equation (5). The identification is here based on the variation in children moving from the same region to different regions, with different region qualities. Using those fixed- or random effects will "control away" unobserved characteristics that are shared by families in the same region and with similar parent income.

If I assume that moving to a better region increases long run outcomes, I expect γ_0 to be positive. The β_a's indicate the average effect of moving at a particular age given no change in the neighborhood quality. The β_as are going to tell us if there are heterogeneous effects of moving depending on age. The interaction effects λ_a show if there are ages at which a child's human capital development seems particularly sensitive for region quality. I also include a vector X of similar control variables as in in

Section 2.1. However, since I use parent income both in the calculation of $\triangle_i$ and in the fixed effects, it is not contained in X.

3 Data

In the first part of this section I explain the construction of the variables used in the study. The second part gives an overview of the moving patterns in my data. All data were obtained from the Umeå SIMSAM lab[2]. The population registers used are collected and supplied by Statistics Sweden. My sample contains all individuals born in Sweden between 1968 and 1976 (called children), as well as their parents. I exclude families with adopted children from the sample to avoid additional sources of heterogeneity.

3.1 Variables

I use *long run average income* as the main outcome variable. Borrowing from the intergenerational mobility literature, I use this concept of income which aims at comparing individuals' earnings over their whole life cycle. For the children I use the average annual income at age 32 to 34, which has been shown to be a good approximation to the average annual income over the whole life cycle for individuals in Sweden if incomes at older ages are not observed (see Nybom and Stuhler (2016) for a discussion of this approximation). There is more data available for the parent generation and I use the average annual income measured between ages of 34 and 50 as a proxy for their long run average income. Importantly, I can measure the parent income for everyone at the same age, as opposed to during the same calendar years (where some parents might be very young, and others much older).

The income measure contains earning from employment and self employment, as well as earnings related transfers such as sick leave payments and parental benefits. Earlier studies on earnings formation and human capital have traditionally been using the log of income as the outcome variable. However, this implies that observations with average income of zero have to be dropped from the analysis. More recent studies in the intergenerational mobility and neighborhood effect literature have used income expressed in terms of percentile ranks instead of log incomes. Children are ranked relative to other children in the same birth cohort while parents are ranked relative to other parents with children in the same cohort.[3] I will use the long run average incomes transformed into percentile ranks as the main measure of income. However, I also show results based on log incomes for comparison. In order to facilitate interpretation of the percentile ranks, Figure A.1 in the Appendix shows the average child income in SEK for each percentile rank (right Y-axis). The second plot in this figure (left Y-axis) indicates how many SEK one percentile rank represents, at each position in the distribution. The distance between two ranks is largest at the top and bottom of the distribution, while it is very similar for the middle of the distribution.

A large proportion of the daughters in my data (around 40 percent in each cohort) receives maternity leave benefits during the years I measure adult incomes. Due to the cap on this earnings-based transfer as well as the flexible ways to take out the benefits there is significantly more measurement error in the daughters long run income compared to the sons which we need to keep in mind during the analysis.

Cohort is a dummy variable where 0 indicates that the child is born between 1968 and 1971, and 1 if the child is born 1972 - 1976. Using individual year of birth dummies, the results showed that there are

[2]SIMSAM is short for "Swedish Initiative for Research on Microdata in the Social And Medical Sciences", an initiative supported by the Swedish Research Council.

[3]A discussion of using income ranks as opposed to logged incomes can be found in Chetty et al. (2014) and Heidrich (2015).

only statistically significant differences between the two groups of birth cohorts as indicated above.

For both generations the data includes four indicator variables for *educational level*. The first takes the value 1 for individuals with at most at most primary school education and 0 otherwise; the second takes the value 1 for individuals with more than primary school education but at most a high school degree and 0 otherwise; and the third and fourth dummy similarly indicate some college education and a college degree, respectively.

Birth municipality type is another categorical variable indicating if the child was born in a rural area (1), large city (2), or otherwise (0). The classification is taken from the Swedish Association of Local Authorities and Regions municipality grouping based on regional characteristics in 1993.

Metro area shows if a child lives in greater Stockholm, Gothenburg, or Malmö at age 33. The coding of this variable is also based on a classification of municipalities from the Swedish Association of Local Authorities and Regions. The variable is not exogenous to moving and I only use it to predict adult income in the second part of the analysis.

Father (mother) age at birth is the difference between father's (mother's) year of birth and the birth year of their child.

Parent immigration status is coded based on the birth country variable. Even though the data allows for a finer distinction, several tests showed that a very detailed grouping does not increase explanatory power or precision compared with using only the number of parents born outside of Sweden. This variable can therefore take only one out of three values for each child, namely zero, one, or two parents born abroad.

I also construct the variable *continuous family* which is 1 if the parents of a child never separated during childhood. Since actual relationship status is unobservable, especially in register data, I need to make a judgment based on the recorded observations of civil status and parish of the children's mother and father. More specifically, I compare both civil status and parish of the parents in each year from before birth until the child turns 18. If both parents get married during the same year before the child is born, never get a divorce, or get a divorce at the same time (after the child has turned 18), I define the parents as married.

Living in the same parish as from child birth for at least 18 years and having every year the civil status unmarried, I categorize the parents as cohabiting (a common living arrangement in Sweden). The last group of parents considered *continuous family* are parents who were unmarried and living together (cohabiting), but who were later married at some point during their child's upbringing. Even though I do not observe the true family status of the parents, my classification appears to be quite robust. In order to be falsely classified as *continuous family*, parents would have had to get married at the same time with different partners and stay married the same number of years, while living in the same place. Families who are not classified as continuous are instead coded as *separated.*

Father unemployment is a dummy variable which indicates whether the child's father experienced any unemployment before the child turned 18. This variable is mainly based on having received a positive amount of unemployment benefits during at least one year. However, we only observe this variable starting in 1972. For the year 1970 we can use an employment indicator from a different register, but I do not observe any unemployment indicator during 1968, 1969, and 1971. Therefore, for children born before 1972, and especially for the ones born before 1970, this variable contains some measurement error. For example, I do not observe if a father was unemployed when his child, born in 1968, was one

year old. However, assuming that the effect on a child of parent unemployment is larger when the child is older, we probably do not have to be too concerned about this. I do not include mother's unemployment since it turned out to not being predictive of children's long run outcome.

Table 1: Summary of the variables

	Mean	sd	p50	Min	Max	N
Child long run average income	269,984	148,979	255,511	0	10,503,468	766,271
Son long run average income	313,644	169,945	297,868	0	10,503,468	394,450
Daughter long run average income	223,667	104,564	215,069	0	5361,351	371,821
Parents long run average income	427,537	158,613	404,740	0	8061,467	766,271
Daughter education	2.82	0.98	3	1	4	368,458
Son education	2.55	0.94	2	1	4	390,245
Mother education	2.03	0.93	2	1	4	766,271
Father education	1.98	0.98	2	1	4	766,271
Father unemployment	0.22	0.41	0	0	1	766,271
Immigrated parents	0.15	0.45	0	0	2	766271
Continuous family	0.69	0.46	1	0	1	766271
Mother age at birth	25.87	4.22	26	16	36	766271
Father age at birth	28.36	4.54	28	16	40	766271
Birth mun. type	0.55	0.65	0	0	2	766271
Metro area	0.44	0.5	0	0	1	766271

Note: All income measures are expressed in 2010 SEK.

Table 1 gives a summary of the variables described above. Mean son long run average income is around 90,000 SEK (≈10,600 USD) higher than daughter income, and also has a larger variance. In both generations there are observations with zero incomes (slightly more than one percent of all observations). Daughters have on average a little more education than sons. More than two thirds of the children in my sample grow up in continuous families and 22 percent experience father unemployment.

3.2 Family moving patterns in Sweden

The variable containing the number of moves during childhood is constructed by comparing the municipality of residence from one year to the next from birth until the year a child turns 17. I do not consider moves at age 18 or older since the focus of this study is on childhood moves. Also, moves at age 18 are potentially different from earlier moves both due to high school graduation and because children are not necessarily tied to their parents any longer.

I mainly consider moves between municipalities. Changing municipality in Sweden usually entails having to switch schools and adjust to a new physical and social environment. However, I will also show the results using moves between counties instead of municipalities. If we believe that moving affects children at least to some extend because of severed social ties, we would expect the effects of moving to be similar when considering counties compared to municipalities. Moving at least to the next county instead of the next municipality will on average entail a larger distance between the origin and the destination and thus less opportunities to keep up social ties in the place of origin.

