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Intergenerational mobility and equal opportunity, evidence from Finland

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Tiivistelmä

Tutkimuksessa tarkastellaan ylisukupolvista liikkuvuutta siitä näkökulmasta, miten paljon lasten tuloasema ja siihen vaikuttavat muuttujat, kuten koulutusaste ja erilliset tulomuuttujat, riippuvat heidän lähtökohdistaan, lapsuuskodin tuloasemasta.

Tutkimuksessa käytetään 10 % väestöotosta vuosilta 1995-2012. Sen avulla voidaan tarkastella, miten vuosina 1980-1982 syntyneiden tulot ja koulutusaste vuosina 2011-2012 (noin 30-vuotiaina) riippuu tuloasemasta heidän lapsuudessaan (kotitalouden ekvivalentit keskitulot vuosina 1995-1999). Aineisto sisältää laajan joukon tulorakennetta kuvaavia muuttujia, jotka on poimittu tulonjaon kokonaisaineistosta ja mahdollistaa tarkastelun pääkäsitteiden, tuotannontekijätulot, bruttotulot ja käytettävissä olevat (ekvivalentit) tulot avulla. Näiden avulla voidaan tarkastella yksityiskohtaisesti liikkuvuuden eri vaikutuskanavia.

Suomessa lasten ja vanhempien bruttotulojakaumien välinen järjestyskorrelaatiokerroin on 0,223. Siis 10 prosenttiyksikön parannus lähtöasemassa (vanhempien tulojakaumassa), johtaa 2,3 prosenttiyksikön parannukseen lasten tuloasemassa. Tämä luku on merkittävästi alempi kuin Yhdysvalloissa estimoitu arvo 0,341, mutta myös hiukan suurempi kuin muissa Pohjoismaissa (Chetty et al. 2014). Suomessa tuloliikkuvuus on merkittävästi suurempaa (vanhempien asema vaikuttaa vähemmän) kuin Yhdysvalloissa. Näissä tutkimuksissa määritelmät ovat aika yhdenmukaiset. Kuten odotettua, tuloliikkuvuus on käytettävissä olevissa (tuotannontekijä-) tuloissa jonkin verran suurempaa (vähäisempää), mutta erot ovat varsin pienet.

(Vanhempien) tulojakauman huipulla tuloliikkuvuus vähenee. Koulutuksella on suuri merkitys tulojen kannalta. Tulokset osoittavat, että eri tutkintojen suorittamisasteet, koulutusvuodet ja henkilökohtaiset ansiotulot riippuvat merkittävästi vanhempien tuloasemasta. Koulutusvuosina mitattuna 10 prosenttiyksikön parannus lähtöasemassa (vanhempien tulojakaumassa), johtaa

keskimäärin 3 kuukauden lisäykseen. Lisäksi lasten saamissa pääomatuloissa näkyy voimakas hyppy ylöspäin vanhempien jakauman huipulla (ylin tuloprosentti).

Suomesta löytyy maakuntatasolta ns. ”Kultahattu -käyrä”. Tämän mukaan maakuntien sisäisillä tuloeroilla on negatiivinen korrelaatio ylisukupolvisen liikkuvuuden kanssa.

Aluetasolla liikkuvuutta voidaan mitata myös absoluuttisesti arvioimalla, miten korkealle pienituloisten perheiden lapset yltävät valtakunnallisessa tulojakaumassa. Tulosten mukaan maakunnan matala työttömyysaste, ja (tuotannontekijätuloissa mitatut) matala köyhyysaste ja laaja keskiluokka viittaavat suurempaan absoluuttiseen liikkuvuuteen. Tosin tulokset ovat epätarkkoja, osin siksi että alueita on vain 19. Näiden aluetasolla havaittujen korrelaatioiden perusteella ei tietenkään voi tehdä päätelmiä syy-seuraussuhteista.

Abstract

Register based Finnish data are used to study intergenerational mobility. The conditional expectation of child income rank given parent income is linear in percentile ranks over most of the income range. On average, a 10 percentile increase in parent income rank is associated with a 2.2 percentile increase in a child's income rank, somewhat higher than in the Scandinavian countries. At the top of parent income distribution, we observe relatively more immobility and enhanced educational outcomes. Second, there is some variation in intergenerational mobility across NUTS level 3 regions within Finland. Third, we explore the factors correlated with upward mobility. The results suggest that regions with high relative (absolute) intergenerational mobility have less income inequality in gross or disposable (factor) income.

Keywords: inequality, intergenerational mobility, regional analysis

JEL codes: H0, I2, J6, R2

1. Introduction

Since early 1980s there has been widening annual income inequality, especially in the United States and in the United Kingdom. There has been surge in top incomes as the poverty rates have increased. The income distribution has been polarized. Top incomes have been most affected in Anglo-Saxon countries while in Europe, including Netherlands, France and Switzerland display hardly any change in top income shares (Atkinson and Piketty 2007).

In any given year, people may have incomes which are transitorily high or low for reasons such as unemployment, illness, good or bad luck, or exceptional economic events. Therefore, it may be wrong to focus on inequality in a "snapshot". As the concern for increasing income inequality has entered policy discussions, it has often been countered with changing the topic to income mobility and arguments that policy-makers should direct more attention towards information about mobility patterns than cross-sectional measures of income inequality.[1]

The reasoning is based on the equalization argument: if increased annual income inequality is associated with increased income mobility, it is possible that inequality of income measured over several years, the life-cycle, or over generations has fallen.[2] Thus, annual income distributions give an incomplete and sometimes even distorted picture of longer-term economic well-being. Similarly, the recent rise in income inequality would be of less importance if it had been accompanied with a rise in mobility.

What unites these statements is a concern with income mobility as an equalizer of longer-term incomes along with the judgment that the extent of such equalization is of ethical relevance. What is important is how income or wealth evolves over time, especially across generations.
Intergenerational mobility, so the argument goes, is what matters for normative evaluation. These arguments have resurfaced in the after-Piketty debates on inequality and public policy, but have been present for a long time.

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[1] Measuring economic mobility gives information about changes of individuals moving in the income distribution. There is no consensus on how income mobility should be measured. One may weight the possible directions of income change (up vs. down) differently, or emphasise particular status in the income distribution, e.g. escaping poverty (see Fields 2010; Fields and Ok 1999). Second, there exist alternative measurement scales, change in income ranks or in actual income; absolute or relative change, see Jäntti and Jenkins (2014) for an excellent fresh review of mobility literature.

[2] For example, to seriously evaluate the various hypotheses on the relationship between economic growth and income inequality, one should be careful enough to specify whether one should measure annual, possibly transitory, change in inequality or the change measured over a longer (possibly life-long) time span.

Milton Friedman (1962) writes as follows in *Capitalism and Freedom*: “Consider two societies that have the same annual distribution of income. In one there is great mobility and change so that the positions of particular families in the income hierarchy varies widely from year to year. In the other there is great rigidity so that each family stays in the same position year after year. The one kind of inequality is a sign of dynamic change, social mobility, equality of opportunity; the other, of a status society. The confusion between the two kinds of inequality is particularly important precisely because competitive free enterprise capitalism tends to substitute the one for the other.”

Here Friedman (1962) introduces “equality of opportunity” which has received a great deal of attention in recent years. John Roemer (1998) has attempted to formalize the concept by distinguishing between two types of factors, circumstances and effort, to which snapshot inequality might be attributed: “separate the influences on the outcome a person’s experiences into circumstances and effort: the former are attributes of a person’s environment for which he should not be held responsible, and effort is the choice variable for which he should be held responsible”, Roemer (1998).

A move towards equality of opportunity would reduce the influence of circumstances on outcome. But whether one can separate out circumstances from effort, empirically or even conceptually, is debatable. For children, the question of distinction between circumstances and effort does not arise. However, in the intergenerational context one person’s effort leads to another person’s circumstances, see discussion in Kanbur and Stiglitz (2016).

In an intergenerational context, Roemer (1998) has many precursors. Nancy Stokey (1998) writes as follows: “But we care about the sources of inequality as well as its extent, which is why we distinguish between equal opportunity and equal outcomes. To what extent is the claim that our society provides equal opportunity justified? How can we tell?....I am going to take the position that if economic success is largely unpredictable on the basis of observed aspects of family background, then we can reasonably claim that society provides equal opportunity. There still might be significant inequality in income across individuals, due to differences in ability, hard work, luck, and so on, but I will call these unequal outcomes. On the other hand, if economic success is highly predictable on the basis of family background, then I think it is difficult to accept the claim that our society provides equal opportunity. In this case accidents of birth-- unequal opportunity--are primary determinants of economic status…. Consequently, on a first pass we can judge whether there is equal opportunity by looking at parents and their children to see whether the economic success of the children is determined in large part by the success of their parents."

Pragmatism under the guise of predictability has given guidance to empirical work which adopts this "independence of origin" view.[3] The theoretical work often describes mobility in terms of transition matrices (the probability of moving from one income level to another), while empirical work focuses on correlations, typically simple correlations between the child and parent incomes. Transition probabilities characterize mobility completely and show how mobility relates to ranking of social welfare over two successive generations (Atkinson 1981a & b) or dynastic welfare (Kanbur & Stiglitz 2016).

This paper follows the work by Chetty et al. (2014), although it has a more limited scope. In the first part, we present new evidence on intergenerational income mobility in Finland on the national level. In our analysis, we focus on the 1980–1982 birth cohorts and those individuals that were living in Finland in 1995-1999 and 2011-2012, using a 10% population sample. The children's income is measured as mean total household income in 2011 and 2012, when they are approximately 30 years old. Their parents' income is measured as mean household (equivalent) income between 1995 and 1999 (the earliest years in our data with register data on income) when the children are between the ages of 14 and 19. These definitions follow closely those used by Chetty et al. (2014).

We begin by considering the intergenerational elasticity of income (IGE) obtained by regressing log child income on log parent income (Solon 1992). It has been argued in the literature that this canonical log-log specification yields unstable estimates of mobility because the relationship between log child income and log parent income is nonlinear and the estimates are sensitive to the treatment of children with zero or very small incomes. When restricting the sample by

[3] Well before Stokey (1998), Shorrocks (1978b) and Atkinson (1981a, 1981b) had characterized equality of opportunity in terms an intergenerational transition probability matrix with identical rows, implying zero correlation between parents' income and children's prospects. But Atkinson emphasizes that some reversal of income positions may indicate both increased mobility and higher social welfare, laying bare the limitations of the "independence of origin" view.

dropping the top and bottom 1% of the child and parent income distributions, the estimates stabilise, and we obtain an IGE estimate of 0.236.

To obtain an arguably more stable summary of intergenerational mobility, we turn to rank-rank (Spearman) correlation coefficients. We rank children based on their incomes relative to other children in the same birth cohort. We rank parents of these children based on their incomes relative to other parents with children in these birth cohorts. We characterize (im)mobility based on the slope of this rank-rank relationship, which estimates the Spearman correlation coefficient between children's and parents' positions in the income distribution.

We find nonlinearity at both tails of the parent income distribution using local quadratic fits of the rank-rank relationship. Intergenerational mobility is relatively low at the very top of parents' income distribution. OLS regression indicates that a 10 percentile point (pp) increase in parent rank is associated on average with a 2.23 percentile increase in a child's income rank. Our estimates of the level of mobility in Finland are somewhat lower than prior results for the Scandinavian countries, but higher than estimates for the USA in Chetty et al. (2014). The results are reasonably robust to alternative specifications of income and population sub-groups.

Children's college degree completion rates are related to parent income ranks. A 10 pp increase in parent income is associated with a 4.2 pp increase in bachelor's degree and a 2.8 pp increase in master's degree completion rate using OLS regressions. The former relationship is nearly linear, but there is detectable nonlinearity in the master's degree completion rates with better educational outcomes at the top of parents' income distribution. In years of education a 10 pp increase in parent income is associated with a 3 month increase on average. Outcomes based on personal capital income of children show some symptoms of transmission of economic advantage between generations by previously given private gifts and inheritance with an exceptionally high share of personal capital income for those children in their early 30's who were in the top one percent in childhood.

In the second part of the article, we study variation in intergenerational mobility across NUTS level 3 regions in Finland. We assign children to regions on where they lived in 1995 (where they grew up, irrespective of whether they left that region afterwards). In regional analysis, we continue to rank both children and parents based on their positions in the national income distribution, which allows us to predict children's absolute outcomes as in Chetty et al. (2014).

Assuming a linear relationship, allows one to express the conditional expectation of a child's rank given his parents' rank with just two parameters: a slope and an intercept. The slope measures "relative mobility": the difference in outcomes between children from top versus bottom income families within a region. The intercept measures the expected rank for children from families at the very bottom of the income distribution. Combining the intercept and slope for a region, one can calculate the "absolute mobility at percentile p": the expected rank of children from families at any given percentile p of the national parent income distribution (Chetty et al. 2014). We focus on absolute mobility at p = 25, which they call ‘‘absolute upward mobility.’’ This statistic is a linear predictor of the mean income rank of children with parents in the bottom half of the income distribution.

Absolute upward mobility ranges from 42.2 to 47.2 in Finnish NUTS 3 regions (much less than the range from 35.8 to 46.2 among the 50 largest US Commuting Zones). Chetty et al. (2014) argue that measuring absolute mobility is valuable because decrease in relative immobility has ambiguous normative implications on (Pareto) dominance criteria, as they may be driven by worse outcomes for the rich rather than better outcomes for the poor. Obtaining new data on absolute upward mobility is important, since we know little about how the prospects of children from low-income families vary across areas when measured on a common absolute scale. Prior cross-country analysis has focused exclusively on differences in relative mobility.

However, absolute upward mobility is highly correlated with relative mobility: areas with high levels of relative mobility (low rank-rank slopes) tend to have better outcomes for children from low income families. This paper adds to the literature, starting with Chetty et al. (2014), by providing within-country comparisons of mobility where variables are measured using the same data sources across all areas. Therefore, it offers some advantages over the cross-country comparisons (e.g. Bjorklund and Jäntti 1997; Corak 2013), since differences in measurement and methods make it difficult to reach definitive conclusions from cross-country comparisons (Solon 2002).

In the final part of the paper, we correlate the spatial variation in mobility with regional characteristics. We find a negative, but statistically imprecise correlation between income inequality within the generation of parents and relative income mobility across generations, a version of the "Great Gatsby Curve". Income inequality is here measured using gross and disposable income which directly bear upon the economic resources available to the young adults in their childhood.

On the other hand, the results suggest that the regions with high absolute upward mobility tend to have a more compressed factor income distribution, and lower unemployment rate. These correlations disappear if inequality measures for gross or disposable income are used instead. However, there are only a few regions (19) available for the estimations and correlations are imprecisely estimated. We follow Chetty et al. (2014) in construction of regional variables. The construction implicitly assumes that the spatial differences in mobility are driven by factors that affect children while they are growing up rather than after they enter labour market, see Chetty and Hendren 2016, for some supporting evidence. Naturally our or their descriptive analysis does not shed light on whether the differences in outcomes across areas are due to any causal effects. [4]

The paper is organized as follows. Section 2 defines the measures of intergenerational mobility used in the study and discuss their analytical properties. The data are described in Section 3. The empirical results are presented in Section 4. Section 5 concludes.