The municipality structure in Sweden has undergone many changes since 1970. Many municipalities have been merged with or broken out of other municipalities, sometimes several times. All original municipality coding in the data has been carefully revised and updated in order to not wrongfully classify a change in a municipality code as a move. This has been done using official documentation of the Swedish municipality reforms from Statistics Sweden. The residence is recorded only once every year in December, so that the number of moves observed in the data can be seen as a lower limit to the true number of moves.

Moving at age 6 then means that the child was registered in a different location in December in the year she turned 6 compared to the previous year. Table 2 shows the number of moves during childhood, both on the municipality and the county level. Focusing on the municipality level, we find that roughly 65 percent of the children never move, and 99 percent of all families moves 4 times or less. The maximum number of moves recorded is 16.

Table A.1 in the Appendix shows the age at the time of the move for all children that move exactly once between municipalities during their childhood (160.871 individuals). More than half of those families move when their child is four years old or younger. Age 15 is when the smallest number of families move (only 1.61 percent of this sample).

Table 2: Childhood moves

Municipality level			County level		
Number of moves	Frequency	Percent	Number of moves	Frequency	Percent
0	512,797	64.96	0	634,138	80.33
1	160,871	20.38	1	95,869	12.14
2	72,668	9.21	2	42,129	5.34
3	26,665	3.38	3	11,607	1.47
4	10,213	1.29	4	3,924	0.50
5	3,774	0.48	5	1,175	0.15
6	1,475	0.19	6	383	0.05
7	544	0.07	7	119	0.02
8	235	0.03	8	47	0.01
9	96	0.01	$\geq$9	34	0.00
10	43	0.01			
11	25	0.00			
$\geq$12	19	0.00			
Total		100.00			100.00

Table 3 shows the distribution of moving quality by parent income quartile. We can see that parents in the top income quartile are overrepresented among the one time movers (if all families were equally likely to move once, the number of observations would be very similar in each row). The average move quality is decreasing in parent income. This could be driven by the fact that high income parents probably already live in rather good neighborhoods which leaves less room for improvement. Interestingly, for all parent income levels, move quality is centered around just above zero. This means that families move on average to regions that are just slightly better for their children compared to their region of origin.

Table 3: Distribution of moving quality

Parent inc. quartile	Mean	sd	Min	p25	p50	p75	Max	N
1	0.63	5.75	-46.2	-2.65	0.55	3.97	42.4	34,053
2	0.48	5.18	-38.5	-2.47	0.44	3.44	36.1	34,531
3	0.33	4.88	-41.6	-2.54	0.33	3.25	41.0	39,008
4	0.27	4.58	-41.5	-2.54	0.27	3.07	40.1	52,366
Total	0.41	5.05	-46.2	-2.55	0.38	3.36	42.4	159,958

Note: Moving quality is measured as the difference in quality between the destination and the origin region. The quality of a region is based on the long run adult outcome of the children of permanent residents in each region.

Table A.2 in the Appendix shows the number of moves by parent income quartile. As already noted above, parents in the top income quartile are overrepresented among the one time movers. In addition, they also constitute the group of families who move most often two or three times during their kid's childhood. On the other hand, parents in the bottom part of the income distribution are the ones moving most often (four or more times). Thus, it seems that fewer moves a small is associated with high income for the parent generation, while moving often is associated with low parent income.

4 Results

The first part of this section discusses the results for the effect of childhood moves on long run average adult income separately by gender. The second part focuses on how the quality of the move effects a child, i.e. controlling for the fact that some families move to areas which are better or worse for their child, as well as on the timing of the move.

4.1 Moving cost estimates

The results of the baseline regressions from equations (1) and (2) for the children in my data set are summarized in Table 4. The first column in Table 4 shows the estimates and their standard errors pretending we have perfect experimental data. Son income rank is regressed on six dummies for the number of moves an individual has experienced during childhood. The last dummy groups together 6 and more moves, since there are few families moving more often than that. According to the estimates, moving once does not affect long run income while moving twice or more often is associated with larger and larger costs in terms of long run income.

In Model (2) for each gender I add parent income as well as the interaction between parent income and moving. The moving effects are now larger, for sons ranging from 2.88 to 16.3 percentile ranks less in long run income depending on the number of childhood moves given a parent income rank of 0. Given parents with income rank 100, one time movers earn approximately just as much as non-movers. Sons whose parents are in the top of the income distribution will have lower long run incomes if they move more than once during childhood (3,88 to 13.29 percentile ranks less). The effects for daughters show a similar pattern but are in general smaller. The parameter estimate on parent income rank is 0.18 and thus smaller than in the intergenerational mobility literature (0.24 for Sweden, see Heidrich, 2015).

Table 4: Baseline results

	Sons			Daughters		
Income rank	(1)	(2)	(3)	(1)	(2)	(3)
Moves=1	0.15	-2.88***	-1.53***	1.36***	-1.46***	-1.01***
	(0.115)	(0.234)	(0.234)	(0.108)	(0.205)	(0.206)
Moves=2	-1.93***	-6.88***	-3.86***	0.28	-3.26***	-2.06***
	(0.167)	(0.336)	(0.338)	(0.151)	(0.281)	(0.283)
Moves=3	-3.96***	-9.43***	-5.85***	-1.21***	-4.56***	-3.29***
	(0.275)	(0.517)	(0.516)	(0.240)	(0.414)	(0.415)
Moves=4	-6.02***	-8.60***	-4.47***	-2.43***	-4.49***	-2.72***
	(0.440)	(0.780)	(0.779)	(0.377)	(0.614)	(0.613)
Moves=5	-10.25***	-14.55***	-10.10***	-5.07***	-4.27***	-2.58**
	(0.729)	(1.150)	(1.146)	(0.611)	(0.959)	(0.953)
Moves≥6	-14.81***	-16.29***	-12.02***	-10.12***	-8.25***	-6.77***
	(0.934)	(1.310)	(1.311)	(0.648)	(0.874)	(0.876)
P. income rank		0.18***	0.17***		0.18***	0.14***
		(0.002)	(0.002)		(0.002)	(0.002)
Moves=1 # PIR		0.03***	0.02***		0.03***	0.02***
		(0.004)	(0.004)		(0.004)	(0.004)
Moves=2 # PIR		0.07***	0.04***		0.04***	0.02***
		(0.006)	(0.005)		(0.005)	(0.005)
Moves=3 # PIR		0.08***	0.05***		0.04***	0.03***
		(0.009)	(0.009)		(0.007)	(0.007)
Moves=4 # PIR		0.05***	0.02		0.03**	0.02
		(0.014)	(0.013)		(0.012)	(0.011)
Moves=5 # PIR		0.12***	0.10***		-0.00	-0.01
		(0.022)	(0.022)		(0.020)	(0.020)
Moves≥6 # PIR		0.12***	0.11***		0.03	0.03
		(0.031)	(0.030)		(0.023)	(0.023)
Imgr. parents=1			-1.96***			-0.21
			(0.169)			(0.153)
Imgr. parents=2			-4.20***			1.03***
			(0.250)			(0.223)

	Sons			Daughters		
	(1) cont.	(2) cont.	(3) cont.	(1) cont.	(2) cont.	(3) cont.
Cont. fam.=1			5.29***			2.13***
			(0.101)			(0.091)
Unemployed			-2.20***			-1.09***
			(0.109)			(0.097)
F. educ.=2			0.64***			1.05***
			(0.099)			(0.090)
F. educ.=3			1.29***			2.53***
			(0.175)			(0.166)
F. educ.=4			0.42*			3.92***
			(0.184)			(0.175)
M. educ.=2			1.09***			1.52***
			(0.100)			(0.091)
M. educ.=3			1.68***			3.22***
			(0.160)			(0.152)
M. educ.=4			0.82***			4.76***
			(0.190)			(0.183)
Born Metro			-0.21*			1.31***
			(0.097)			(0.091)
Born Rural			-2.38***			-0.72***
			(0.152)			(0.138)
F. age/birth			-0.06***			0.04**
			(0.015)			(0.013)
M. age/birth			0.30***			0.31***
			(0.016)			(0.015)
Cohort			-0.98***			0.47***
			(0.087)			(0.081)
Constant	61.21***	52.48***	43.36***	38.39***	29.62***	17.83***
	(0.053)	(0.104)	(0.356)	(0.050)	(0.094)	(0.324)
Observations	394450	394450	394450	371821	371821	371821
Adjusted R2	0.003	0.046	0.061	0.001	0.051	0.068

Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

The third model for sons and daughters also includes the covariates discussed in Section 2.1, i.e. parent immigration status, unemployment, education, age at birth, as well as continuous family, starting out living in a rural area or a large city, and child cohort group. The parameter estimates of the covariates are all statistically significant and have the expected signs: parents born outside of Sweden, father unemployment, and being born in a rural area decrease child long run income, while growing up in a continuous family and having educated parents increases child income. We can see that parent education is the only variable in the model that has a stronger effect on long run income for daughters than for sons. The estimates of the moving effects decrease as a result of introducing the controls. There is hardly any effect on the precision of the estimates while the share of the variance explained by this model rises, as expected. The marginal effects of moving depend on parent income. In order to simplify interpretation of the results, I redo the analysis using grouped moves instead: children who move one to three times during their childhood are grouped as "movers" and children who move more than three times are classified as "extreme movers". Children who spend their complete childhood in one region are referred to as "stayers". The output for this regression can be found in Table A.3 in the Appendix.
Figures 1 and 2 show the marginal effects of being a mover or an extreme mover (i.e. compared to being stayers) on long run outcome for sons and daughters, by parent income rank.

The negative effect on long run adult income in terms of percentile ranks is largest for those children who grow up in low income families. At the bottom of the parent income distribution, a mover son can expect a 2.6 ranks lower income as adult compared to a stayer, and an extreme mover has a 7.2 percentile ranks lower expected income. The reduction in percentile ranks in the middle of the parent income distribution are 1.2 and 4.2 percentile ranks. Being a mover does not lower the expected long run income of a son if his parents are located in the top ten percent of the income distribution. However, those sons with top income parents still have on average lower incomes compared to stayers if they move more than three times.

Focusing on the daughters in Figure 2, we can see that the effects are in general smaller (the largest reduction in long run income is -3.6 percentile ranks for extreme movers with parents in the bottom of the income distribution). Also, with parents in the highest income quintile, there is either no effect or a positive effect of being a mover compared to being a stayer. Similar to the sons, however, daughters with high income parents have on average lower incomes than stayers if they move more than three times during childhood.

In order to get a better understanding of the results we can translate some of the percentile ranks into monetary values. Since the relationship between all observed incomes in the distribution and the ranks 1-100 is not too far from being linear, each percentile rank is actually quite close to representing one percent of income. To highlight this I take the average income rank of stayers by parent income decile and compute the marginal effects of moving and extreme moving in terms of ranks based on the results in Table A.3. Then, I transform those resulting ranks for stayers, movers, and extreme movers for the ten parent income groups back into monetary values using the child income distribution.

Figure 3a shows the average son income by parent income decile for stayers, movers, and extreme movers in terms of SEK. Figure 3b shows the same information in terms of percentages. In the bottom decile of the parent distribution, a mover son can expect a 2.4 percent lower income compared to stayers. For an extreme mover, this difference amounts to 6.6 percent lower income. At the fifth decile of the

Figure 1: Marginal effects of moving (Sons)

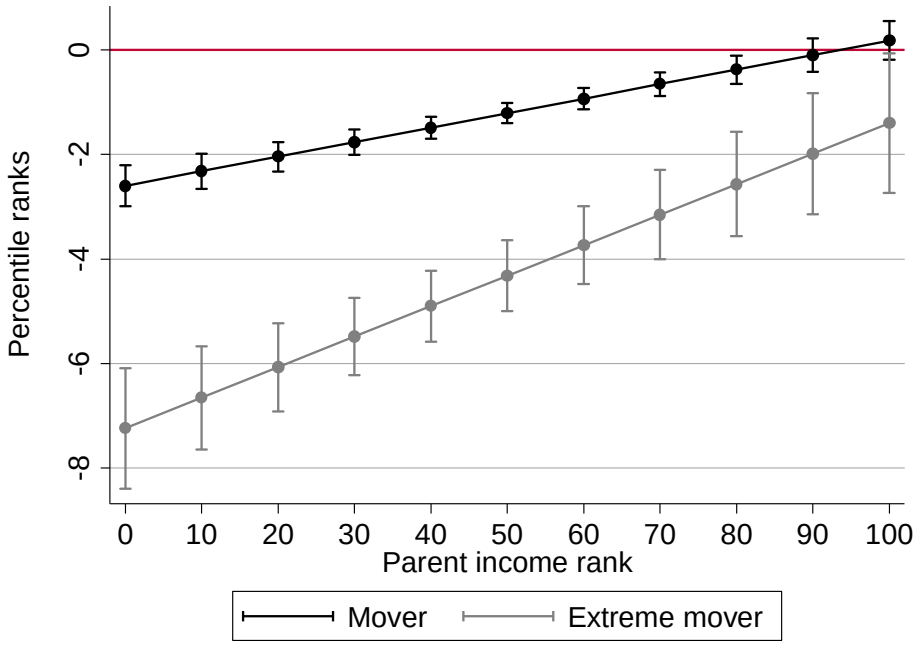
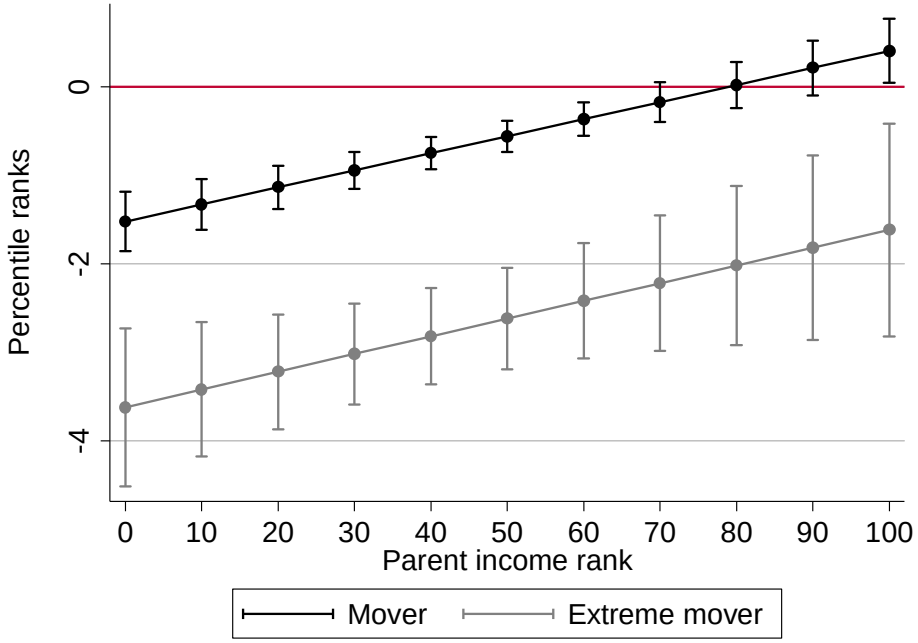


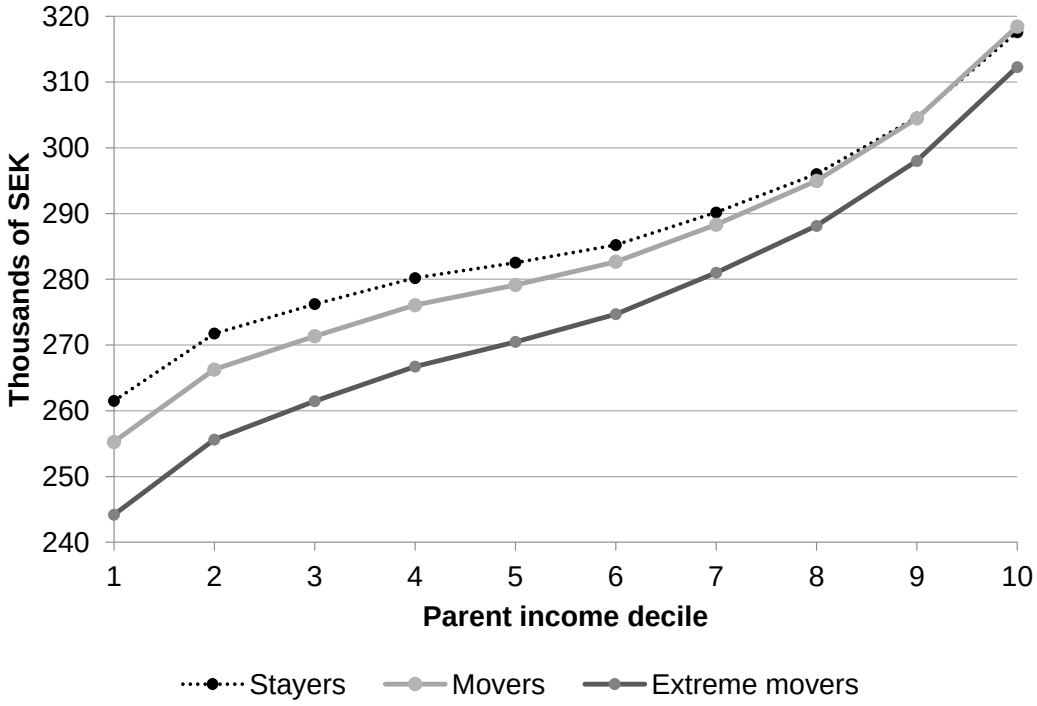
Figure 2: Marginal effects of moving (Daughters)