[4] Chetty and Hendren (2016) show that a substantial portion of the spatial variation documented in Chetty et al. (2014) is driven by causal effects of place by studying families that move across areas with children of different ages.

2. Methods

The paper gives estimates of the extent to which child's income (or other intermediate outcomes) depends on his parents' income. Following Chetty et al. (2014) we divide measures of mobility into two classes that capture different normative concepts: relative mobility and absolute mobility.[5] We use simple summary statistics to measure these two concepts empirically and compare their properties and rates of mobility across areas.

The canonical measure of relative (im)mobility is the intergenerational income elasticity (IGE), i.e. elasticity of child income, y_c with respect to parent income, y_f.

$$\beta_e = \frac{\partial E\left(\log y_c \mid y_f = y\right)}{\partial \log y}. \qquad (1)$$

The IGE is a relative (im)mobility measure because it measures the difference in (log) outcomes between children of high versus low income parents.

The IGE is commonly estimated by the regression coefficient

$$\beta_e = \rho \frac{\sigma_c}{\sigma_f}, \qquad (2)$$

where ρ is the Pearson correlation between log child income and parent income, and σ_i the standard deviation, $i = c, f$.

Both β_e and ρ present simple scale-invariant measures of the degree to which child income depends on parent income. However, the IGE depends on the ratio of standard deviations of income (2), and therefore on how inequality changes across generations (Solon 1992).[6] Intuitively, there is greater latitude for the response in children's incomes for a given increase in parents' incomes when inequality is greater among children than among parents.

To obtain stable measures of IGE it is preferable to use average, longer term real income variables to control for short term income fluctuations. Due to transitory income fluctuations,

[5] Jäntti and Jenkins (2011) give a comprehensive survey on the methodology and tools of mobility analysis.
[6] The IGE is not structurally invariant w.r.t. to interventions in the dispersion parameters (assuming a constant correlation coefficient) in the (bivariate) income process, unless this ratio is left unchanged (Engle et al. 1983).

estimates that rely on short-term averages of fathers' earnings seriously underestimate of the intergenerational elasticity (attenuation bias, see Solon 1992 and Mazumder 2005).

In addition, the child and parent income are usually measured at different ages. If the income inequality changes along the lifecycle, the estimates would vary with the age when the parent (or child) income is measured. Persistent shocks to permanent income would lead to a steady increase in income inequality over the working-life showing up as increasing (child) age profile of intergenerational income elasticities.

The above considerations would suggest that ρ is more suitable than β_e as a measure of income (im)mobility when undertaking regional comparisons since ρ controls for differences in marginal distributions. But controlling is only done to a rather limited extent, since changes in inequality are only one distributional feature in the underlying bivariate distribution and uses one specific measure of inequality to do so, see Jäntti and Jenkins (2015). However, the use of copulas allows for the modelling of the marginals and dependence structure of a multivariate probability model separately (Sklar 1959).

One can fully control for differences in marginal distributions using the Spearman rank correlation rather than the Pearson correlation. Regressing the child's rank, $r_c = F_c(y_c)$ on his parents' rank, $r_f = F_f(y_f)$ yields a regression coefficient, the rank-rank slope β_p, which is trivially the same as the correlation between child and parent income ranks, because both marginal distributions would have standard uniform distributions. [7] The rank-rank slope β_p measures the association between a child's position in the income distribution and his parents' position in the distribution, having the advantage in the intergenerational context of focusing on positional change. [8]

[7] In the paper the percentile rank in the income distribution of children, $r_c = 100 F_c(y_c)$ is regressed on the parent's percentile rank, $r_f = 100 F_f(y_f)$ in the income distribution of parents.

[8] D'Agostino and Dardanoni (2009) provide an axiomatic characterisation of the Spearman rank correlation as a measure of exchange mobility, thereby taking it beyond being a mere 'statistical' index.

We estimate both the IGE and the rank-rank slope to distinguish differences in mobility from differences in inequality and to provide a comparison to the prior literature. However, we focus primarily on rank-rank slopes because they should prove to be more robust across specifications and are thus more suitable for comparisons across areas from a statistical perspective.

The above begs the question of whether we are interested in immobility if there is a lack of a log-linear or linear rank-rank relationship in regression. In the case of joint normality in log income (1) exactly holds:

$$E(\log y_c \mid y_p) = \mu_c + \beta_e(\log y_f - \mu_f), \quad with \quad \beta_e = \rho \frac{\sigma_c}{\sigma_f}. \tag{3}$$

Under weak conditions (3) gives the best linear unbiased estimator (BLUE).

Conditions to guarantee exact linearity in the rank-rank regression are relatively weaker:

$$E(F_c(y_c) \mid y_f) = E(F_c(y_c) \mid F_f(y_f) = p) = \alpha_r + \beta_r p. \tag{4}$$

Cumulative distribution functions have uniform distributions. Therefore, the formula for BLUE implies that $\alpha_r = 0.5(1-\beta_r)$, and there is only one free estimable parameter in (4).

To allow for nonlinearity in (3) and (4) we will use nonparametric methods, local polynomial regression introduced by Cleveland (1979). Local polynomial regression solves for

$$\min_{\beta} \sum_{i=1}^{n} \left[y_i - \sum_{j=0}^{m} \beta_j (x_i - x_0)^j \right]^2 K_h(x_i - x_0). \tag{5}$$

In (5), h controls the size of the neighbourhood around x_0, and K_h controls for the weights, where $K_h(z) \equiv \frac{K(z/h)}{h}$, and K is a kernel function.[9] Denoting the solution to (5) by $\hat{\beta}$, gives the local fit, $\widehat{m}^{(0)}(x_0) = \hat{\beta}_0$ and local slope $\widehat{m}^{(1)}(x_0) = \hat{\beta}_1$, at point x_0.

[9] In the estimations, the Epanechnikov kernel is used which is the best in asymptotic minimax sense. Asymptotically a local quadratic regression using its optimal bandwidth sequence is preferred to the local linear regression with its optimal bandwidth sequence. Here the local quadratic regression is used primarily to get a smooth fit for the slope, since the asymptotic advantage does not provide finite sample guarantees.

The rank-rank slope is the measure of relative mobility. A regional measure of absolute mobility is based on a regional fit for the expected value of child's rank in the national distribution conditional on the parent's rank (4). We use simple summary statistics to measure these two concepts empirically and compare their properties and rates of mobility across areas.

Chetty et al. (2014) introduce measures of absolute mobility which are used to estimate the mean outcomes of children conditional on the income position of parents. If outcome is measured by income ranks, absolute income mobility involves not only the rank-rank slope but also the intercept term. Absolute mobility may have greater normative interest than relative mobility. Increases in relative mobility, a lower IGE or rank-rank slope, could be undesirable if they are accompanied by worse outcomes for those in the upper part of the distribution, depending on how welfare is weighted. In contrast, increases in absolute mobility at a given income level, holding fixed absolute mobility at other income levels, may increase welfare if one respects the Pareto principle and if welfare depends purely on income.

Absolute upward mobility is measured as the mean rank (in the national child income distribution) of children whose parents are at the 25th percentile of the national parent income distribution. At the national level, this statistic is mechanically related to the rank-rank slope and does not provide any additional information about mobility.[10] However, when we study regions within Finland, a child's rank in the national income distribution is effectively an absolute outcome because incomes in a particular region have little effect on the national distribution.

Another measure we report is the probability of rising from the bottom quintile to the top quintile of the income distribution (Corak and Heisz 1999, Chetty et al. 2014), which can be interpreted as a measure of the fraction of Finnish children who achieve the ''American Dream.'' If the quintiles are defined in the national income distribution, these transition probabilities can be interpreted as measures of absolute outcomes in small areas.

To give a more complete picture of mobility than those that take the "independence of origin view" (measures based on the expected rank conditional on parents' rank), a nonparametric

[10] If the rank-rank relationship is linear and since the child and parent percentile ranks each have a mean of 50 by construction in the national distribution, the mean rank of children with parents at percentile p is $50+\beta_p(p-50)$, and the slope is the only free parameter in the linear national rank-rank relationship. Intuitively, if one child moves up in the income distribution in terms of ranks, another must come down.

(10x10) transition matrix by income decile will be provided to characterise the joint distribution of child and parent income for our core sample at the national level. However, paucity of observations rules out a regional level analysis based on transition matrices.

The appropriate measure of intergenerational mobility may depend on one's normative objective. We will look at the nonlinearity in the rank-rank regression to find if there is any significant non-linearity in the change in the child's expected position in the income distribution with respect to the parents' position in the distribution. Since tail dependence in income distributions is notoriously difficult to determine, the use of copulas is more adept at finding curvature in the estimated relationships at the top and at the bottom of the income distribution, than the use of marginal income distributions, see e.g. Landersø and Heckman (2017).

3. Data

The data, provided by Statistics Finland, are based on a ten percent population sample drawn from the resident population in 1995–2012. Statistics Finland has collected for the individuals in the sample, data on employment, income, education, family status and other demographics. The data are collected from linked administrative registers covering the whole Finnish population in 1995–2012. (Register) households are formed around each sampled individual by combining individual register data with register data of all individuals dwelling in the same housing units. This information is drawn from the register covering all housing units and their occupants in Finland.

Our base data set consists of individuals living in private households. Those living in institutions are excluded in the present study. The data spanning 1995–2012 allow for following children who are born in the 1980–1982 birth cohorts up to about 30 years of age. Our base data set consists of children who were born between 1980 and 1982, and were living in Finland in 1995-1999 and 2011-2012. The sample is not restricted on the basis of citizenship status. In what follows we briefly summarize the key variable and sample definitions.

For most of our analysis, we measure income at the household level. In the data, we can link children's household income in 2011-2012 to their childhood household income. The parents cannot be identified directly in our data but we have access to variables describing the characteristics of childhood household including household income. For example, we can identify children with a single parent and account for cohabitation. Similarly, household income and individual characteristics of the child, including items of personal income, in 2011-2012 are used to study intergenerational income mobility and labour market and educational outcomes conditional on parent income.

Our measure of household income in 2011-2012 includes not only married but also cohabiting adults. This is important due to the deinstitutionalization of marriage. The Scandinavian countries have been leading this trend and since early 2000's over 40 percent of live births are born to unmarried woman whereas in 1979 the corresponding figure was 12 per cent (Statistics Finland). However, to exclude cohabiting groups of young adults who live together in order to save money, or because of the convenience of living with another, or a need to find housing, we exclude from our primary analysis sample those children who live in households with more than two adults or with children over 13 years of age in 2011-2012. The primary analysis sample is referred to as the core sample.

The income data of parents are calculated using five year averages in real (equivalent) income in 1995-1999.[11] Some variables refer to the population level estimates of the whole Finnish household population extending beyond our primary analysis sample. The base data set includes individual and household level data on 474,299 persons (based on 10 per cent population sample) who have been living in Finnish households in each year in 1995-1999.[12] After restrictions our primary analysis sample consists of 16,982 observations for children who are born in the 1980–1982 birth cohorts. Chetty et al. (2014) have extensively studied intergenerational mobility in the USA using quite similar definitions for their primary sample but they have population level data with substantially more observations available.

The income variables are obtained from the registers underlying the Finnish total statistics on income distribution (Statistics Finland 2006).[13] They include the annual income of both the households and the sampled individuals. The variables include the amount of annual income and its composition from different income sources, e.g. labour and capital income and take account of direct taxes and cash transfers from the government.[14]

Statistics Finland has top-coded all observations in the top one percent of the income distribution (the one percent of those having the highest incomes) with the corresponding means in the top one percent. [15] These top-coded observations are included in the analysis to reduce the effects of outliers and measurement error in the upper tail of the income distribution in

[11] Since the analysis is based on household data, in calculating mean household income we can account for changes in household composition. For example, a child matched to married parents in 1995 who divorce in 1996 will be matched to the income of two original parents in 1995 but to the income of the single parent after 1995.
[12] Our population excludes individuals living in institutions. The mean of population in Finland is 5 145 489 in 1995-1999.
[13] The income data are collected from administrative registers covering the whole population and are more accurate than, say, data based on interviews, imputations and estimations as is commonly done in countries without access to register data. Register based panel data have an additional advantage, as sample attrition is relatively low in comparison to survey data. Because the income registers start from 1995, we cannot link children in their early thirties (age 32 in 2012) to their parents' income before 1995.
[14] In the absence of interview data, the concepts of our income data do not meet fully the national and international recommendations for income (Canberra Group 2001). For example, we do not have access to some sources of capital income that are either tax-exempt (imputed net rent from owner-occupied housing) or are currently taxed at the source, e.g. interests from bank deposits. The same applies to private transfers among households. Taxes paid and cash transfers from public sector are covered completely, transfers even in the case when they are tax-exempt.
[15] The underlying population data are confidential. To guarantee the confidentiality of the individuals included in our sample Statistics Finland has top-coded all observations in the top one percent of the income distribution in each sample year.

calculating the mean income in 1995-1999. Top-coded income data means that there is some amount of tied ranks in the top income group which may have some effect in estimations.

The variables in the data include household income with its many components: labour earnings, capital income of households, and public cash transfers received and paid by households. Factor income is composed of labour income, the sum of wage and entrepreneurial income, and capital income. Adding cash transfers gives gross income which is our main income variable. [16] The definition of gross income is close to the income measure that Chetty et al. (2014) use.[17] Main difference is in the treatment of cash transfers. In Finland, as in other European countries, the scope and scale of public income transfers is much larger than in the USA.[18] Public redistribution policies naturally affects the level and distribution of market income and estimates of intergenerational income mobility.

Disposable income is formed from the income components by summing factor income with cash transfers received and subtracting transfers paid by households. We use a measure of real household income which has been equivalised accounting for differences in household size and composition.[19] In calculations each household member is assumed to have access to an income level which is obtained by dividing total household income by an equivalence scale denoting the number of equivalent adults in the household. The (modified) OECD-equivalence scale gives weight one to the first member in the household, weight 0.5 to each additional member in the household over 13 and 0.3 to those under 13 years of age.

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[16] The income sources that define gross income are: capital income, labour (earned) income which includes both wage income (employed) and entrepreneurial (self-employed) income, and cash transfers received. Capital income includes rents, dividends, taxable interest payments, private pensions and capital gains. Entrepreneurial income accrues to self-employed from agriculture, forestry and firms. Wage income consists of money wages, salaries, value of managerial stock options and compensations in kind, deducting work expenses related to these earnings. Public cash transfers received include, housing benefits and child benefits, unemployment and welfare assistance, unemployment and sick insurance and national and occupational old age, disability and unemployment pensions. Disposable income is obtained by subtracting income transfers paid which include direct taxes and social security contributions paid by the household members.

[17] Their baseline income measure includes labour earnings and capital income as well as unemployment insurance, Social Security, and disability benefits. It excludes non-taxable cash transfers such as Temporary Assistance to Needy Families and Supplemental Security Income, in-kind benefits such as food stamps, all refundable tax credits such as the EITC, non-taxable pension contributions (such as to 401(k)s), and any earned income not reported to the IRS.

[18] However, our income variables do not include public transfers in kind, which are extensively used in the Nordic countries and can be considered as one defining characteristics of the Nordic welfare model.

[19] Cost-of-living-index data (Statistics Finland) have been used to transform nominal annual values to real values, in 2012 prices.

The results may depend on the way we define or restrict the data. Income in a single year is a noisy measure of lifetime income, which attenuates estimates of intergenerational persistence (Solon 1992). The income data of parents is calculated using five year averages in real (equivalent) income in 1995-1999.[20]

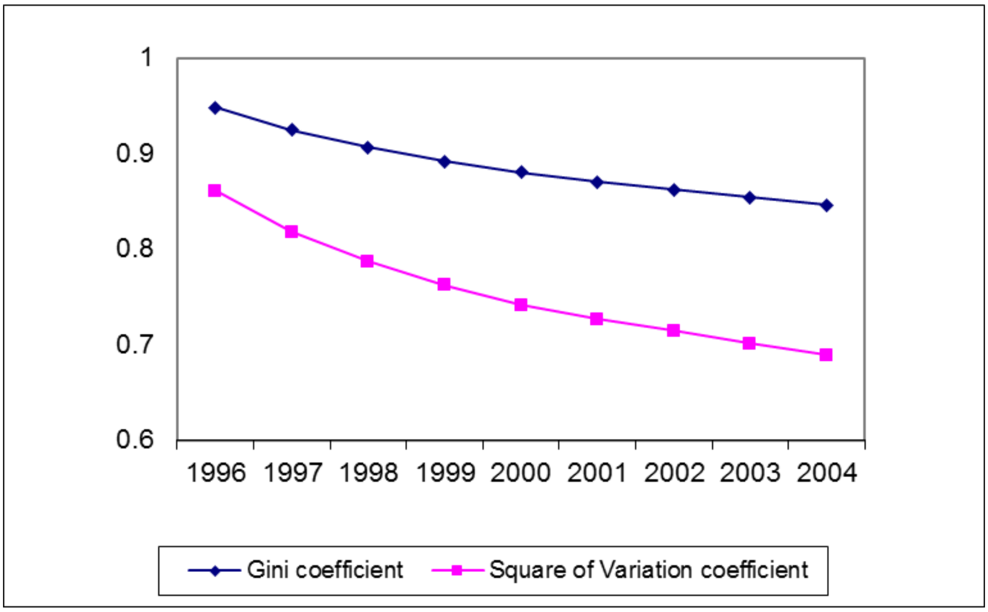

Figure 1. Income stability in disposable income vs. time horizon

Notes: This figure presents the evolution of Shorrocks's (1978a) rigidity index as the time horizon is extended from 2 to 10 years, for two inequality indices: the Gini coefficient and the square of the variation coefficient. Shorrocks's index has in the numerator the inequality of *T*-period cumulated mean income, and in the denominator a weighted average of the inequality in each year, with the weights equal to the ratio of the mean income in that year to the mean income over *T* years. The time profile of the Shorrocks's index shows the degree to which equalization occurs as the period is extended.

Figure 1 shows the Shorrocks's (1978a) income rigidity indices for the Gini coefficient and the square of the variation coefficient. The rigidity index tells that 70 (74) percent of the income equalization observed over a ten-year time horizon, has taken place in the first five years in the case of the Gini coefficient (the square of the variation coefficient, respectively), see Rantala & Suoniemi (2010).

[20] Chetty et al. (2014) find that the rank-rank slope in (4) is virtually unchanged by adding more years of data beyond 5 years: the estimated slope using 15 years of data to measure parent income (0.350) is only 2.8% larger than the baseline slope of 0.341 using 5 years of data.

Similarly, in measuring the child's income one should guard against the year to year variation of income and preferably control for short term income fluctuations. The estimates may well vary with the age when the child income is measured. Figure A1 (in the Appendix) shows that income mobility in factor income, which is the most variable income component as it consists mainly of earnings, is highest in young adults (20-29 years old, in 1995). But incomes stabilise after that and there is relatively little change in the age gradient of income mobility in the five-year age brackets, covering the range from 20 to 64 years of age, in 1995 (Rantala & Suoniemi 2010).

4. Results

4.1. Mobility at the national level

The empirical analysis is divided into two parts. The first characterise the relationship between parent income and child income and other outcomes, such as education level, at the national level, and the latter presents some results on the regional level, using 20 Finnish regions.

We first present estimates of relative mobility and evaluate the robustness of the estimates to alternative sample (and income) definitions. In the analysis, we use the core sample (1980–1982 birth cohorts) and measure parent income as mean household (equivalent) gross income from 1995 to 1999 and child income as mean household (equivalent) gross income in 2011–2012, when children are approximately 30 years old.

Intergenerational elasticity and log income correlation

Figure 2 presents a binned scatter plot of the mean log income of children versus the mean log income of their parents on a restricted sample, see below. In the figure, the horizontal axis is divided into 100 equal-sized (log income) bins and mean child log income, $E(\log y_c \mid y_f = y)$, is plotted versus mean log parent income, $\log y_f$, in each bin. The conventional method to analyse the dependence between child and parent income is to regress the log of child income on the log of parent income (as discussed in Section 2), excluding observations with zero income. The regression coefficients and standard errors reported in this and all subsequent binned scatter plots are estimated on the underlying microdata using OLS regressions. This regression yields an estimated IGE of 0.236 as shown in the first column of row 3 in Table 1. The above estimate has been obtained by restricting the sample by dropping observations in the bottom and top one percent of both parent income and child income.[21] To obtain a nonparametric representation of the conditional expectation of child income given parent income we have used local quadratic fit estimated on the underlying microdata (Cleveland 1979).

[21] The value of Finnish IGE is substantially lower than the baseline estimate, 0.344 that Chetty et al. (2014) report for the USA but is somewhat higher than the values reported for Canada and the Scandinavian countries, for Canada and Denmark, see Chetty et al. (2014), for Norway, see Pekkarinen et al. (2017), and for Sweden, see Björklund and Jäntti (1997).

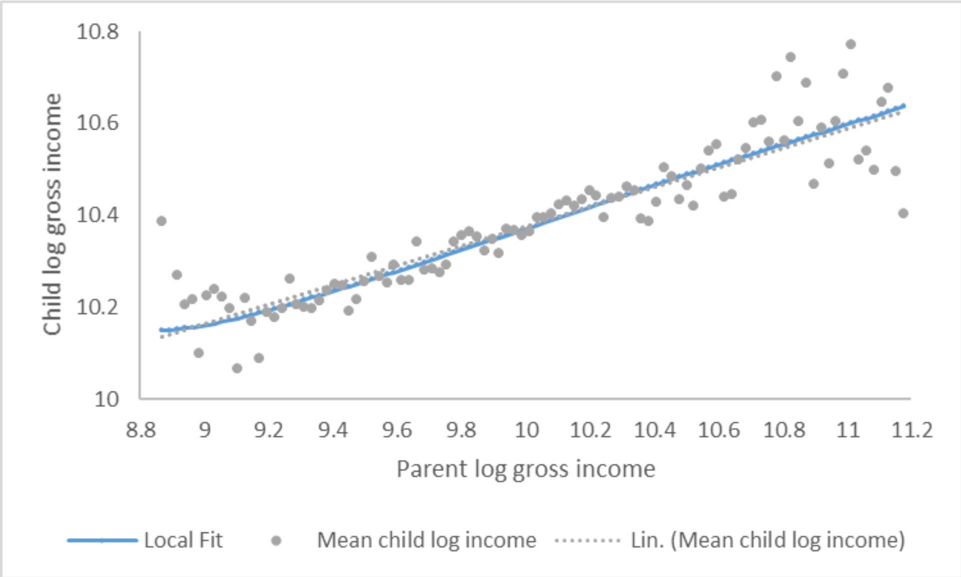

Figure 2. Association between children's and parents' logarithmic incomes

Notes: Nonparametric binned scatter plot of the relationship between child log income and parent log income are based on the sample (1980–1982 birth cohorts) and baseline household income definitions for parents and children. Child income is the mean of 2011–2012 household equivalent gross income (when the child is approximately 30 years old), whereas parent income is mean household equivalent gross income from 1995 to 1999. Incomes are in 2012 euros. To construct scatter plot, we bin parent income into 100 equal-sized bins and plot the mean level of child income versus mean level of parent income within each bin. For estimation, we have dropped the bottom and top one percent of the parent distribution. In estimating the local quadratic fit on micro data children in the bottom and top one percent of the child distribution are excluded from the log income series. In the figure, the linear log-log relationship is depicted in dashed lines. The estimates are obtained from regressions on the microdata.

Earlier research has established that elasticity estimate may turn out to be quite sensitive to changes in the regression specifications. There are two reasons for this.

First, the log-log specification discards observations with zero income and the way these zeros are treated can change the IGE dramatically. In our data, the income variables have been bottom-coded with either 120 € or 1,200 € in annual real equivalised income (2012 prices). Including the zeros by assigning those with zero income an income of 120 € gives the IGE estimate 0.224 as shown in row 1 of Table 1. If instead we treat those with zero income as having an income of 1,200 €, the estimated IGE becomes 0.227 (row 2 of Table 1). Chetty et al. (2014) find that small differences in the way children's income is measured at the bottom of the distribution can produce substantial variation in IGE estimates. Above we found that restricting the sample to observations between the 2nd and 99th percentile of parent income yields a somewhat higher IGE estimate of 0.236.[22]

Second, the relationship between log child income and log parent income may be nonlinear, as Chetty et al. (2014) and Corak and Heisz (1999) have found out using US and Canadian tax data, respectively. By (2), the local estimate of the elasticity is dependent on the (local) variances of the child and parent income distributions. These variances may not be constant over the whole income range giving instability in elasticity estimates in the case of a constant correlation coefficient. Because of this, the IGE is sensitive to the point of measurement in the income distribution. The variances are more likely to vary at the ends of the income distribution, particularly at the low end of the distribution, as the treatment of zeros illustrates.

In our data, the nonlinearity of the elasticity estimate is illustrated by Figure A2 (in the Appendix) which shows local quadratic fits for the expected value (3), see also (5). The relationship between log child income and log parent income is highly nonlinear at the low end of the parent income distribution. The panels in Figure A2 show that small differences in the way children's income is measured at the bottom of the distribution can produce substantial variation in the local IGE estimates. But at higher incomes the relationship stabilises, and dropping observations in the bottom and top one percent of both parent income and child income produces a relationship which is nearly linear but for a small convex section at the low part of the income distribution. Figure A3 (in the Appendix) shows, how the log-log slope in Figure 2 changes along the income range as it is estimated by a local quadratic fit. We conclude that in Finland, the estimates of IGE are remarkably stable across the main part of the income distribution, in contrast to Chetty et al. (2014) [23]

Columns (b)–(h) in Table 1 present the baseline specification in column (a) for alternative subsamples. Columns (b)–(f) split the sample by the child's gender and the family status in 1995. Columns (g)-(h) split the sample by mother tongue.[24] Across these subsamples, the IGE

[22] Bottom-coding has little influence on the measurements which use gross or disposable income. However, factor income is frequently observed with zero values, and in this case bottom-coding has more influence on the specific values of the IGE one observes.
[23] Bratsberg et al. (2007) report that the relationship between the logarithm of child and parent income is convex in Denmark (and in Scandinavia more generally) and concave in the US for measures of wage earnings.
[24] Finland has two official languages. The majority of the population speaks Finnish and a minority (under 6 percent in the mid 1990's) speaks Swedish.

estimates range (in rows 1-3) from 0.168 (for children of cohabiting parents, recoding zeros to 120 €) to 0.239 (for female children, dropping the bottom and top one percent). Some variation in the estimates is caused by differences in the child or parent income dispersion across subsamples, see (2).[25] For comparison, the log income correlation coefficients are also presented in Table 1.

Rank-Rank estimates

Here we consider the rank-rank slope, the second and arguably more stable measure of relative mobility discussed in Section 2. We measure the percentile rank of parents based on their positions in the distribution of parent incomes in the core sample. Similarly, we define children's percentile ranks based on their positions in the distribution of child incomes within their birth cohort.[26] Importantly, this allows us to include zeros in child income. Following Chetty et al. (2014), we hold these ranks fixed based on positions in the aggregate distribution, even when analysing subgroups. Figure 3 presents a binned scatter plot of the mean percentile rank of children, $r_c = 100F_c(y_c)$, versus their parents' percentile rank, $r_f = 100F_f(y_f)$.

The conditional expectation of a child's rank given his parents' rank has been estimated by a local quadratic fit on micro data. Using an OLS regression, we estimate that a 1 percentage point (pp) increase in parent rank is associated with a 0.223 pp increase in the child's mean rank, as reported in row 4 of Table 1. In contrast, Chetty et al, (2014) report almost perfectly linear fit. They report an OLS slope of 0.341 in the USA, 0.180 in Denmark and 0.174 in Canada.

The conditional expectation, $100E(F_c(y_c) \mid F_f(y_f) = p)$, shows some nonlinearity at both ends of the parent income distribution. Figure 4 shows the local nonlinearity estimates which are quite modest up to a marked increase in the top (15 percent) part of the parent income distribution.

[25] Instability may occur if the income distribution is not well approximated by a bivariate log-normal distribution with constant variance, covariance parameters.

[26] In the case of ties, we define the rank as the mean percentile rank for the individuals in that group.

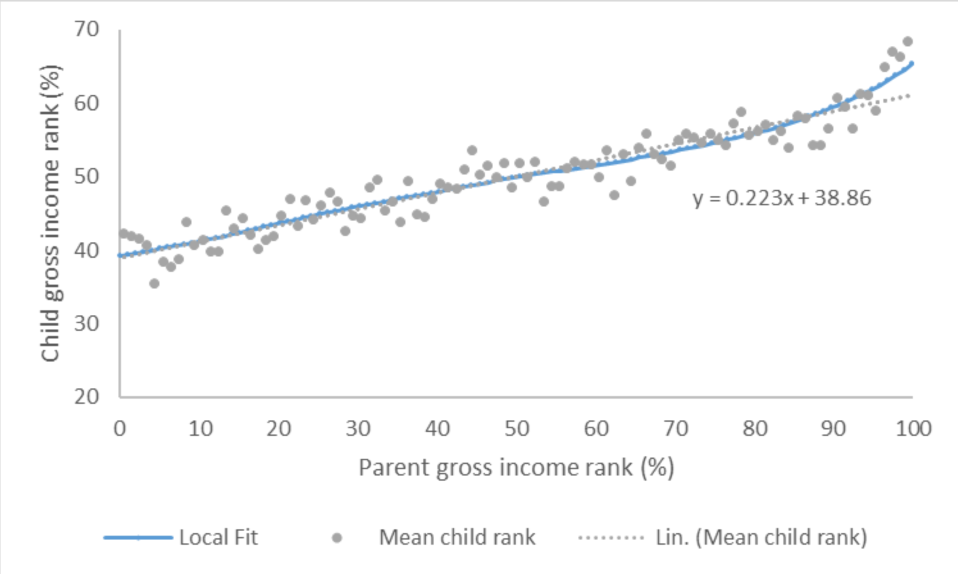

Figure 3. Association between children's and parents' percentile ranks

Notes: The figure plots the mean child percentile rank within each parent percentile rank in 100 equal-sized (centile) bins and presents nonparametric estimate of the relationship between children's and parent's percentile ranks, using a local quadratic fit on the microdata. Both figures are based on the core sample (1980–1982 birth cohorts) and baseline income definitions for parents and children. Child income is the mean of 2011–2012 household (equivalent) income (when the child is approximately 30 years old), and parent income is mean household income from 1996 to 1999. Children are ranked relative to other children in their birth cohort, and parents are ranked relative to all other parents in the core sample. In the figure, the linear fit is depicted in dashed lines. The coefficient estimates reported on the figures are obtained from OLS regressions on the microdata.