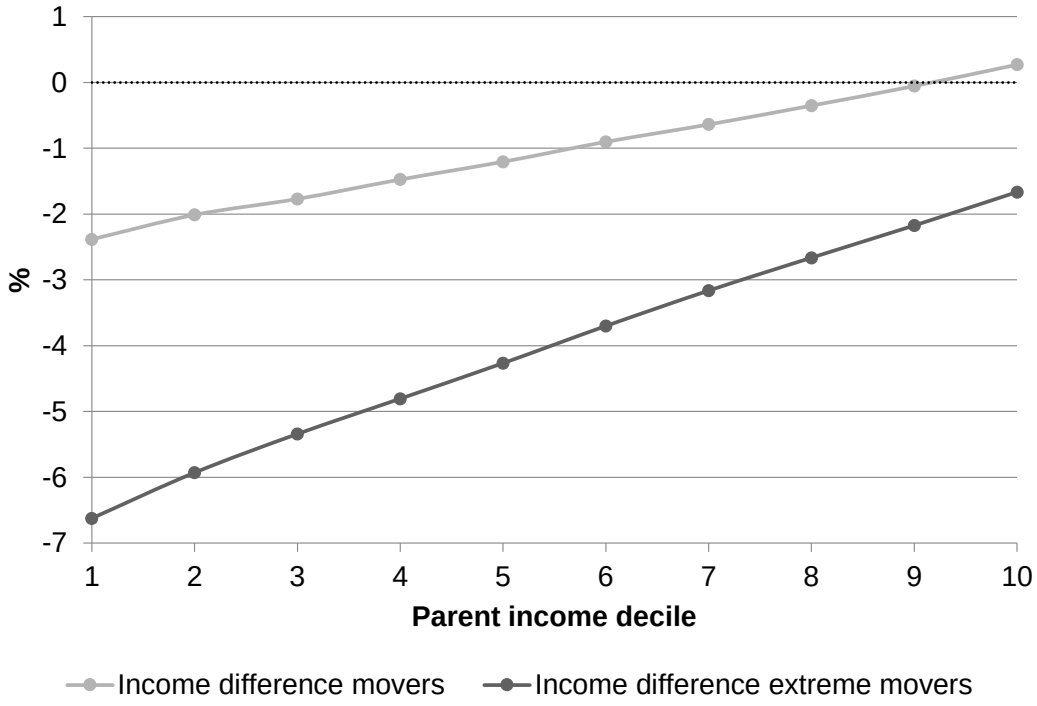
Note: The two figures show the estimated effects of moving 1-3 times (Movers) and more than 3 times (Extreme movers) on long run average income for sons and daughters, given parent income. The bars indicate 95%-confidence intervals.

Figure 3: Effects of moving on son long run adult income

(a) Levels of income



(b) Percent of income



parent distribution, the differences between stayers and movers, and stayers and extreme movers, are approximately 1.2 percent and 4.3 percent, respectively. Focusing on the top decile of families, we can see that moving a few times on average slightly increases incomes (+0.2 percent) while moving often still leads to a reduction of expected income by about 1.7 percent. Comparing those numbers with the results in percentile ranks we see that the two are approximately equivalent to each other.

According to my results childhood moving has statistically significant effects on long run adult income. The economic significance of the results is less easily determined. However, a reduction of average annual income by 1.2 to 4.3 percent for children with median-income parents, and up to 6.6 percent lower income for children with low-income parents, can hardly be categorized as negligible.

4.1.1 Robustness checks

One could think that moves between municipalities are not informative enough in order to attribute the effects of moving to disruptions in child human capital development. Families can in practice just move a very short distance, across the border to the next municipality. Maybe there are different underlying reasons that make families move short distances compared to long distances. In order to strengthen the argument that moving between municipalities indeed causes damage due to the disruption in the social and physical environment, I check the effect of moves between larger geographic units.

As shown in Table 2 in Section 3.2 above, there is less movement between counties than between municipalities. Table 5 shows the total number of family moves broken down by the number of county moves included in the municipality moves. For example, of all 69,928 families that move two times during childhood between municipalities, 24,692 (35%) move within the same county while 29,129 (42%) move to a different county every time they move.

Table 5: Frequency of moves between municipalities and between counties

		Municipality							
		0	1	2	3	4	5	6	Total
County	0	499,408	84,909	24,692	5,485	1,566	400	176	616,636
	1	0	71,022	16,107	4,237	932	296	89	92,683
	2	0	0	29,129	7,953	2,417	662	337	40,498
	3	0	0	0	7,851	2,288	698	257	11,094
	4	0	0	0	0	2,468	807	450	3,725
	5	0	0	0	0	0	682	412	1,094
	6	0	0	0	0	0	0	541	541
	Total	499,408	155,931	69,928	25,526	9,671	3,545	2,262	766,271

The first robustness check is to redo the analysis in Section 4.1 using county moves instead of municipality moves. The results are shown in the second columns in Tables A.4 (sons) and A.5 (daughters) in the Appendix. The first columns just repeat the earlier results when using moves between municipalities, in order to facilitate the comparison. The estimates using inter-county moves are very similar to the estimates from municipality moves, some effects are slightly larger and some slightly smaller. The standard errors are larger using county moves, probably due to the smaller number of observations. The estimated parameters for the covariates are almost identical, as is the adjusted R^2.

A possible explanation for why the results are so similar is that children experience similar disrup-

tions in their development when moving between counties or between municipalities. The important point is that even a municipality change in Sweden normally implies a change in school (or pre-school) and thus leads to a disruption in social and educational networks. Therefore, for a child it does not matter much if she moves 50 or 500 kilometers.

Since the estimates in Model (2) are not all significantly larger than in Model (1), it is unlikely that inter-county moves are driving all the results even in the municipality analysis. I show this by repeating the analysis using moves between municipalities, but this time excluding all families that move across counties. That is, I use only the observations in the first row of Table 5 (616,636 families in total). If the moves between counties were driving the results of the moving costs using inter-municipality moves, the effects should change notably when we exclude just those county moves. The results are shown in column (3). Some estimates are larger and some are smaller than the ones from Models (2) and (3) (and less precisely estimated), but the findings are in general again very similar.

These results show that the negative effects on long run income from moving during childhood are very robust in terms of the geographic unit chosen. We can be quite convinced that long distance moves are not driving the estimated moving costs on the municipality level.

One additional question is if the chosen measure of outcome, namely the rank of children's long run average outcome, is somehow affecting the results. The last column in Tables A.4 (sons) and A.5 (daughters) therefore presents the estimates of the moving costs equation using logged incomes instead of the income ranks for sons. The parent income on the right hand side is kept in terms of ranks in order to facilitate comparison. Assuming parent income to be at the median, the estimates fro the logged income specification indicate that one move during childhood reduces son long run income by approximately 1.5 percent. From Figure 3b we can see that the effect of moving a few times at parent income decile 5 is on average 1.2 percent lower income. The results are therefore quite similar to each other, taking into account that there are no observations with zero-incomes in the log model, and that the rank-percentage conversion is based on averages by parent deciles. The parameter estimates for the covariates all have the expected sign and are highly significant.

4.2 Effects of quality and timing of the move

The results in Section 4.1 suggest that moving during childhood is costly in terms of adult long run income. In this section, I test whether the timing of the move or the type of move matter, given that a family moves.

First, I estimate the parameters of the income equation (4) for all municipalities on the sample of stayers. There are 285 municipalities and the average adjusted coefficient of determination for those 285 equations is 0.25 (standard deviation 0.04, min. 0.14 and max. 0.4). Thus, the included variables explain on average one quarter of the variance in the long run child incomes. With those estimates I then predict the long run income for children who move once during their childhood in two regions each, once in their origin and once in their destination region. The difference of those two predictions for each child is the change in municipal quality $\triangle_i$. In some regions there are too few stayers in order to sensibly make predictions and the number of observations is therefore slightly smaller than than the number of one time movers in the sample (the number of observations of stayers for included region is at least 100 and the mean is 1,780) .

I estimated equation (5) using four age groups: 1-5 years old, 6-11 years, 12-15 years, and 16-17 years. The results are summarized in Table 6 (the results using 17 individual years of age can be found in Table A.6 in the Appendix). The estimates shown in this table are from a model using parent income quartile by origin municipality fixed effects which is supposed to absorb unobserved differences between the regions that affect the moving behavior of families. The correlation between the fixed effects and the explanatory variables is small but significant, 0.2 for sons and 0.3 for daughters which is an indication to use fixed effects rather than random effects. I perform Hausman's specification test to compare the estimator assumed to be consistent and inefficient (fixed-effects) to the efficient but possibly inconsistent estimator (random-effects) (Hausman, 1978). I reject the null (that the second estimator is efficient and consistent) on the 0.001% significance level.

Comparing Models (1) and (2) for the sons (and Model (3) and (4) for the daughters), we see that including the covariates reduces the main age effects by about one third (more for the daughters). The baseline category here is moving at age 1-5 and the average long run income for one-time movers is clearly decreasing in age at move for sons. The main age effects are less precisely estimated for the daughters but we see a similar trend here as well. The estimate of the effect of $\triangle_i$ for sons is 0.3, which means that sons who move at ages 1-5 to a one percentile better neighborhood (i.e. a region where sons very similar to them obtain long run average incomes as adults that are on average 1 percentile rank higher compared to children in the mover's region of origin), will increase their expected long run income by 0.3 percentile ranks. About one third of a region's quality is thus 'taken up' by a son if he moves there before the age of six.

The interaction effect for ages 6-11 is not significant, but it is significantly negative for the older two age groups. Figure 4 shows the marginal effects of $\triangle_i$ by age group as well as their 95 percent confidence intervals. From age 12, it is uncertain if moving to a region that usually produces higher income adults is beneficial for sons. From age 16, moving to a higher quality region has either no effect, or a negative effect on long run incomes (the marginal effect is negative on the 5 percent significance level). The picture looks slightly different for daughters. The confidence intervals are larger and there is no clear negative trend of the benefits of better regional quality over age. Just as in Section 4.1, the effects are also smaller in size compared to the sons. The marginal effect for the oldest age group for girls is not significantly different from zero, while it was negative for boys.

These results show that children who move at younger ages have on average higher adult incomes than children who move when they are older. Secondly, there is a strong negative trend of the effect of neighborhood quality on long run incomes over sons' age. In particular, even if a family moves to a significantly better area, their son will potentially have a lower adult income if he is over 15 at the time of the move, compared to if they moved when their son was younger. If we think that the marginal effect of moving quality is actually negative for boys who move at age 16 or 17, this could be explained by the fact that children move down in the local distribution of school performance. If a family moves to a better area (measured in future adult income of the permanent child residents), their son will on average rank lower in the new, higher achieving municipality compared to the origin municipality. This can potentially lead to lower self esteem, a different peer group, or studying less - all of which can ultimately lead to lower adult earnings.

Table 6: Timing and quality of the move

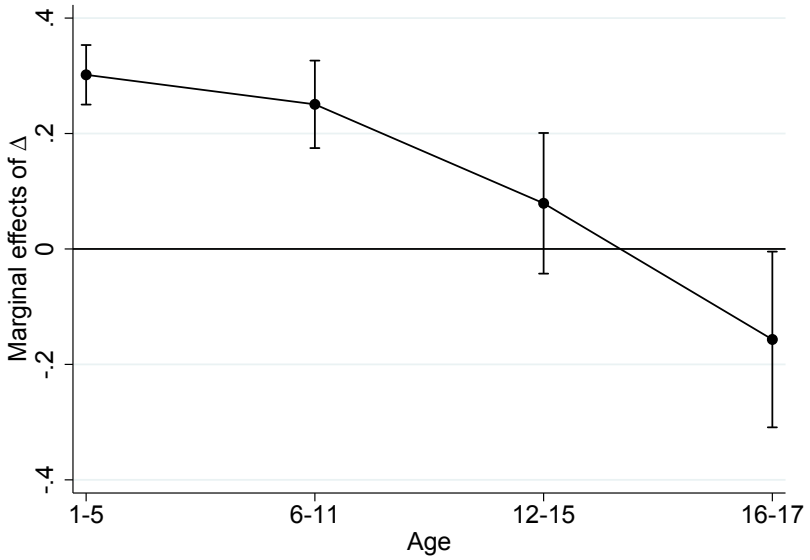
	(1)	(2)	(3)	(4)
Child income	Sons	Sons+cov	Daughters	D.+cov
Moving age 6-11	-0.97***	-0.57*	-0.74***	-0.35
	(0.243)	(0.244)	(0.221)	(0.223)
Moving age 12-15	-3.10***	-1.94***	-1.66***	-0.94**
	(0.385)	(0.389)	(0.348)	(0.354)
Moving age 16-17	-5.40***	-3.88***	-3.22***	-2.26***
	(0.486)	(0.493)	(0.400)	(0.408)
Change in municipality quality △	0.33***	0.30***	0.18***	0.19***
	(0.026)	(0.026)	(0.029)	(0.029)
Moving age 6-11 # △	-0.08	-0.05	0.07	0.07
	(0.043)	(0.044)	(0.049)	(0.050)
Moving age 12-15 # △	-0.29***	-0.22***	0.03	0.03
	(0.065)	(0.066)	(0.074)	(0.076)
Moving age 16-17 # △	-0.53***	-0.46***	-0.16	-0.16
	(0.079)	(0.081)	(0.083)	(0.084)
Immigrated parents=1		-2.27***		-0.42
		(0.355)		(0.332)
Immigrated parents=2		-3.77***		0.32
		(0.510)		(0.479)
Continuous family=1		4.95***		1.89***
		(0.219)		(0.203)
Father was unemployed		-2.97***		-0.96***
		(0.266)		(0.248)
Father's education=2		0.76**		1.48***
		(0.251)		(0.233)
Father's education=3		1.87***		3.60***
		(0.378)		(0.353)
Father's education=4		1.42***		5.09***
		(0.376)		(0.350)
Mother's education=2		1.10***		1.17***
		(0.256)		(0.237)
Mother's education=3		1.77***		2.86***
		(0.351)		(0.326)
Mother's education=4		1.70***		4.43***
		(0.391)		(0.364)
F. age/birth		-0.15***		0.04
		(0.034)		(0.031)
M. age/birth		0.29***		0.26***
		(0.037)		(0.034)
Cohorts 72-76		-1.17***		0.26
		(0.204)		(0.189)
Constant	61.53***	54.99***	39.85***	27.45***
	(0.127)	(0.769)	(0.118)	(0.716)
Observations	82,236	80,139	77,722	75,589
R2	0.005	0.036	0.003	0.048

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

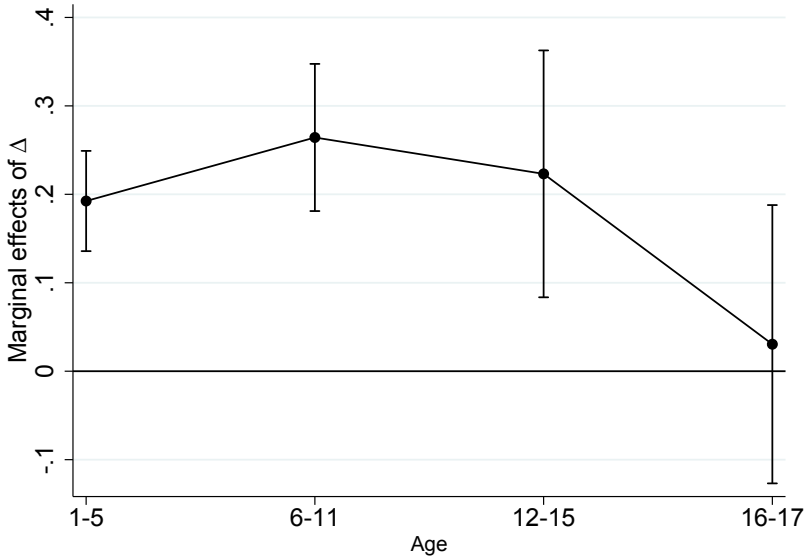
Note: These estimates are based on the sample of one-time movers only and include origin-by-parent income quartile fixed effects. The base category is moving at age 1-5. The municipality type at birth has a zero effect and is omitted from the output. Including parent income rank in the equation yields nearly identical results.