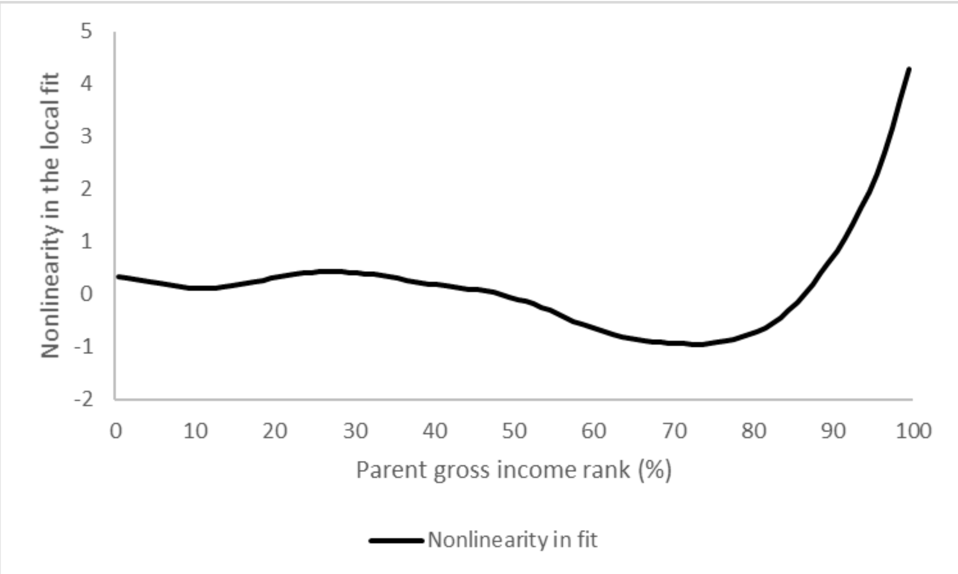

Figure 4. Nonlinearity in the association between children's and parents' percentile ranks

Notes: Nonlinearity in the relationship between child percentile rank and parent percentile rank, based on the sample (1980–1982 birth cohorts) and baseline household income definitions for parents and children, see Figure 2. Children are ranked relative to other children in their birth cohort, and parents are ranked relative to all other parents in the core sample. Nonlinearity in the fit is obtained by the difference between a local quadratic fit (Cleveland 1979) and a linear regression on micro data.

The rank-rank slope estimates are generally quite similar across subsamples, as shown in columns (b)–(h) of Table 1. The results may depend on the way we define the data. Income in a single year is a noisy measure of lifetime income, and may cause some attenuation bias (Solon 1992). The income data of parents is calculated using five year averages in real income in 1995-1999. In Section 2 we presented the time pattern of Shorrocks's income rigidity indices as the time horizon is extended to justify our choice. [27]

Our definition of gross income is close to the income measure that Chetty et al. (2014) use. Main difference is in the treatment of cash transfers. In Finland, as in other European countries, the scope and scale of public income transfers is much larger than in the USA.[28] Public redistribution policies naturally affects the level and distribution of market income and estimates of intergenerational income mobility.

For comparison and robustness of our findings we present results using disposable (household equivalent) income instead of gross income (row 6 in Table 1). If taxes and transfers do not generate rank reversals, using post-tax income instead of pre-tax income would have no effect on rank-based measures of mobility. In Finland, taxable income is based on personal income, not family income as in some other countries, such as France, with practically no reductions nor amendments based on family or married status, such as the number of children. However, the Nordic dual income tax model treats capital and earned income differently. In those income groups facing high marginal tax rates in earned income, capital income is taxed using much lower rate.[29] We estimate that a 1 percentage point (pp) increase in parent rank is associated with a 0.216 pp increase in the child's mean rank (row 6 in Table 1). Redistribution of income by taxation could lower the local rank-rank slope at higher levels of parental income, with the

[27] Chetty et al. (2014) find that the rank-rank slope (4) is virtually unchanged by adding more years of data beyond 5 years: the estimated slope using 15 years of data to measure parent income (0.350) is only 2.8% larger than the baseline slope of 0.341 using 5 years of data.

[28] However, our income variables do not include public transfers in kind, which are extensively used in the Nordic countries and can be considered as one defining characteristics of the Nordic welfare model.

[29] Introduction of the dual income tax model in 1993 created strong incentives to shift earned income to capital income for those in the highest marginal tax brackets (Pirttilä and Selin 2011). In the 2000's there has been a decrease in the (Reynolds-Smolensky) progressivity of taxation in Finland (Riihelä, Sullström & Suoniemi 2008). The decrease has been affected most by changes at the high end of the income distribution. Similarly, the main factor that has driven up the top income shares in Finland since the mid 1990's is in a sudden increase in the share of capital income, as top incomes have become more and more composed of dividend income (Riihelä et al. 2008). However, there has not been much change in the horizontal inequality of taxation, which accounts for the post-tax income rank reversals. Instead, a strong correlation between the level of before-tax income and share of capital income gives an explanation for the decrease in progressivity of taxation.

corresponding effect on the overall slope estimate.[30] On the other hand, in Finland incentives to shift earned income to capital income (see footnote 20) at the top incomes lower marginal tax rates and redistribution at the very top.

When public cash transfers are included in the income definition Landersø and Heckman (2017) report intergenerational elasticity estimates for the USA which are close to the estimates reported in Chetty et al. (2014) and somewhat higher than their estimate, obtained by excluding public transfers.[31] They argue that the Scandinavian countries display greater income mobility largely a consequence of redistributional tax, transfer, and wage compression policies. For comparison, we present results using factor (household equivalent) income instead of gross income (Table 1, row 5). Factor income gives a higher slope estimate, as expected, but the effect is quite modest. We estimate that a 1 percentage point (pp) increase in parent rank is associated with a 0.232 pp increase in the child's mean rank (row 5 in Table 1).

Decile transition matrix

Table 2 presents a decile transition matrix, (i,k): the probability that a child is in decile k of the child income distribution conditional on his parent being in decile i of the parent income distribution. Chetty et al. (2014) are particularly interested in the probability of moving from the bottom quintile to the top quintile, a simple measure of success which they label as 'achieving the American dream'. This probability is 11.7 % in Finland, compared with 11.7% in Denmark (Chetty et al. (2014) refer to Boserup, Kopczuk, and Kreiner (2013)), 13.4% in Canada (Corak and Heisz 1999) and 7.5% in the United States. In this sense, the chances of achieving the American dream are considerably lower for children in in the United States than in these other countries. On the other hand, a whole 24.3 percent of children in the top decile of the parent income distribution stay in the same decile of the child income distribution in Finland.

[30] Landersø and Heckman (2017) find that including taxation in the income definition reduces the Danish intergenerational elasticity estimate.
[31] Landersø and Heckman (2017) find that intergenerational income elasticity based on gross income, excluding public transfers, is 0.352 for Denmark. The corresponding estimate for the US is 0.312. The elasticity estimate for Denmark drops by around 20 percent to 0.271 when public transfers are included in the measure of income. This illustrates the important role of redistribution in Denmark. For the US, the corresponding estimate jumps to 0.446, bringing Landersø and Heckman close to the estimates reported in Solon (1992) and Chetty et al. (2014). Including taxation in the income definition reduces the Danish intergenerational elasticity estimate further.

4.2. Intermediate outcomes: education level, employment and personal income

Higher education is widely viewed as a pathway to upward income mobility. However, inequality in access to universities could limit intergenerational mobility. We supplement our analysis of intergenerational income mobility by studying the relationship between parent income and some intermediate outcomes for children: education level, employment and some personal income variables, such as labour and capital income.

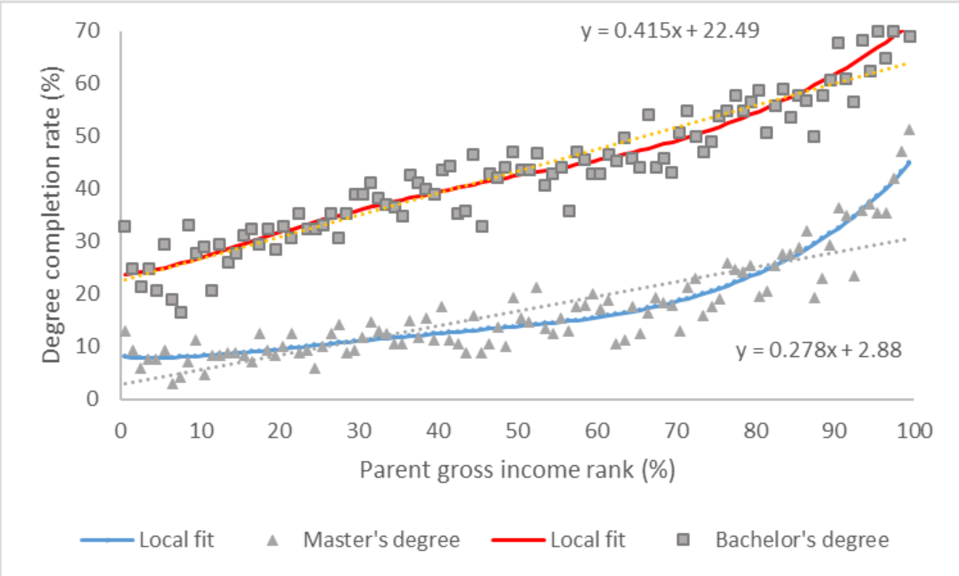

Figure 5. Association between children's education level and parents' percentile rank

Notes: The figure presents nonparametric binned scatter plots of the relationship between children's completion rates for bachelor's and master's degree versus parents' percentile rank. Completion of master's degree requires completion of bachelor's degree and the variables take this into account. Plots are based on the core sample (1980–1982 birth cohorts). Parent rank is based on mean household gross income from 1995 to 1999. The points plot the fraction of children completing the degree before 2012 within each parent percentile rank bin, 100 equal-sized (centile) bins. Nonparametric estimates of the relationship between children's education level and parent's percentile income ranks, are obtained using local quadratic fits on the microdata. The coefficient estimates reported on the figures are obtained from OLS regressions on the microdata.

Figure 5 presents binned scatter plots of the degree completion rates of children versus the percentile rank of parent household income using the core sample. Degree completion is defined as obtaining the degree before 2012. The slopes and nonparametric estimates of the conditional expectations, based on local quadratic fits (Cleveland 1997), are estimated using regressions of the outcome of interest on parent income rank on the microdata. The relationship between bachelor's degree completion rates and parental income rank is again nearly linear, with a slope of 0.415 (row 7, column (a) in Table 1). That is, moving from the lowest income (bin covering one percentile) to highest-income parents (bin covering one percentile) increases the completion rate by 41.5 percentage points. Chetty et al. (2014) report a substantially higher estimate, 0.675 for the USA. They consider college attendance which is defined as attending college in one or more years between the ages 18 and 21. In contrast, our variable, education level is based on degree completed before 2012. The completion rates for bachelor's degree are higher in Finland than in the Scandinavian countries (Statistics Finland 2013) but markedly lower than the college attendance rates in the USA.[32]

For the completion rate of a master's degree the corresponding slope estimate is 0.278 (row 8, column (a) in Table 1). But in this case the nonparametric estimate for the expected completion rate, estimated by a local quadratic fit, is clearly nonlinear with the degree completion rates starting to rise rapidly in the top quintile of the parent income distribution. Inequality in access to universities which offer graduate programs may limit intergenerational mobility of students with low income parents. There is some failure to promote greater educational mobility despite welfare state providing for free university-tuition. How can we increase access to higher education for children from low income families? Is the further expansion of higher education and relaxing the rationing in higher education, which limits the number of graduates a solution to this problem in Finland?

Perceived (short run) losses in earnings while studying in the university and higher risk aversion in low income families are not the main explanation. We agree with Chetty et al. (2014) that the strength of these correlations indicates that much of the divergence between children from low- versus high-income families emerges well before they enter the choice between labour market and higher education.

Landersø and Heckman (2017) claim that both in Denmark and the USA, much of the average association between parental resources and the educational attainment of children can be explained by factors set in place by age 15, including child skills. Further they point to wage compression and the higher levels of welfare benefits as being counterproductive in providing incentives to pursue education. The low returns to education in Denmark may help to explain

[32] We do not have access to data on college attendance to maintain comparability with Chetty et al. (2014). In addition, cross-country institutional differences may confound international comparisons that rely on education level. One cannot control for all cross-country institutional differences. One problematic issue is the minimum school leaving age, 16 years after 9 years of education in Finland in comparisons of years of education.

the disconnect between the egalitarian childhood policies in Denmark and the roughly equal levels of educational mobility in Denmark and the US. In contrast, we found that the educational mobility is substantial higher in Finland than in the USA, although there is some lack of mobility if the master's degree is the measure of education level.

Observing the other end of education ladder, row 10 in Table 1 reports the estimation results for educational attainment which is based on the rates of those having no degree before 2012. They have completed at most comprehensive school education with 9 years of education. There is a clear negative slope in regressions of the outcome of interest on parent income rank. The relationship is again virtually linear, with a slope of -0.127 (row 10, column (a) in Table 1). This means that moving from the lowest-income to highest-income parents lowers the expected rate of staying with no post comprehensive school education by 12.7 percentage points, ranging from lowest income parent (bin covering one percentile) at 17.8 pp to 3.6 pp to the parent with highest income (bin covering one percentile).

Summarizing educational outcomes with years in education, the corresponding slope estimate is 0.026 (row 9, column (a) in Table 1). In line with the expected completion rates for master's degree, the nonparametric estimate for the expected years of education, estimated by a local quadratic fit, is clearly nonlinear with the years of education starting to rise rapidly at the top quintile of the parent income distribution (Figure A4). Moving from the lowest income to highest-income parents increases the expected years of education by more (by 3.1 years) than the estimate 2.6 years, based on the slope coefficient, would indicate.

These correlations between educational outcomes and parent income ranks do not vary significantly across subsamples, as shown in columns (b)–(h) in Table 1. But there is a tendency for higher slope estimates for those population groups attaining higher rates of education.[33] In those subsamples, children, particularly with parents at the high end of the income distribution have higher levels of education attainment.

[33] For example, females have substantially higher education levels than males in younger age cohorts such as those considered here. This shows up in the estimates of column (c).

Next, we consider individual outcomes based on employment and personal income definitions for the children.[34] In Finland unemployment was quite high in younger age cohorts in 2011-2012, and the mean activity rates in 2011-2012 were 84.5 and 89.2 percent in the groups 30-34 and 35-39 years of age, respectively (Statistics Finland 2012, 2013). Top panel in Figure A5 (in the Appendix) shows an increase in expected values of children's mean months in employment (in 2011-2012), conditional on parent income rank. The employment outcome seems to steady after the 80'th percentile point in parent income distribution.[35]

Similarly, there is a steady increase in expected values of mean personal earned income in 2011-2012, conditional on parent income rank (centre panel in Figure A5). We chose to measure the personal income outcome in euros and not in terms of income ranks because now the results are comparable with the top panel and can be combined to give a rough idea of mean earnings per month.

The bottom panel which shows corresponding expected values of personal capital income is an interesting one considering equal opportunities, although this income variable has less bearing on the gross income of children. The levels in expected values are nearly constant with at most 300-1000 €'s in a year until the top decile in the parent income distribution. In the top income decile, the capital income jumps up and at the top (parent income) one percent the observed mean value of children's capital income is 12,130 €'s (mean in 2011-2012) indicating early transmission of parent's wealth.[36] We do not show the results for these outcomes separately by gender or other population groups reported in Table 1.[37]

[34] Chetty et al. (2014) main concern is that children of higher income parents may be more likely to marry, exaggerating the observed correlation in family income relative to individual income. Our purpose is to shed more light on the mechanisms by which the intergenerational income (im)mobility operates.

[35] There is a slight decrease in the expected months in employment at the top of parent income distribution. Apart from differences in child-bearing age, a reason may be those still studying for the highest education levels. Education will influence not only the overall income level but also the life-cycle profile with people with low education usually having a flatter income profile, while people with higher education start earning income later but afterwards have a more rapidly growing income profile.

[36] Over 50 percent of property income of those children with parents in the top one percent are composed of dividends and returns to similar assets indicating previously given gifts or inheritance.

[37] Results available on request. Chetty et al. (2014) and Chadwick and Solon (2002) report that using individual income to measure the child's rank has differential impacts by the child's gender. For male children, using individual income instead of family income reduces the rank-rank correlation much less than for female children from the baseline specification. The change may be larger for women because women from high income families tend to marry high-income men and may choose not to work.

4.3. Regional variation in mobility

In the second part, we turn to studying the variation in intergenerational mobility across areas within Finland. We begin by defining measures of geographic location, and present estimates of relative and absolute mobility by geographic areas.

Geographical Units

To characterize the variation in children's outcomes across areas, we permanently assign each child to a single region based on the NUTS level 3 areas where the household lived in 1995.[38] We interpret this region the area where a child grew up. Naturally the region where a child grew up does not necessarily correspond to the region which he lives in when we measure his income (at age 30) in 2011–2012. In our core sample, 42% of children live in a different region in 2012 relative to where they grew up.[39]

Finland is a small country with over 5 million inhabitants, and a homogenous population with relatively few immigrants. Are there any significant differences in intergenerational mobility at the regional level such as have been observed at the international level (Corak 2013) or in the USA at the Commuting zone (CZ) level (Chetty et al. 2014)?

As an illustration, Figure 6 plots the regional estimates of intergenerational income elasticities vs. the regional Gini coefficients calculated using disposable (equivalent) mean household income in 1995-1999. The Gini coefficients are calculated using our whole data (474,299 observations). The underlying regional estimates of IGE's and the Gini coefficients are reported in Table A1.

[38] NUTS (Nomenclature des Unités Territoriales Statistiques) is the regional classification system of the EU, according to which all common regional statistics of the EU are compiled. The official NUTS division is recommended to be used as the primary regional division in statistics. The NUTS classification is defined in the Regulation of the European Parliament and of the Council No. 1059/2003. In the Finnish NUTS regions formed the NUTS 3 level until 11 July 2003.

[39] There are 8 children (0.05 percent of observations), with no region code in 2012.

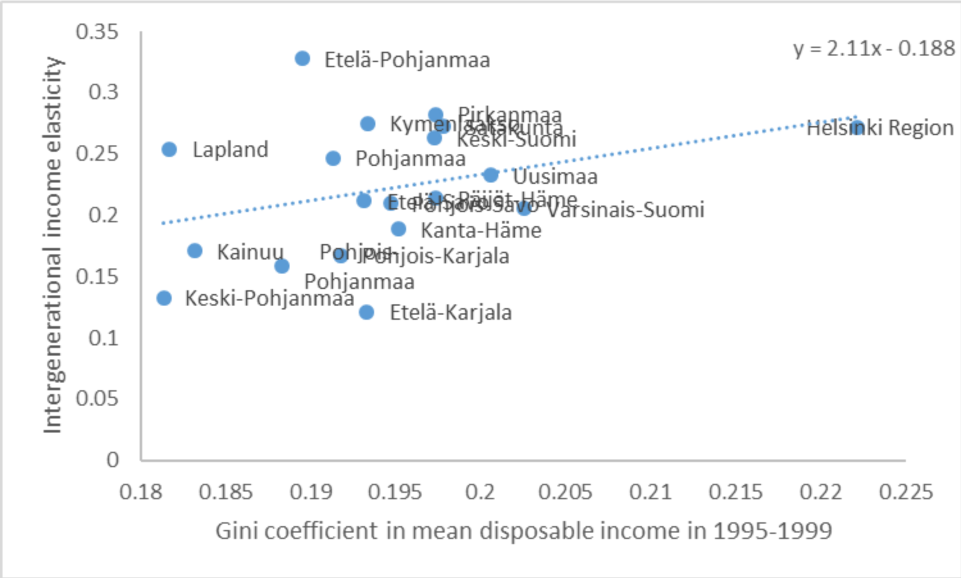

Figure 6. The Great Gatsby Curve, association between regional IGE's and income inequality

Notes: The figure presents regional estimates of IGE's. Child income is the mean of 2011–2012 household gross income (when the child is approximately 30 years old), whereas parent income is mean (household equivalent) gross income from 1995 to 1999. Incomes are in 2012 euros. In regional estimations, we have dropped the bottom and top one percent of the national child and parent income distributions, leaving 16 327 observations. The Gini coefficients are calculated using mean disposable (equivalent) household income from 1995 to 1999 using the whole data, 474,299 observations.

Using regional data in Finland, Figure 6 produces a version of the ''Great Gatsby'' curve (Krueger 2012). This curve has attracted attention because it suggests that more inequality in present incomes is likely to make household income play a stronger role in determining the adult outcomes of their children, for international data see Corak (2013).

Recall that the intergenerational income elasticities may be unstable because the income distribution is not well approximated by a bivariate log-normal distribution with a constant log income covariance matrix. This will make it difficult to obtain reliable comparisons of mobility across samples or geographical areas using the IGE. Therefore, we will turn to more stable measures of mobility which are based on ranks in the child and parent income distributions.

Measures of relative and absolute mobility

In what follows, we measure mobility at the NUTS level 3 using the core sample (1980–1982 birth cohorts) and the definitions of parent and child household income described in Section 3. Importantly, we continue to rank both children and parents based on their positions in the national income distribution, rather than the distribution within their regions.

We examine the rank-rank relationship in NUTS level 3 regions in Finland. Assuming a linear rank-rank relationship, one can summarize the conditional expectation of a child's rank given his parents' rank in each region using two parameters: a slope and an intercept. [40] These two parameters of the rank-rank relationship in region a are estimated by regressing child rank on parent rank:

$$r_{i,a(i)} = \alpha_{a(i)} + \beta_{a(i)} p_{i,a(i)}. \tag{6}$$

Above $r_{i,a(i)}$ is the national income rank (among children in the birth year cohort) of child i who grew up in region $a(i)$. Similarly, $p_{i,a(i)}$ denotes his parent's rank in the national income distribution of parents.[41]

The slope of the rank-rank relationship $\beta_{a(i)}$ in equation (6) measures the degree of relative mobility in region $a(i)$, see Section 2. Table A2 (in the Appendix) reports the results on regressing child income rank on parent income rank, separately for the 20 regions in Finland. In Helsinki (Capital) region, $\beta_{a(i)} = 0.277$ which is at the higher part of regional estimates in Finland. In Helsinki region, the difference between the expected ranks of children born to parents at the top and bottom of the income distribution is 27.7 percentage points.[42] There is

[40] We note that linearity of the rank-rank relationship may be in question in some regions: Here our small number of observation may be responsible since Chetty et al. (2014) claim that linearity is a remarkably robust property across the US CZs.
[41] We always measure percentile ranks on a 0–100 scale and slopes on a 0–1 scale, so α ranges from 0 to 100 and β ranges from 0 to 1 in the equation (6).
[42] Interestingly, the estimate for Helsinki region is near the lowest value among the 50 US CZ's, 26.4 pp in Salt Lake City. The highest value is 39.7 in Charlotte.

more relative mobility (i.e., less persistence of income across generations) in e.g. Kanta-Häme, where the corresponding difference is 17.3 pp.

Chetty et al. (2014) define absolute mobility at percentile p in region a, as the expected rank of a child who grew up in the region a with parents who have a national income rank of p:

$$\bar{r}_{a,p} = \alpha_a + \beta_a p. \tag{7}$$

Their main interest is in the average absolute mobility for children from families with below-median parent income in the national distribution, which they denote ‘absolute upward mobility’. Assuming a linear rank-rank relationship, the average rank of children with below-median parent income equals the average rank of children with parents at the 25th percentile in the national distribution, $\bar{r}_{a,25} = \alpha_a + 25\beta_a$.

In Finland, the estimate of absolute upward mobility is 43.4 pp in Helsinki region, compared with 47.2 pp in Kanta-Häme. Therefore, children who grew up in Kanta-Häme in households in the 25th percentile of the national parent household income distribution are on average almost 4 percentile points higher in their birth cohort’s income distribution at age 30 than are children who grew up in Helsinki Region.

Absolute mobility is higher in Kanta-Häme for below median families. But part of the greater relative mobility in Kanta-Häme comes from worse outcomes for children from high income families. These two rank-rank relationships cross at the 62nd percentile, see Figure 7 that plots rank-rank relationships in three regions in Finland, one of which (Helsinki) has less relative mobility than the others. Below the 62nd percentile, children in Kanta-Häme have better outcomes than those in Helsinki, but above the 62nd percentile, the reverse is true.

The third region in Figure 7 is Lapland. There is higher relative mobility in Lapland than in Helsinki region. The difference between the expected ranks of children born to parents at the top and bottom of the income distribution is 22.2 pp in Lapland (22.3 pp at the national level). However, the absolute mobility is higher in Helsinki region for almost all percentiles p of the parent income distribution. The gap in absolute outcomes is largest at the top of the income distribution and nearly zero at the bottom. Hence, the greater relative mobility in this comparison originates from poor absolute outcomes at the bottom of the distribution and relatively, even worse outcomes at the top.

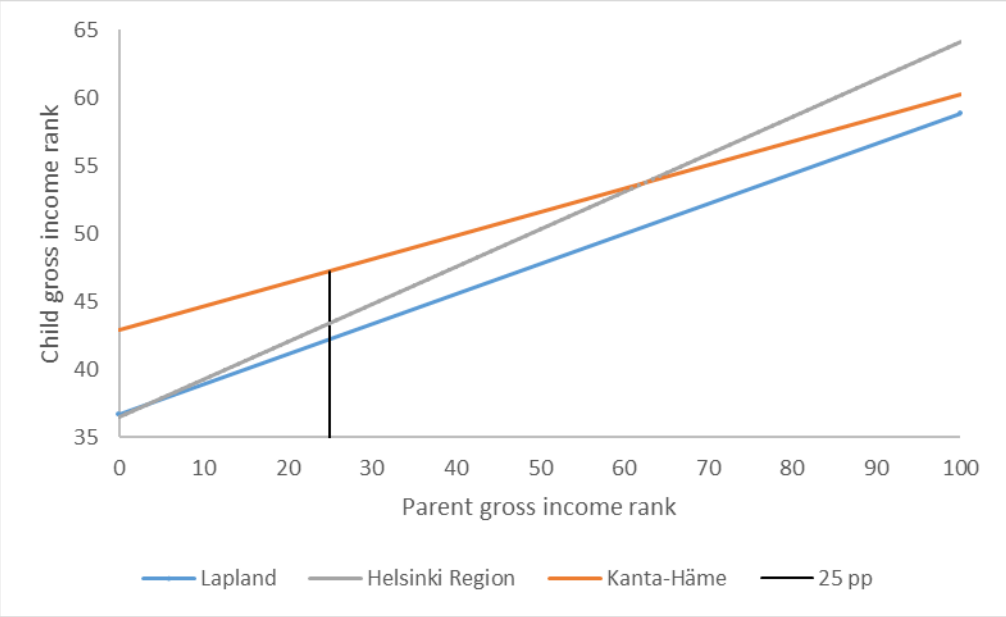

Figure 7. Absolute mobility in three regions in Finland.

The figure illustrates how regional estimates influence the estimation of absolute mobility (based on ranks in the national distribution) across the whole income range. The estimates of absolute upward mobility at 25 pp, are indicated by the vertical line. For regional estimation results, see Table A2 (in the Appendix).

Correlates of intergenerational mobility

Chetty et al. (2014) find that intergenerational mobility varies substantially across areas within the United States. To help in giving insight and developing new models of intergenerational mobility they report correlations of mobility statistics with various factors that have been discussed in the sociology and economics literature, such as segregation and inequality. Naturally, such correlations cannot be interpreted as causal mechanisms.

They cite prior work which has argued that segregation has harmful effects on disadvantaged individuals through various channels: reducing exposure to successful peers and role models, decreasing funding for local public goods such as schools, or hampering access to nearby jobs. They find that more racially segregated areas have less upward mobility. In addition, segregation of poverty has a strong negative association with upward mobility, whereas segregation of affluence does not (Chetty et al. 2014). These results suggest that the isolation of low-income families (rather than the isolation of the rich) may be most detrimental for low-income children's prospects of moving up in the income distribution. Unfortunately, we do not have currently access to such data, as to construct similar measures of income segregation in Finland.

Income levels and inequality

We explore the correlation between intergenerational mobility and properties of the local income distribution, mean income levels and inequality. Table 3 shows that the (log) mean level of household income in a region (as measured by the means of household (equivalent) income in 1995-1999) is negatively (but not significantly) correlated with relative mobility but there is no correlation with upward mobility. Chetty et al. (2014) did not find any correlations. In the case of gross (equivalised) household income, the range from the lowest-income region to the highest-income is in Finland from 22 400 € to 31 500 € a year, considerably less than in the US data. In the late 1990's Finland experienced a fast, export driven economic growth after the economic crisis of early 1990's and devaluation of national currency. In Table 3 we find negative correlation with relative mobility and the mean annual income growth in 1996–1999.