Figure 4: Marginal effects of moving quality

(a) Sons



(b) Daughters



Note: The plots show the marginal effect of change in municipal quality on adult long run income by age at childhood move for all one-time movers. The bars indicate 95 percent confidence intervals.

The interpretation of these results depends on the assumptions we are willing to make on both the human capital production function and moving costs. If we for simplicity assume that region quality affects human capital production in the same way and amount at each age, a child who moves earlier to a better neighborhood will, ceteris paribus, have higher human capital as an adult simply because she spent more time in this better region. If we abstract from any moving costs, long run adult income would then be a linearly decreasing function of child age at move, for a given $\triangle_i$. If moving costs in terms of long run income were positive (as the results in Section 4.1 strongly suggest), but constant over age, i.e. if the disruption of moving would have the same effect on adult human capital at any age, long run adult income would still be a linearly decreasing function of child age at move for a given $\triangle_i$, but on a lower level compared to zero moving costs. The results in this section however indicate that adult human capital is actually exponentially decreasing in age at childhood move, due to the decreasing marginal effect of moving quality over child age.

There are (at least) two different explanations for this. One possibility is that moving hurts only a certain part of human capital production, and this part is especially sensitive to disruptions during the teenage years. The effect of moving on adult income may work through weakening a child's social identity and network of friends, peers, and teachers. In this case, moving at older ages hurts long run income more because a strong social identity and a reliable social network are critical for human capital development at age 16 and 17, but not before that.

A second explanation is the compensation property of the human capital production function. If we assume that parents compensate for the disruption caused by childhood moving, my results simply indicate that there is less time to compensate for any harm done when there are only one or two years left of childhood human capital production. In practice, both explanation could explain part of the findings.

5 Discussion and concluding remarks

I used Swedish register data for nine cohorts born 1968 to 1976 to study the effect of moving between regions during childhood on long run adult income. In addition, I analyzed the effect of the timing and quality of the move. The literature on childhood human capital production suggests that shocks to the skill formation process can result in large differences in the stock of adult human capital. Moving is one such potential shock. The child is taken out of her usual environment and needs to re-build a social identity at the new home, get to know her new class mates, teachers, and neighborhoods. Early-intervention program evaluations have shown that the childhood environment strongly affects children's non-cognitive skills and social attachment, which are both very important for adult outcomes (Heckman and Carneiro, 2003).

The analysis of moving patterns revealed that 35 percent of all children born between 1968 and 1976 moved at least once between municipalities during childhood. Children with high income parents are over-represented among the families that move 1-3 times. Low income families are more likely than high income families to move four or more times with their children. On average families moved to regions that are very similar to their origin in terms of expected long run income for their child.

I estimated the effect of moving during childhood on long run income controlling for factors that affect both selection into moving as well as child long run income as adult. My results suggest statistically and economically significant effects of childhood moving on adult income that depend strongly on parent income. At the bottom of the parent distribution, a son that moves one to three times during childhood

can expect to have an adult income that is 2.6 percentile ranks lower than if he had never moved. Sons with parents located at the median of the income distribution loose 1.2 and 4.2 percentile ranks by moving and extreme moving, respectively, while sons with parents in the very top only experience a loss in adult income when moving more than three times. I also show that percentile ranks can approximately be interpreted as percent of income. For daughters, the results are similar but smaller in size. Also, moving up to three times is not associated with a negative effect on adult long run income for daughters if their parents are located in the top twenty percent of the parent income distribution.

In order to test the robustness of my results, I repeated the analysis using only moves between counties instead of municipalities, using moves between municipalities but only within counties, and moves between municipalities using log son income as outcome. The results are neither sensitive to the definition of moving nor to the transformation of the income variable used.

In the next part, I analyzed if the timing of move or the quality of the move matter. In order to do so, I constructed a variable called change in municipality quality for all children that move once. Municipal quality is measured by the outcome of children with similar characteristics who spend their entire childhood in one region. The change in quality for the mover children is then the difference in the predicted outcome in the region of destination and region of origin, if they had spent all their childhood in one region.

My results show that, given that a family moves to a region that is similar to their region of origin, the loss in adult income is increasing in age at the move. Moving at age 16 compared to moving at 4, for example, reduces the expected adult income for sons by about 4 percentile ranks. It is therefore preferable in terms of child long run outcome to move when the child is young. Taking into account moving quality, i.e. the change in municipal quality from before and after the move, we saw that there are sizable benefits for children of moving to higher quality regions. Moving to a 10 percentile rank better region between ages 1-5, for instance, improves sons' adult long run income by 3 percentile ranks. However, those benefits disappear and then potentially become negative for sons if the move happens after he turned 12 and 16, respectively.

Further research is needed to determine what is driving these results. If we assume that childhood moving affects long run adult incomes by hampering the creation of social networks and identity, my results suggest that the later years of childhood are particularly crucial for building this type of human capital which is then capitalized during adulthood. It is also important to better understand how parents compensate for the disruptions caused by moving a child into a new environment. If it is relatively easy to compensate for the disruption we would also expect my results to show a decrease in the benefit of a higher quality region with child age, since the older a child is the less time there is to compensate.

Half the families, however, do not move to regions that are better for their child. This could reflect the fact that parents put on average very little weight on their child's expected utility when making a moving decision, compared to their own expected utility. Alternatively, parents could be unaware of the effects of moving on the utility of their children. Parents could also have the wrong expectations or insufficient understanding of the quality of different regions and their child's human capital production function. Therefore, a fruitful direction for future research is to deepen our understanding of which aspects of the childhood human capital production function are driving the estimated effects of moving on adult income, how parents' beliefs about the child human capital production function are formed, and how the preferences of parents look like when they decide to move their family.

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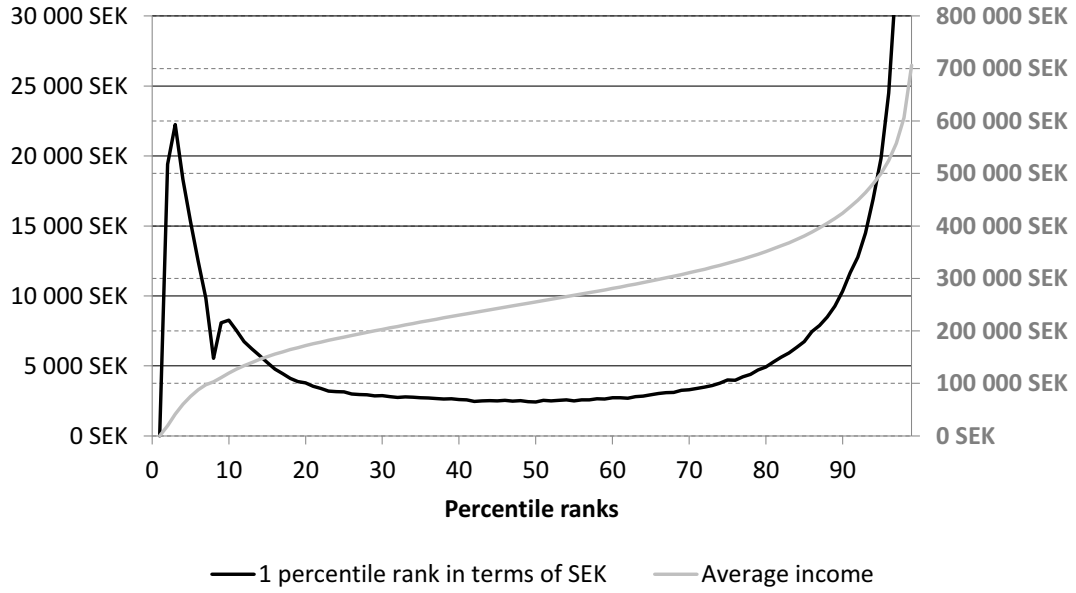
Appendix

A Figures

Figure A.1: Child income distribution: ranks and SEK



Note: The black line shows the number of SEK that each percentile in the child income distribution corresponds to (measured on the left Y-axis). The gray line shows the average adult long run income by percentile rank (measured on the right Y-axis). The distance between two percentile ranks measured in SEK is large in the tails of the distribution and around 2,500 SEK in the middle of the distribution.