Prior work has documented a positive correlation between income inequality and intergenerational income elasticity across countries, which suggests that greater inequality within a generation could reduce social mobility (Corak 2013). We examine whether there is an analogous relationship using national income ranks across areas within Finland by correlating relative and upward mobility with the Gini coefficient of mean household (equivalised) income in 1995-1999 within each region.[43] The Gini coefficients have been calculated by dropping the top one per cent in the national income distribution.[44]

The correlation between the Gini coefficient of gross income and relative immobility is rather high, point estimate 0.419 (Table 3). However, it is not significant at the 95-percent significance level. Similar result hold with respect to the Gini coefficient of disposable income, but with respect to the Gini coefficient of factor income (not significant) negative correlation is observed. The alternative measures of inequality, poverty rate (the proportion of individuals under the poverty threshold) and the size of the middle class (the proportion of individuals between two thresholds that define middle class income) give qualitatively similar but not very encouraging results in terms of statistical significance.[45] Regionally constructed age-standardised index of mental health is negatively correlated with relative immobility.[46] This is an interesting curiosity.

The regional estimates of absolute upward mobility give somewhat different results. The correlation between the Gini coefficient of factor income and absolute upward mobility is negative, -0.246 (not significant at the 95-percent significance level). This holds also for the poverty rate in factor income (-0.197) which uses poverty threshold based on mean factor income, and for regional mean unemployment rates (-0.334) in 1995-1999. Regionally defined size of the 'middle class' in terms of factor income is positively correlated with our estimates of

[43] In calculating the Gini coefficients, Chetty et al. (2014) use the mean family income (from 1996 to 2000) of the parents in CZ's. In our case, the number of observations using the child-parent pairs is not large enough, but we use all observations in our data, instead. Our measure may better account for the possible society level benefits of equity, whereas equity among the parents captures only a part of benefits.

[44] Dropping those in the top 1% is motivated by Chetty et al. (2014) who find that the correlation between mobility and the top 1 percent income share is much weaker than that with the Gini coefficient.

[45] The poverty threshold is defined following EU recommendations. Persons are classified as being at-risk-of-poverty or social exclusion when they live in a household, whose (disposable, gross, factor) monetary income per consumption unit is below 60 per cent of the regional median income. Middle class is defined following Atkinson and Brandolini (2011). Persons are classified as belonging to middle class when they live in a household, whose (disposable, gross, factor) monetary income per consumption unit is above 75 and below 200 per cent of the regional median income.

[46] The index of Mental Health describes through three dimensions the prevalence of mental health problems as a proportion to the population of the same age. It is composed of three (equally weighted) indicators: (1) Suicides and suicide attempts leading to hospitalisation, (2) Entitlement to special refunds for psychosis-related medication, and (3) Disability pensions due to mental health issues.

absolute upward mobility with the value of 0.302. The results would suggest that regions with high absolute mobility tend to have less unemployment and a more compressed factor income distribution but lack statistical precision. Among the 99 percent of the factor income distribution (we have dropped the top 1%) earned income is the overwhelming component of factor income. A closer look into the functioning of local labour markets may prove to be helpful. Interestingly, these correlations are lower or disappear if inequality measures for gross or disposable income are used instead.

However, there is little variation in the absolute upward mobility measures in Finnish regions, compared to corresponding values among the US CZ's.[47] In addition, there are only a few regions (19) available for the estimations and upward mobility is not estimated with great precision (Table A2).[48]

If the expected value of child income rank conditional on the parent income rank is linear, as convincingly demonstrated by Chetty et al. (2014), it is equal to the BLUE. At the national level:

$$100E(F_c(y_c)\,|\,100F_f(y_f)=p)=50+\beta_r(p-50),$$

and there is only one free estimable parameter, β_r in the rank-rank regressions, recall (4). A meaningful regional estimate for the intercept in (6) requires that there are substantial differences in the concentration of regional income ranks when the ranks accord to the national child and parent income distributions.[49]

In our case, the intercept in the regional regression: $\bar{r}_{a,p}=\alpha_a+\beta_a p,$ can be written as

$$\alpha_a=\bar{\mu}_{a,c}-\bar{\mu}_{a,f}+(1-\beta_a)\bar{\mu}_{a,f}, \tag{8}$$

[47] Intergenerational mobility varies substantially across the US commuting zones. Some of which are ‘‘lands of opportunity’’ with high rates of mobility across generations and with relative mobility comparable to Canada and Denmark.
[48] We drop one region, Åland from the estimations because of the small number of observations (only 62 rank-rank pairs).
[49] In addition, one should have available sufficiently many regions to rule out rivalry in mobility among the regions, which gives negative correlation across the regions.

where $\bar{\mu}_{a,c} - \bar{\mu}_{a,f}$, is the difference between mean child and parent ranks (in the respective national income distributions) in region a, and the term $(1-\beta_a)\bar{\mu}_{a,f}$ takes into account of the coefficient of relative mobility, $(1-\beta_a)$ and mean parental endowment $\bar{\mu}_{a,f}$. If there is maximal amount of social mobility $\beta_a = 0$, then trivially all children in region a have equal expected rank, $\bar{\mu}_{a,c}$. By construction the properly weighted regional estimates produce the national level parameters with only one free parameter.

The estimation of absolute upward mobility measure depends strongly on the intercept term, for illustration see Figure 7. In our regional data, the correlation between the estimated intercept, $\alpha_a = \bar{\mu}_{a,c} - \bar{\mu}_{a,f} + (1-\beta_a)\bar{\mu}_{a,f}$, and coefficient of mobility $(1-\beta_a)$ is quite high, 0.770. This suggests that the limited regional variation (with only 19 regions available) in the concentration of national income ranks and relative mobility interferes with an accurate estimation of the absolute upward mobility measures in Finland. Obtaining more observations with population level data would lead to more precise estimation as the current results are based on a 10% sample. Nevertheless, we get some encouragement in finding that the correlation patterns of relative and absolute mobility measures are different, but do not stand in stark contrast to previous findings.

5. Conclusion

The primary motivation for economic mobility studies is to measure the extent to which longer-term incomes are distributed more, or less equally than incomes in a single year. The long run perspective shifts the focus to how income or wealth evolves over time, especially across generations. To assess the extent of dynastic inequality, one has to account for intergenerational transmission of economic advantage and disadvantage between parents and children. Depending on social preferences, one may give individuals welfare weights that depend on their position in the income distribution, or weight possible directions of income change (up vs. down) differently, or emphasise a particular section in the income distribution.

Here we have taken a first step in the analysis and our empirical work adopts the "independence of origin" view. The next step would take a more complete view using transition probabilities from one income level to another. Transition probabilities characterize mobility completely and may be used to relate mobility to rankings of social welfare over successive generations, as in Shorrocks (1978b), Atkinson (1981a) and Kanbur & Stiglitz (2016).

$$\text{(i)} \quad \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \qquad \text{(ii)} \quad \begin{bmatrix} \tfrac{1}{2} & \tfrac{1}{2} \\ \tfrac{1}{2} & \tfrac{1}{2} \end{bmatrix}$$

In terms of transition probabilities over successive generations the transition matrix (i) represents more intergenerational mobility, "complete reversal", whereas the matrix (ii) represents equal opportunities and "independence of origin" view. These examples show that equal opportunity may well run into a conflict with some rankings of social welfare.

This paper has used register data to present new evidence on intergenerational income mobility in Finland for a single set of birth cohorts, consisting of young adults. On the national level, the regression of child's expected income rank conditional on parent's income rank shows nonlinearity at the tails of the parent income distribution. We find relatively low intergenerational mobility at the very top of parents' income distribution.

Our regional analysis suggests a negative correlation between income inequality within the generation of parents and relative income mobility across generations, a version of the "Great

Gatsby Curve". Income inequality is here measured using gross and disposable income which directly bear upon the economic resources available to the young adults in their childhood. On the other hand, the results suggest that the regions with high absolute upward mobility tend to have lower unemployment rate and a more compressed factor income distribution when the children were young. These (imprecisely estimated) correlations disappear if inequality measures for gross or disposable income are used instead.

Our estimates of absolute upward mobility are uniformly lower across the regions in Finland, compared with the US CZ's, where mobility varies substantially across areas. In Finland lack of regional variation (and low number regions) may be a hurdle, impeding the search for meaningful cross-sectional correlations between mobility and regional measured variables. In Finland, the tax-and-transfer programs are more extensive than the corresponding programs in the United States. Egalitarian childhood policies, and nationwide tax, transfer, and wage compression policies equalise market outcomes and dampen the regional variation in income inequality.

Is Finland the land of opportunity with regional homogeneity, small differences in income inequality and few problems of segregation across the regions? However, our results on individual level educational outcomes, and outcomes based on employment, show that there is room for improvement. The chances that a child reaches the top decile of the national income distribution are still low for those who occupy the other end of income distribution in childhood. On the other hand, there is a high probability of staying at the top in both comparisons. This is demonstrated with an exceptionally high share of personal capital income for those children in their early 30's who were in the top one percent in childhood.

Our analysis does not indicate that absolute upward mobility in Finland is a problem that could potentially be tackled using specific regional policies. But a closer look into the functioning of local labour markets or impediments to educational and labour mobility may prove to be helpful.

In Finland, annual income inequality rose significantly after mid 1990s (Riihelä, Sullström & Tuomala 2007, 2010). The period of major income equalization from the mid-1960s to the mid-1990s has been reversed, taking the annual values of the Gini coefficient back to the levels of inequality, found 40 years ago. In Finland, the phase of increasing income inequality has occurred much later than in the United States and in the United Kingdom, where income inequality has widened since early 1980s.

Whether current inequality influences intergenerational mobility is an important question, see the recent review by Corak (2013). Emerging body of evidence argues that more inequality in present incomes is likely to make household income play a stronger role in determining the adult outcomes of their children. Correlational evidence suggests that countries with greater inequality in incomes (Gini coefficient) tend also to be those countries in which a greater amount of economic advantage and disadvantage is passed on between parents and children.

A natural question given the recent rise is, whether there will be a decline in intergenerational mobility in the future. Re-emergence of private wealth in the developed world, as argued in Piketty (2014), gives a greater role to private gifts and inheritance in the transmission of economic advantage between generations. Our results show some symptoms of these transmissions in outcomes based on personal capital income of children.

Table 1 Intergenerational Mobility Estimates

		(a)		(b)		(c)		(d)		(e)		(f)		(g)		(h)	
Child's outcome	Parent's income def.	Core sample		Male Children		Female children		Married		One parent		Cohabiting union		Finnish		Swedish	
		β	ρ	β	ρ	β	ρ	β	ρ	β	ρ	β	ρ	β	ρ	β	ρ
1. Log gross income	Log gross income	0.224	0.192	0.229	0.189	0.220	0.197	0.222	0.187	0.205	0.152	0.168	0.153	0.219	0.187	0.234	0.229
recoding zeros to 120 €		(0.009)		(0.013)		(0.012)		(0.010)		(0.025)		(0.032)		(0.009)		(0.035)	
2. Log gross income	Log gross income	0.227	0.200	0.231	0.197	0.225	0.205	0.226	0.195	0.207	0.159	0.168	0.153	0.221	0.193	0.223	0.231
recoding zeros to 1200 €		(0.009)		(0.012)		(0.012)		(0.010)		(0.024)		(0.032)		(0.009)		(0.033)	
3. Log gross income	Log gross income	0.236	0.213	0.233	0.207	0.239	0.219	0.233	0.207	0.220	0.175	0.183	0.163	0.231	0.207	0.210	0.214
dropping top and bottom 1 %		(0.008)		(0.012)		(0.012)		(0.010)		(0.024)		(0.034)		(0.009)		(0.035)	
4. Gross income rank	Gross income rank	0.223		0.225		0.221		0.223		0.203		0.179		0.217		0.222	
		(0.007)		(0.011)		(0.011)		(0.009)		(0.021)		(0.029)		(0.008)		(0.033)	
5. Factor income rank	Factor income rank	0.232		0.235		0.228		0.228		0.232		0.195		0.226		0.228	
		(0.007)		(0.011)		(0.011)		(0.009)		(0.022)		(0.029)		(0.008)		(0.034)	
6. Disposable income	Disposable income ra	0.216		0.220		0.211		0.217		0.187		0.173		0.210		0.212	
		(0.007)		(0.011)		(0.011)		(0.009)		(0.021)		(0.029)		(0.008)		(0.034)	
7. Bachelor degree	Gross income rank	0.415		0.375		0.487		0.409		0.357		0.204		0.408		0.503	
		(0.013)		(0.018)		(0.018)		(0.015)		(0.034)		(0.048)		(0.013)		(0.059)	
8. Master's degree	Gross income rank	0.278		0.241		0.326		0.287		0.222		0.183		0.276		0.310	
		(0.010)		(0.013)		(0.015)		(0.012)		(0.023)		(0.032)		(0.010)		(0.050)	
9. Education in years	Gross income rank	0.026		0.025		0.030		0.025		0.023		0.014		0.026		0.031	
		(0.001)		(0.001)		(0.001)		(0.001)		(0.002)		(0.003)		(0.001)		(0.003)	
10. Compreh. school	Gross income rank	-0.127		-0.151		-0.116		-0.099		-0.129		-0.071		-0.119		-0.116	
		(0.008)		(0.013)		(0.009)		(0.008)		(0.027)		(0.039)		(0.008)		(0.030)	
Number of observations		16 982		8 503		8 479		12 987		2 873		1 122		16 013		793	

Notes: Each cell in this table reports the coefficient from a univariate OLS regression of an outcome for children on a measure of their parents' incomes with standard errors in parentheses. All rows report estimates of slope coefficients from linear regressions of the child outcome on the parent income measure. Column (a) uses the core sample of children, which includes all children in our sample (10% population) who are (i) born in birth cohorts 1980–1982, (ii) have been living in Finland in 1995-1999, and 2011-2012. Those with mean household equivalent income over the years 1995–1999 zero or under the threshold have been bottom-coded to the thresholds given in rows 1-2. Row 3 drops the observations in the bottom and top 1% of the national child and parent income distributions. Columns (b) and (c) limit the sample used in column (a) to males or females. Columns (d), (e) and (f) limit the sample to children whose parents were married, unmarried or were cohabiting in 1995. Columns (g) and (h) limit the sample to children whose mother tongue is Finnish or Swedish in 1995. College degree completion rates are defined as completing the degree by 2012, similarly for those with no further education beyond the comprehensive school. Education in years have been calculated on education status using ISCED 2011-classification. Income percentile ranks are constructed by ranking all children relative to others in their birth cohort based on the relevant income definitions and ranking all parents relative to other parents in the core sample. Ranks are always defined on the full sample of all children; that is, they are not redefined within the subsamples in columns (b)–(h). The number of observations corresponds to the specification in row 4 and subsequent rows. The number of observations is approximately 4% lower in row 3 which drops the observations in the bottom and top 1% of the national child and parent income distributions.