B Tables

Table A.1: Child age at move
(one time movers only)

Age at move	Frequency	Percent
1	29,812	18.61
2	23,315	14.56
3	19,092	11.92
4	15,397	9.61
5	12,460	7.78
6	10,256	6.40
7	8,494	5.30
8	6,094	3.80
9	5,342	3.34
10	4,826	3.01
11	4,084	2.55
12	3,659	2.28
13	3,440	2.15
14	2,895	1.81
15	2,578	1.61
16	4,228	2.64
17	4,196	2.62
Total	160,168	100.00

Table A.2: Moving and parent income

	Parent income quartile					
	1	2	3	4	Total	
Moves	Row percent	Row percent	Row percent	Row percent	Frequency	Row percent
0	26.11	26.89	25.60	21.40	511,065	100.00
1	21.29	22.35	25.06	31.30	160,168	100.00
2	22.44	20.57	23.44	33.55	72,236	100.00
3	26.06	19.65	21.37	32.92	26,474	100.00
4	31.20	20.16	19.33	29.31	10,113	100.00
5	39.46	20.24	18.39	21.91	3,725	100.00
6	47.05	19.71	17.99	15.25	1,456	100.00
$\geq$7	61.65	18.59	10.68	9.08	936	100.00
Total	25.00	25.00	25.00	25.00	786,173	100.00

Note: This table shows the distribution of families by parent income for each number of move. If parent income was independent of the number of moves, each cell would contain a quarter of the families (25 percent). Instead, we can see that parents in the top quartile are over represented among families that move one to 3 times, while families in the bottom quartile are over represented among the families that move four and more times.

Table A.3: Effect of moving on income, using mover groups

Income rank	Sons	Daughters		Sons cont.	Daughters cont.
Mover	-2.60***	-1.52***	F. educ.=4	0.35	3.88***
	(0.199)	(0.172)		(0.184)	(0.175)
Extreme mover	-7.24***	-3.62***	M. educ.=2	1.10***	1.52***
	(0.588)	(0.455)		(0.100)	(0.091)
Parent income rank	0.17***	0.14***	M. educ.=3	1.67***	3.22***
	(0.002)	(0.002)		(0.160)	(0.152)
Mover # PIR	0.03***	0.02***	M. educ.=4	0.80***	4.75***
	(0.003)	(0.003)		(0.190)	(0.183)
Extreme mover=2 # PIR	0.06***	0.02*	Born Metro	-0.21*	1.32***
	(0.011)	(0.009)		(0.097)	(0.091)
Imgr. parents=1	-1.98***	-0.22	Born Rural	-2.39***	-0.72***
	(0.169)	(0.153)		(0.152)	(0.138)
Imgr. parents=2	-4.20***	1.03***	F. age/birth	-0.06***	0.04***
	(0.250)	(0.223)		(0.015)	(0.013)
Cont. fam.=1	5.40***	2.20***	M. age/birth	0.31***	0.31***
	(0.101)	(0.091)		(0.016)	(0.015)
Unemployed	-2.24***	-1.11***	Cohort	-0.97***	0.48***
	(0.109)	(0.097)		(0.087)	(0.081)
F. educ.=2	0.63***	1.05***	Constant	43.11***	17.67***
	(0.099)	(0.090)		(0.356)	(0.324)
F. educ.=3	1.26***	2.51***	Observations	394,450	371,821
	(0.175)	(0.166)	Adjusted R2	0.061	0.068

Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A.4: Robustness check (Sons)

	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
			Municipality						
Income rank	Municipality	County	(within county)	Log		cont.	cont.	cont.	cont.
Moves=1	-1.53***	-1.77***	-1.38***	-0.0401***	Cont. fam.=1	5.29***	5.53***	5.22***	0.1011***
	(0.234)	(0.288)	(0.300)	(0.00584)		(0.101)	(0.100)	(0.113)	(0.00244)
Moves=2	-3.86***	-3.64***	-4.35***	-0.0925***	Unemployed	-2.20***	-2.24***	-2.12***	-0.0394***
	(0.338)	(0.437)	(0.529)	(0.00907)		(0.109)	(0.109)	(0.120)	(0.00262)
Moves=3	-5.85***	-5.99***	-6.89***	-0.1433***	F. educ.=2	0.64***	0.59***	0.59***	0.0083***
	(0.516)	(0.753)	(1.054)	(0.01438)		(0.099)	(0.099)	(0.107)	(0.00230)
Moves=4	-4.47***	-5.41***	-3.76*	-0.1148***	F. educ.=3	1.29***	1.21***	1.19***	0.0204***
	(0.779)	(1.209)	(1.899)	(0.02244)		(0.175)	(0.175)	(0.198)	(0.00409)
Moves=5	-10.10***	-8.38***	-6.09	-0.2339***	F. educ.=4	0.42*	0.31	-0.10	0.0106*
	(1.146)	(1.941)	(3.179)	(0.03473)		(0.184)	(0.185)	(0.217)	(0.00444)
Moves≥6	-12.02***	-17.94***	-12.40*	-0.2887***	M. educ.=2	1.09***	1.08***	1.06***	0.0176***
	(1.311)	(2.428)	(5.011)	(0.04040)		(0.100)	(0.100)	(0.108)	(0.00232)
P. income rank	0.17***	0.17***	0.17***	0.0030***	M. educ.=3	1.68***	1.65***	1.45***	0.0247***
	(0.002)	(0.002)	(0.002)	(0.00005)		(0.160)	(0.160)	(0.180)	(0.00380)
Moves=1 # PIR	0.02***	0.02***	0.02***	0.0005***	M. educ.=4	0.82***	0.77***	0.61**	0.0081
	(0.004)	(0.005)	(0.005)	(0.00010)		(0.190)	(0.190)	(0.218)	(0.00459)
Moves=2 # PIR	0.04***	0.04***	0.03***	0.0010***	Born Metro	-0.21*	-0.34***	-0.28*	-0.0092***
	(0.005)	(0.007)	(0.009)	(0.00014)		(0.097)	(0.096)	(0.110)	(0.00232)
Moves=3 # PIR	0.05***	0.06***	0.06***	0.0014***	Born Rural	-2.38***	-2.38***	-2.73***	-0.0360***
	(0.009)	(0.012)	(0.019)	(0.00023)		(0.152)	(0.152)	(0.162)	(0.00353)
Moves=4 # PIR	0.02	0.04*	-0.03	0.0007*	F. age/birth	-0.06***	-0.05***	-0.04*	-0.0012***
	(0.013)	(0.020)	(0.036)	(0.00037)		(0.015)	(0.015)	(0.016)	(0.00036)
Moves=5 # PIR	0.10***	0.11**	-0.03	0.0028***	M. age/birth	0.30***	0.31***	0.30***	0.0055***
	(0.022)	(0.036)	(0.070)	(0.00058)		(0.016)	(0.016)	(0.018)	(0.00039)
Moves≥6 # PIR	0.11***	0.12	0.07	0.0033***	Cohort	-0.98***	-0.94***	-0.87***	0.0505***
	(0.030)	(0.067)	(0.133)	(0.00076)		(0.087)	(0.087)	(0.096)	(0.00204)
Imgr. parents=1	-1.96***	-2.00***	-2.05***	-0.0435***	Constant	43.36***	42.27***	42.80***	12.1874***
	(0.169)	(0.169)	(0.191)	(0.00420)		(0.356)	(0.348)	(0.388)	(0.00847)
Imgr. parents=2	-4.20***	-4.22***	-4.13***	-0.0924***	Observations	394,450	394,450	318,148	389,854
	(0.250)	(0.250)	(0.284)	(0.00655)	Adjusted R2	0.061	0.061	0.055	0.041

Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A.5: Robustness check (daughters)