Table 2. Decile Transition Matrix (%)

	Child Decile										
Parent Decile	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	
1.	16.8	14.7	12.1	11.5	9.4	8.4	8.3	6.7	6.3	5.8	100
2.	13.6	14.1	12.4	11.4	10.6	9.8	8.5	8.1	6.7	4.7	100
3.	11.6	11.2	12.4	11.0	11.5	10.4	9.1	8.7	7.3	6.9	100
4.	9.3	12.7	12.8	9.7	10.1	10.6	11.4	9.2	8.7	5.7	100
5.	8.2	10.2	9.5	11.2	10.3	10.7	10.7	10.7	10.1	8.2	100
6.	9.7	8.4	10.7	10.1	10.7	10.0	10.4	11.1	10.8	8.2	100
7.	7.4	8.7	9.5	10.5	11.5	10.8	11.0	10.4	10.3	10.1	100
8.	6.4	7.2	7.5	9.3	10.1	11.7	11.8	12.1	12.1	11.8	100
9.	8.7	7.2	7.8	8.1	9.5	9.3	10.2	12.2	12.6	14.3	100
10.	8.3	5.7	5.3	7.3	6.4	8.2	8.5	10.9	15.1	24.3	100

Notes. Each cell reports the percentage of children with (household equivalent) gross income in the decile given by the column conditional on having parents with household income in the decile given by the row for the 16,982 children in the core sample (1980–1982 birth cohorts). See notes to Table 1 for income and sample definitions.

Table A1. Regional Estimates of Intergenerational Income Elasticities and Regional Gini Coefficients.

Region	Elasticity	s.e.e.	s_x/s_y	ρ	R^2	Obs.	Gini coefficients Disp. income	Gross income	Factor income	N
Uusimaa	0.233	(0.030)	0.870	0.203	0.041	1 426	0.201	0.244	0.393	38 992
Varsinais-Suomi	0.206	(0.030)	0.910	0.187	0.035	1 313	0.203	0.247	0.426	39 870
Helsinki Region	0.272	(0.023)	0.917	0.249	0.062	2 138	0.222	0.270	0.419	78 690
Satakunta	0.272	(0.038)	0.888	0.242	0.059	819	0.198	0.244	0.441	22 301
Kanta-Häme	0.189	(0.052)	0.843	0.159	0.025	511	0.195	0.240	0.433	15 137
Pirkanmaa	0.282	(0.031)	0.848	0.240	0.057	1 362	0.197	0.243	0.430	39 852
Päijät-Häme	0.214	(0.043)	0.894	0.191	0.037	644	0.197	0.243	0.440	18 403
Kymenlaakso	0.275	(0.044)	0.867	0.238	0.057	641	0.193	0.239	0.436	17 676
Etelä-Karjala	0.121	(0.056)	0.891	0.108	0.012	399	0.193	0.240	0.441	13 061
Etelä-Savo	0.211	(0.046)	0.891	0.188	0.036	580	0.193	0.237	0.448	16 034
Pohjois-Savo	0.209	(0.037)	0.907	0.190	0.036	851	0.195	0.243	0.448	23 875
Pohjois-Karjala	0.167	(0.044)	0.904	0.151	0.023	616	0.192	0.240	0.464	16 294
Keski-Suomi	0.263	(0.038)	0.866	0.228	0.052	877	0.197	0.245	0.441	24 491
Etelä-Pohjanmaa	0.328	(0.041)	0.852	0.279	0.078	765	0.189	0.234	0.419	18 650
Pohjanmaa	0.247	(0.044)	0.926	0.228	0.052	580	0.191	0.236	0.407	16 029
Keski-Pohjanmaa	0.133	(0.072)	0.820	0.109	0.012	287	0.181	0.227	0.405	6 539
Pohjois-Pohjanmaa	0.159	(0.033)	0.813	0.129	0.017	1 389	0.188	0.236	0.420	33 497
Kainuu	0.171	(0.059)	0.907	0.155	0.024	339	0.183	0.231	0.457	8 993
Lapland	0.254	(0.043)	0.836	0.212	0.045	728	0.182	0.230	0.449	18 858
Åland	0.171	(0.135)	0.945	0.162	0.026	62	0.201	0.235	0.353	2 249
All	0.236	(0.008)	0.904	0.213	0.045	16 327	0.204	0.253	0.436	469 491

Notes: This table reports estimates of intergenerational income elasticities for the 20 NUTS level 3 regions in Finland. The income elasticities are estimated using the core sample (1980–1982 birth cohorts) and the baseline household income definitions described in Table 1. The measures in columns (1) and (4) are derived from within-region OLS regressions of child log income on parent log income, In the estimations, we have dropped the bottom and top 1% of the national child and parent income distributions. Column (1) reports the slope coefficient from this regression, which is equal to the intergenerational income elasticity. Column (4) reports the intergenerational income correlation coefficient. Column (3) reports the dispersion ratio which is calculated by dividing the standard deviation of parent log income with the corresponding values of child log income. The standard errors of the elasticity estimate are given in column (2). Column (5) reports the coefficient of determination in within-region OLS regressions, and column (6) gives the number of observations (child-parent pairs) in the region. The Gini coefficients, reported in columns (7), (8) and (9) are calculated using mean (equivalent) household income from 1995 to 1999 within each region. The Gini coefficients have been calculated by dropping the top one per cent in the national income distribution. Column (10) gives the number of observations used to calculate the Gini coefficients in the region.

Table A2. Regional Estimates of Intergenerational Rank-Rank Slope Estimates and Absolute Mobility Coefficients.

	Slope	s.e.e.	Intercept	E Rank(25)	s.e.e.	E Rank(100)	s.e.e.	R^2	IGRank diff.	Obs.
Uusimaa	0.211	(0.026)	40.75	46.02	(1.130)	61.83	(1.341)	0.042	-4.62	1 471
Varsinais-Suomi	0.191	(0.027)	40.46	45.22	(1.063)	59.51	(1.484)	0.035	-2.18	1 364
Helsinki Region	0.277	(0.021)	36.50	43.42	(1.031)	64.17	(0.967)	0.070	-10.09	2 295
Satakunta	0.251	(0.034)	38.67	44.95	(1.167)	63.77	(2.045)	0.062	4.31	845
Kanta-Häme	0.173	(0.045)	42.90	47.23	(1.626)	60.23	(2.595)	0.028	2.48	526
Pirkanmaa	0.242	(0.027)	36.71	42.76	(1.002)	60.91	(1.551)	0.055	-0.80	1 408
Päijät-Häme	0.204	(0.039)	38.41	43.49	(1.404)	58.76	(2.300)	0.040	0.41	673
Kymenlaakso	0.241	(0.039)	37.47	43.50	(1.508)	61.57	(2.150)	0.056	-2.01	655
Etelä-Karjala	0.126	(0.048)	43.51	46.66	(1.829)	56.10	(2.766)	0.016	-0.09	423
Etelä-Savo	0.167	(0.041)	40.69	44.87	(1.308)	57.40	(2.618)	0.027	5.52	593
Pohjois-Savo	0.210	(0.033)	39.58	44.84	(1.140)	60.61	(2.076)	0.043	4.42	879
Pohjois-Karjala	0.167	(0.040)	39.81	43.98	(1.292)	56.49	(2.618)	0.026	5.52	649
Keski-Suomi	0.235	(0.033)	38.74	44.60	(1.176)	62.21	(1.988)	0.054	3.14	907
Etelä-Pohjanmaa	0.290	(0.036)	38.62	45.87	(1.144)	67.61	(2.280)	0.076	8.53	792
Pohjanmaa	0.233	(0.039)	39.65	45.48	(1.454)	62.98	(2.226)	0.056	1.17	598
Keski-Pohjanmaa	0.145	(0.060)	42.18	45.82	(1.854)	56.72	(3.913)	0.019	7.44	299
Pohjois-Pohjanmaa	0.163	(0.028)	39.07	43.14	(0.910)	55.34	(1.734)	0.023	2.53	1 439
Kainuu	0.174	(0.054)	41.24	45.58	(1.673)	58.62	(3.560)	0.029	8.32	351
Lapland	0.222	(0.038)	36.69	42.23	(1.281)	58.85	(2.316)	0.044	1.55	753
Åland	0.138	(0.125)	40.33	43.78	(5.768)	54.12	(5.917)	0.020	-12.91	62
All	0.223	(0.007)	38.86	44.43	(0.286)	61.14	(0.432)	0.050	0.00	16 982

Notes: This table reports estimates of intergenerational mobility for the 20 NUTS level 3 regions in Finland. The mobility measures are calculated using the core sample (1980–1982 birth cohorts) and the baseline household income definitions described in Table 1. The measures in columns (1), (4) and (6) are derived from within-region OLS regressions of child income rank on parent income rank. Column (1) reports the slope coefficient from this regression, which is equal to the difference in mean child income rank between children with parents in the 100th percentile and children with parents in the 0th percentile (divided by 100). The intercept coefficient from this regression is reported in column (3). Column (4) reports the predicted value at parent income rank equal to 25. Column (6) reports the predicted value at parent income rank equal to 100. The standard errors of the estimates are given in columns (2), (5) and (7), respectively. Column (8) reports the coefficient of determination in within-region OLS regressions. Column (9) reports the mean difference between child and parent income ranks, and column (10) gives the number of observations (child-parent pairs) in the region.

Table 3. Intergenerational Mobility and Income Level and Income Inequality

	Relative immobility	Absolute upward mobility
Log mean income, bottom 99%		
Disposable income	0.394	-0.045
	(0.223)	(0.242)
Gross income	0.386	-0.078
	(0.224)	(0.242)
Factor income	0.396	-0.007
	(0.223)	(0.243)
Mean income growth		
Disposable income	0.461	-0.106
	(0.215)	(0.241)
Gross income	0.434	-0.099
	(0.218)	(0.241)
Factor income	0.389	-0.153
	(0.223)	(0.240)
Gini coeffient, bottom 99%		
Disposable income	0.430	-0.094
	(0.219)	(0.241)
Gross income	0.419	-0.184
	(0.220)	(0.238)
Factor income	-0.205	-0.246
	(0.237)	(0.235)
Poverty rate, 60% median		
Disposable income	0.351	0.143
	(0.227)	(0.240)
Gross income	0.382	0.085
	(0.224)	(0.242)
Factor income	-0.228	-0.197
	(0.236)	(0.238)
Size of Middle class, 75-200% median		
Disposable income	-0.393	-0.068
	(0.223)	(0.242)
Gross income	-0.415	0.103
	(0.221)	(0.241)
Factor income	0.230	0.302
	(0.236)	(0.231)
Unemployment rate	-0.228	-0.334
	(0.236)	(0.229)
MentalHealth	-0.560	0.112
	(0.201)	(0.241)
GNP per employed	0.362	0.002
	(0.226)	(0.243)

Notes: Each cell reports correlation coefficients. They are estimated using data for the 19 regions with at least 250 children in the core sample. The dependent variable in columns (1) is relative immobility, the rank-rank slope within each region. In column (2) is a measure of absolute upward mobility, the expected rank of children whose parents are at the 25th national percentile in the core sample (Chetty et al. 2014). The Gini coefficient is defined as the Gini coefficient of mean (equivalent) household income in 1995-1999, for all observations in each region dropping the top 1% in the national income distribution. The poverty rates are calculated by classifying persons as being at-risk-of-poverty when they live in a household, whose (disposable, gross, factor) (equivalent) monetary income is below 60 per cent of the regional median income. The income variables refer to mean values in 1995-1999. Definition of 'middle class' follows Atkinson and Brandolini (2011). Persons are classified as belonging to middle class when they live in a household, whose (disposable, gross, factor) (equivalent) monetary income is above 75 and below 200 per cent of the regional median income. Unemployment rates are calculated using mean values in 1995-1999. The index of Mental Health describes through three dimensions the prevalence of mental health problems as a proportion to the population of the same age. It is composed of three (equally weighted) indicators: (1) Suicides and suicide attempts leading to hospitalisation: The indicator gives the number of suicides (X60-X84, Y870) or suicide attempts leading to hospitalisation among people aged 16-79 years as a proportion to the population of the same age., (2) Entitlement to special refunds for psychosis-related medication: The indicator gives the number of granted entitlements to special refunds for medicines prescribed for treatment of psychosis (severe psychosis and other severe mental disorders, psychosis requiring demanding treatment) as a proportion of the total population., and (3) Disability pensions due to mental health issues: The indicator gives the number of persons aged 16-64 years receiving disability pension (under an earnings-related pension system and/or the national pension system) due to mental and behavioural disorders (F00-F99) as a proportion to the population of the same age. Disability pensions include pensions granted until further notice and fixed-term rehabilitation benefits. Since the prevalence of mental disorders varies considerably in different age groups we use the age-standardised version of the index (ind. 253). The index values (with national mean 100) refer to the mean values in 2000-2002. There is no separate value for Helsinki region available, so Helsinki and Uusimaa share the value instead. The index is obtained from The National Institute for Health and Welfare (2017).
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Appendix 1: Additional figures and tables.

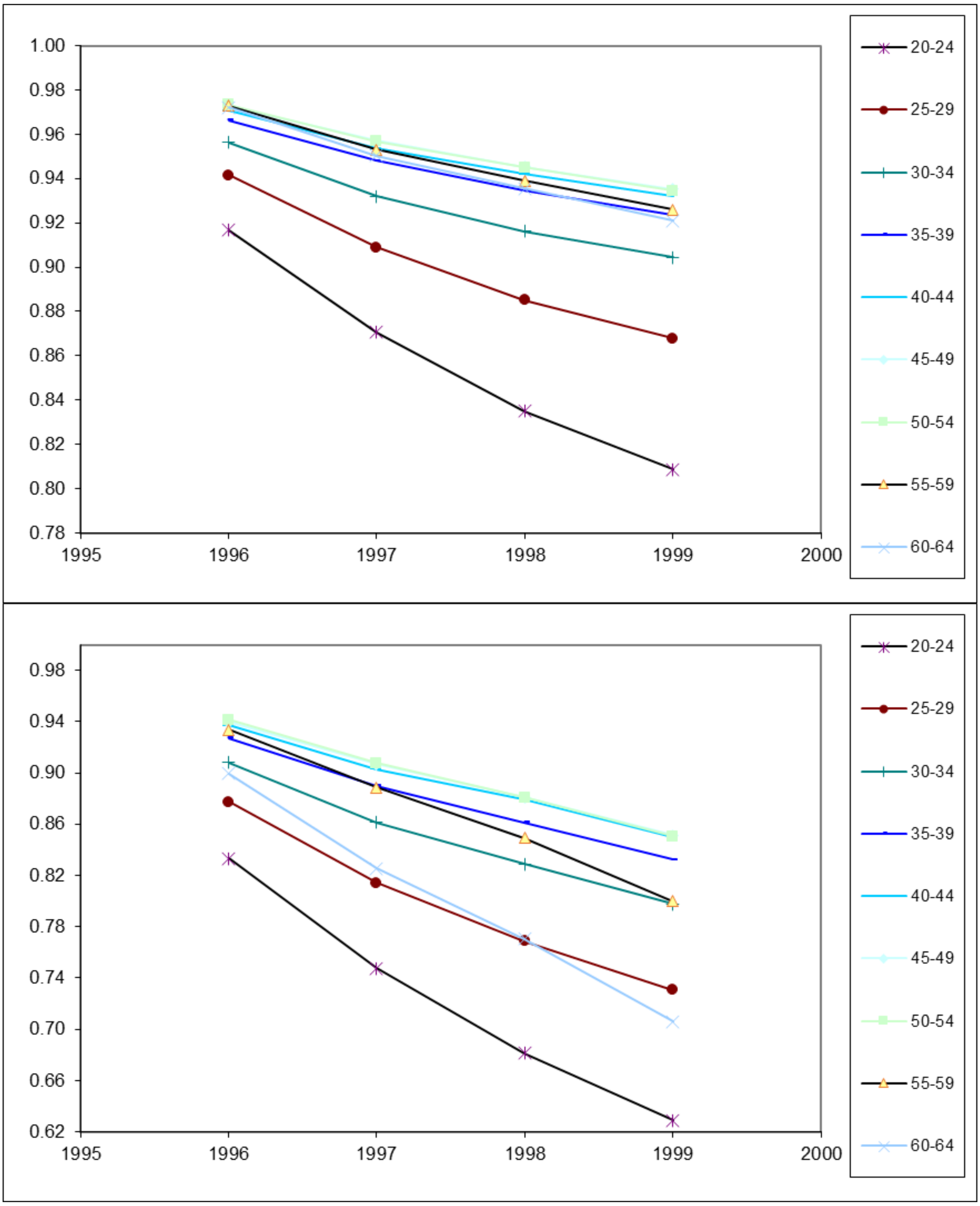
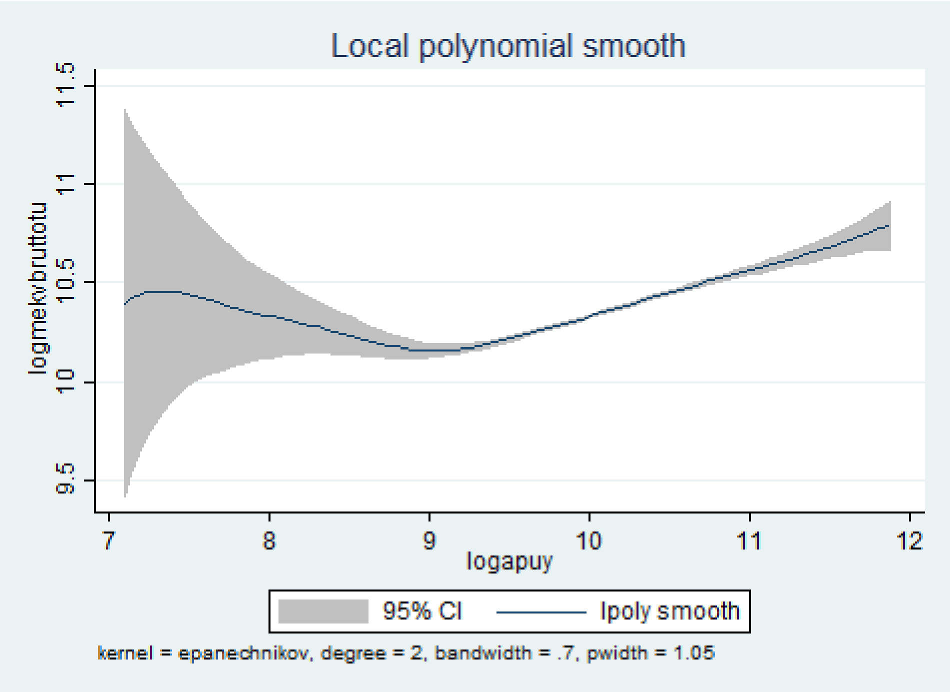


Figure A1. Income stability in disposable income vs. time horizon and age

Notes: These figures present the evolution of Shorrocks's rigidity index as the time horizon is extended for two inequality indices: the Gini coefficient (top panel) and the square of the variation coefficient (bottom panel). Shorrocks's index has in the numerator the inequality of *T*-period cumulated mean income, and in the denominator a weighted average of the inequality in each year, with the weights equal to the ratio of the mean income in that year to the mean income over *T* years.



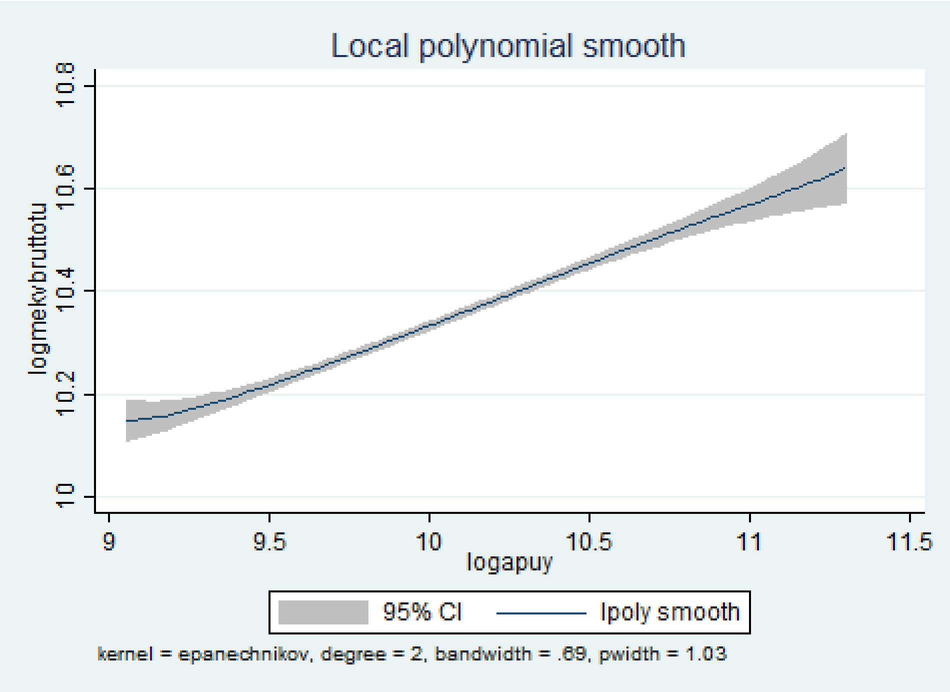


Figure A2. The effect of restricting the sample to elasticity estimation

Notes: Expected mean child log income conditional on parent log income estimated by a local quadratic fit on the microdata (Cleveland 1979). Top panel: zeros down coded to to 1,200 €. Bottom panel: dropping the bottom and top one percent of the distributions. 95 percent confidence intervals are shown using shading areas around the curves.

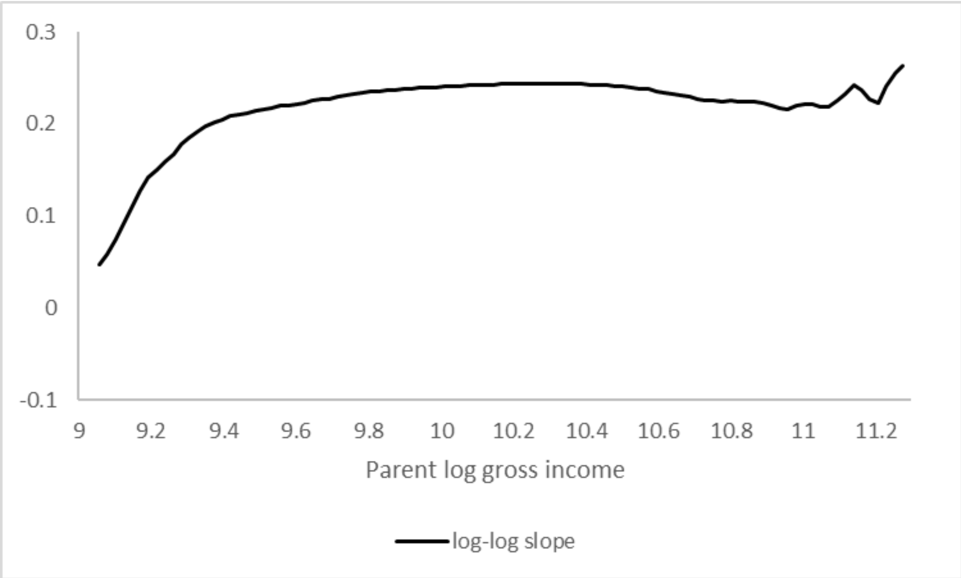


Figure A3. Slope of the association between children's and parents' log incomes

Notes: Nonlinearity in the relationship between child log income and parent log income, based on the sample (1980–1982 birth cohorts) and baseline household income definitions for parents and children, see Figure 2. Evolution of the slope coefficient in obtained by estimating the local quadratic fit on micro data. In estimating the local quadratic fit on micro data children in the bottom and top one percent of the child distribution are excluded from the log income series.

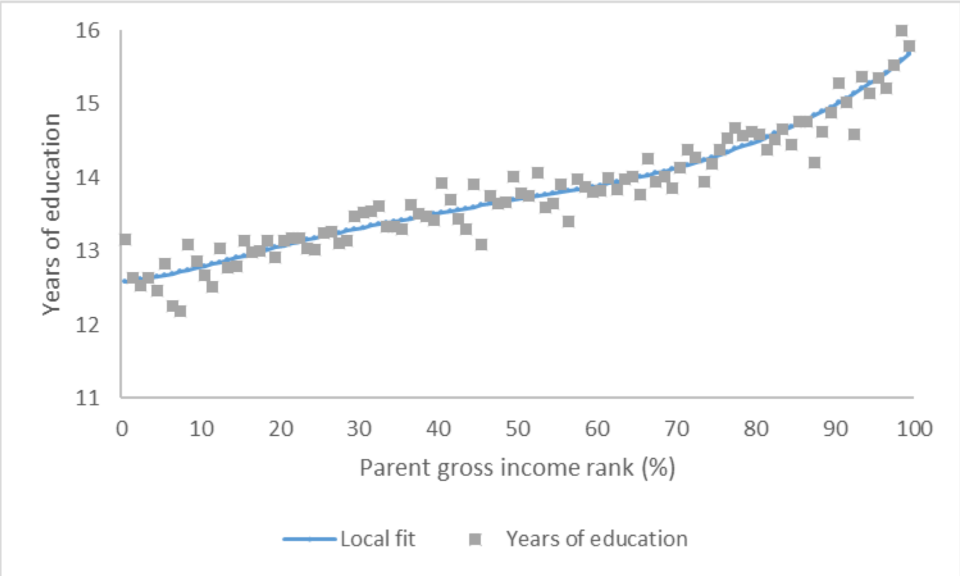


Figure A4. Association between children's years of education and parents' percentile ranks

Notes: The figure plots the mean child years of education within each parent percentile rank bin 100 equal-sized (centile) bins and presents nonparametric estimate of the relationship between children's years of education and parent's percentile income ranks, using a local quadratic fit on the microdata. Both figures are based on the core sample (1980–1982 birth cohorts) and baseline household income definitions for parents. Child years of education are calculated on the basis of education status in 2012 (ISCED 2011-classification). Parent income is mean household (equivalent) income from 1996 to 2000. Parents are ranked relative to all other parents in the core sample.

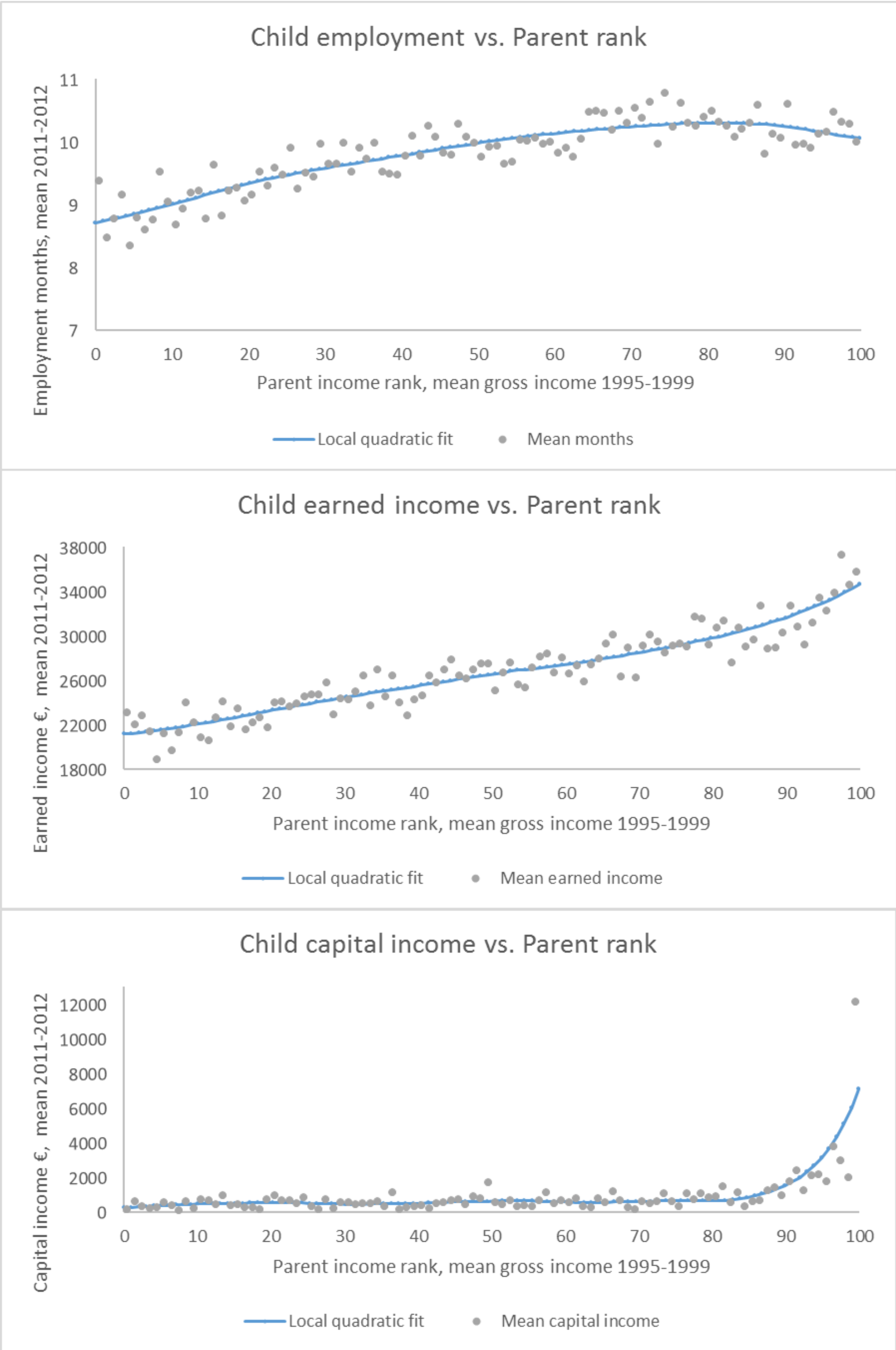


Figure A5. Association between children's outcomes and parents' percentile ranks

Notes: The figure plots the mean child outcome variable within each parent percentile rank bin, 100 equal-sized bins and presents nonparametric estimate of the relationship between children's outcome and parent's percentile income ranks, using a local quadratic fit on the microdata. The figures are based on the core sample (1980–1982 birth cohorts) and baseline household (equivalent) income definition for parents. Children's outcome variables are the mean of 2011–2012 months employed and personal income (when the child is approximately 30 years old), and parent income is the mean from 1996 to 2000. Parents are ranked relative to all other parents in the core sample.