	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
Income rank	Municipality	County	Municipality (within county)	Log		cont.	cont.	cont.	cont.
Moves=1	-1.01***	-0.74**	-1.30***	-0.03***	Cont. fam.=1	2.13***	2.25***	2.09***	0.06***
	(0.206)	(0.250)	(0.262)	(0.006)		(0.091)	(0.090)	(0.102)	(0.002)
Moves=2	-2.06***	-2.36***	-2.11***	-0.07***	Unemployed	-1.09***	-1.11***	-1.07***	-0.02***
	(0.283)	(0.361)	(0.432)	(0.008)		(0.097)	(0.097)	(0.107)	(0.003)
Moves=3	-3.29***	-3.08***	-2.04*	-0.10***	F. educ.=2	1.05***	1.04***	1.02***	0.01***
	(0.415)	(0.621)	(0.827)	(0.013)		(0.090)	(0.090)	(0.098)	(0.002)
Moves=4	-2.72***	-4.45***	-1.47	-0.12***	F. educ.=3	2.53***	2.52***	2.56***	0.03***
	(0.613)	(0.925)	(1.417)	(0.020)		(0.166)	(0.167)	(0.191)	(0.004)
Moves=5	-2.58**	-3.39*	-3.43	-0.14***	F. educ.=4	3.92***	3.92***	3.82***	0.03***
	(0.953)	(1.573)	(2.784)	(0.032)		(0.175)	(0.175)	(0.207)	(0.004)
Moves≥6	-6.77***	-8.91***	-2.80	-0.26***	M. educ.=2	1.52***	1.51***	1.53***	0.03***
	(0.876)	(1.576)	(3.528)	(0.035)		(0.091)	(0.091)	(0.099)	(0.002)
P. income rank	0.14***	0.15***	0.14***	0.00***	M. educ.=3	3.22***	3.21***	3.26***	0.04***
	(0.002)	(0.002)	(0.002)	(0.000)		(0.152)	(0.152)	(0.172)	(0.004)
Moves=1 # PIR	0.02***	0.01	0.02***	0.00***	M. educ.=4	4.76***	4.75***	4.78***	0.05***
	(0.004)	(0.004)	(0.005)	(0.000)		(0.183)	(0.183)	(0.212)	(0.004)
Moves=2 # PIR	0.02***	0.02***	0.02**	0.00***	Born Metro	1.31***	1.25***	1.47***	0.00
	(0.005)	(0.006)	(0.008)	(0.000)		(0.091)	(0.090)	(0.103)	(0.002)
Moves=3 # PIR	0.03***	0.03*	0.01	0.00***	Born Rural	-0.72***	-0.72***	-0.72***	-0.01*
	(0.007)	(0.011)	(0.016)	(0.000)		(0.138)	(0.138)	(0.147)	(0.003)
Moves=4 # PIR	0.02	0.06**	-0.02	0.00**	F. age/birth	0.04**	0.05***	0.03*	0.00
	(0.011)	(0.018)	(0.029)	(0.000)		(0.013)	(0.013)	(0.015)	(0.000)
Moves=5 # PIR	-0.01	0.01	0.03	0.00	M. age/birth	0.31***	0.31***	0.32***	0.01***
	(0.020)	(0.035)	(0.058)	(0.001)		(0.015)	(0.015)	(0.016)	(0.000)
Moves≥6 # PIR	0.03	0.05	-0.03	0.00***	Cohort	0.47***	0.49***	0.51***	0.07***
	(0.023)	(0.048)	(0.079)	(0.001)		(0.081)	(0.081)	(0.090)	(0.002)
Imgr. parents=1	-0.21	-0.23	-0.21	-0.02***	Constant	17.83***	17.21***	17.64***	11.84***
	(0.153)	(0.153)	(0.173)	(0.004)		(0.324)	(0.316)	(0.354)	(0.008)
Imgr. parents=2	1.03***	1.02***	1.14***	-0.01	Observations	371821	371821	298488	368475
	(0.223)	(0.223)	(0.258)	(0.006)	Adjusted R2	0.068	0.068	0.063	0.036

Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001

Table A.6: The effect of timing and quality of the move (17 separate moving ages)

Child	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
income	Sons	Sons+cov	Daughters	D.+cov		cont.	cont.	cont.	cont.
age=2	0.48	0.25	0.43	0.32	age=3 # △	-0.02	-0.01	-0.21	-0.22*
	(0.351)	(0.347)	(0.327)	(0.322)		(0.099)	(0.098)	(0.115)	(0.113)
age=3	0.36	0.16	0.33	0.20	age=4 # △	0.06	0.06	-0.10	-0.08
	(0.371)	(0.368)	(0.349)	(0.344)		(0.104)	(0.103)	(0.122)	(0.120)
age=4	0.67	0.44	0.10	0.09	age=5 # △	-0.04	-0.01	-0.20	-0.21
	(0.396)	(0.393)	(0.374)	(0.368)		(0.111)	(0.110)	(0.129)	(0.127)
age=5	0.10	0.04	0.00	0.07	age=6 # △	0.17	0.18	-0.17	-0.17
	(0.427)	(0.423)	(0.401)	(0.395)		(0.120)	(0.119)	(0.138)	(0.136)
age=6	-0.05	0.06	-0.45	-0.37	age=7 # △	-0.08	-0.05	-0.18	-0.16
	(0.461)	(0.456)	(0.429)	(0.422)		(0.131)	(0.129)	(0.149)	(0.147)
age=7	-0.36	-0.11	0.05	0.18	age=8 # △	-0.13	-0.09	-0.17	-0.17
	(0.502)	(0.497)	(0.457)	(0.450)		(0.148)	(0.147)	(0.169)	(0.166)
age=8	-0.74	-0.42	-0.71	-0.43	age=9 # △	-0.21	-0.12	-0.13	-0.14
	(0.568)	(0.562)	(0.523)	(0.515)		(0.157)	(0.155)	(0.177)	(0.174)
age=9	-0.82	-0.40	-0.95	-0.78	age=10 # △	-0.08	-0.02	-0.02	-0.05
	(0.607)	(0.601)	(0.546)	(0.538)		(0.162)	(0.161)	(0.181)	(0.178)
age=10	-1.49*	-0.86	-0.71	-0.50	age=11 # △	0.03	0.07	0.10	0.08
	(0.627)	(0.621)	(0.574)	(0.566)		(0.173)	(0.171)	(0.199)	(0.196)
age=11	-1.67*	-0.90	-0.82	-0.40	age=12 # △	-0.37*	-0.34	0.08	0.07
	(0.673)	(0.667)	(0.619)	(0.610)		(0.181)	(0.179)	(0.208)	(0.205)
age=12	-1.41*	-0.60	-1.46*	-1.20	age=13 # △	-0.06	0.04	0.06	0.08
	(0.707)	(0.700)	(0.648)	(0.639)		(0.184)	(0.182)	(0.210)	(0.206)
age=13	-2.71***	-1.72*	-0.50	0.07	age=14 # △	-0.28	-0.20	0.08	0.12
	(0.728)	(0.721)	(0.662)	(0.653)		(0.202)	(0.200)	(0.226)	(0.223)
age=14	-4.44***	-3.50***	-1.14	-0.61	age=15 # △	-0.63**	-0.56**	0.39	0.40
	(0.791)	(0.783)	(0.715)	(0.705)		(0.218)	(0.216)	(0.243)	(0.239)
age=15	-3.33***	-2.29**	-2.60***	-1.91**	age=16 # △	-0.33	-0.23	-0.04	0.02
	(0.844)	(0.836)	(0.745)	(0.735)		(0.178)	(0.176)	(0.190)	(0.187)
age=16	-3.94***	-3.01***	-2.02***	-1.68**	age=17 # △	-0.80***	-0.69***	-0.24	-0.15
	(0.672)	(0.667)	(0.598)	(0.590)		(0.187)	(0.185)	(0.185)	(0.182)
age=17	-6.71***	-5.49***	-3.95***	-3.25***	Constant	61.06***	56.18***	39.78***	33.11***
	(0.730)	(0.724)	(0.563)	(0.555)		(0.234)	(0.322)	(0.216)	(0.296)
△	0.74***	0.60***	0.57***	0.24**	Controls	No	Yes	No	Yes
	(0.067)	(0.067)	(0.075)	(0.075)	Observations	82,236	82,236	77,722	77,722
age=2 # △	0.06	0.07	-0.39***	-0.40***	R2	0.006	0.037	0.003	0.048
	(0.093)	(0.092)	(0.107)	(0.106)	corr(u_i, Xb)	-0.182	0.075	-0.103	0.204

Standard errors in parentheses. * p < 0.05, ** p < 0.01, *** p < 0.001