Intergenerational Mobility in Norway: Transition Probabilities and Directional Rank Mobility

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Preface

I would like to thank my supervisors, Espen Bratberg and Kjell Vaage, for first-rate guidance throughout this project. Linda Ademefun, Hanna Iversen and Gary Morris for provideding helpful comments and advice, for which I am grateful.

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Abstract

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This thesis applies newly developed measurers of intergenerational income mobility on register data for Norwegian cohorts born 1950, 1955 and 1960. It looks at two groups: difference between genders and difference between intact and disrupted families.

Significant gaps between sons and daughters in both upwards and in downwards mobility are found. It is found that daughters are more downward mobile and less upward mobile than sons, and the gender-gap seems to somewhat decrease over the time period of the study. The main contribution to this decrease is an increase in upward mobility and a decrease in downward mobility for daughters.

Using the the same methods to study the difference between intact and disrupted families in the 1960 cohort, there seem to be tendency that children of intact families are slightly more upward mobile and slightly less downwards mobile compared to disrupted families.

Data used in this thesis is are provided by the Norwegian Social Science Data Services (NSD). Statistics and data analysis is are done in STATA 13 and the thesis is written in LaTeX.

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Chapter 1

Introduction

Equality of opportunities is generally accepted as an important goal in modern welfare societies. In Norway, this is a typical argument for the provision of free education and healthcare services to all citizens; The idea being that when money does not dictate health and education level, all children have the same chances of succeeding in life.

However, equal opportunities do not necessarily lead to equal outcomes. Research has shown that a person's economic status can be correlated with their parents? economic status. Your parents might affect your success in several ways; through your genetics; your cultural values; your learned behaviour; and also through direct economic investment.

The relationship that describes how dependent or independent a child's economic status is from that of on its parent's economic status is known as "intergenerational income mobility". As the Norwegian welfare system emphasises equal opportunities, one would expect there to be a high level of intergenerational income mobility, meaning that the relationship is fairly independent.

The purpose of this thesis is to use newly developed measures of mobility to study intergeneration income mobility on different groups in Norway.

The thesis assesses whether in fact it is the case that the income level of parents has an impact on a child's mobility. It looks at whether this mobility varies with time and if there are differences between the genders.

Secondly, it will investigate whether family structure matters in mobility.[1] In Norway, the typical family structure has changed over the last 50 years as a result of higher divorce rates, resulting in many children growing up in single-parent or stepparent families instead of the more traditional two-parent family. By using new methodology this thesis will give additional insight to previous studies on intergenerational mobility in Norway.

The structure of the thesis is as follows: In chapter 2, a theoretical model by Solon (2004) of intergenerational income mobility and transmission of human capital will be presented. Following this, a study on how to empirically estimate such a model using regression analysis and common estimation problems will be outlined. In light of the problems identified, the thesis will look at and later utilise alternative measures of intergenerational mobility. The framework laid out in chapter 2 will be used when evaluating sample design and discussing the results at the end of the thesis.

Chapter 3 begins with an overview of relevant research, and captures the overall development in the field of intergenerational mobility research; however, the main focus in the chapter will be articles that use transition probabilities, directional rank mobility measures and earlier findings of intergenerational income elasticities and transition matrixes from Norwegian data. The literature using the new measures illustrate how they could be applied, and the literature on Norwegian data gives a background for comparison against the findings in this thesis.

In chapter 4, the data used will be presented and sample design explained. Towards the end of chapter 4, practical issues computing different measures are laid out. Chapter 5 contains the results of the estimations done. Discussion of the results can be found in chapter 6. Finally, in chapter 7, a short summary and some concluding remarks will be given.

[1] Other subgroups were also considered for this thesis: Such as mobility for individuals with immigration background versus ethnic Norwegians, mobility in urban versus rural areas and a comparison of mobility between different regions in Norway. This was dismissed mostly due to poor data quality, such as a high percentage of data missing.

Chapter 2

Theoretical framework

Roemer (2004) agues that equality of opportunity is "levelling the playing field" to circumstances outside the child's control, but not in terms of difference in parental aspirations and preferences for the child.[1] A society with equal opportunities is compensating for circumstances so that individuals expending the same degree of effort has the same possibility to achieve their objectives (Roemer 2004). Is there an optimal level of intergenerational mobility in a society? To address the question of optimal intergenerational mobility, an economical model could be used.

The model presented here is a version of Solon (2004), built on the classical models of Becker & Tomes (1979, 1986). The main idea of this model is that intergenerational transmission has two main explanations: High earning parents invest more in their children's human capital, and that children of successful parents have higher endowments originating from genetics or from environmental factors present in childhood (Black & Devereux 2011).

After presenting the theoretical model, attention will be given to how to empirically estimate such a model in section 2.2. In section 2.3, a presentation of common estimation problems and how to best deal with these problems in practice will be given. A simple statistical model will show one way of estimating mobility, but it has some shortcomings; it does not say anything about direction of mobility, one

[1] The argument for leaving in parental aspirations and preferences is that the child will be formed by them and in many ways define who you grow up to be.

can not compare sample subgroups and it does not enable you to say anything of mobility in different parts of the income distribution. In section 2.4, alternative measures of mobility that deals with this shortcomings are introduced. These measures could be divided into two categories: Transition probabilities and directional rank mobility measures. It is these measures that will be utilised in the empirical analysis in this work.

The theoretical model is not explicitly transferable to the transitional probabilities and directional rank measures, but gives general insight into which transmission mechanisms that could affect earnings between generations. It also provide a backdrop to help explain the empirical results presented in chapter 5, in the absent of an explicit theoretical framework for the new measures. The estimation of such a model also provide insight in to common estimation problems, which also has affected how research with transitional probabilities and directional rank measures has been carried out, thus is relevant for this work. As will be discussed in section 2.4, research on estimation problems on transition probabilities and directional rank mobility measures is scarce, but some of the concepts introduced in section 2.3 could still be valid. Most research conducted with the transition probabilities and directional rank measures makes use of them in some way.

2.1 A theoretical model

The reason for choosing Solon's (2004) modification is that it includes government's investment in the child's human capital, not only the parent's investment. In Norway education policies have aimed to equalise opportunity for children, by for instance investing in providing a free public education, including University-level, and by subsidising kindergartens. The model is therefore more suited for Norway.

Consider a family, i, consisting of one parent from generation $t-1$, and one child from generation t having to allocate the parent's lifetime earning after tax, $(1-\psi)Y_{i,t-1}$, between the parent's own consumption, $C_{i,t-1}$, and investment in the child, $I_{i,t-1}$, hence the budget constraint:[2]

$$(1-\psi)Y_{i,t-1} = C_{i,t-1} + I_{i,t-1}. \tag{2.1}$$

Assume that the parent can not borrow against prospective future earnings of the child.[3] Tax in (2.1) is progressive, and due to this simplifying assumption, the government's only way of doing redistribution in this model is though a progressive investment in the child's human capital as will be introduced bellow. The parent only cares about his own consumption, (2.1), and the total wealth of his child, (2.6), expressed by the utility function

$$U_i = U(C_{i,t-1}, Y_{it}) \tag{2.2}$$

where Y_{it} being the expected lifetime earnings of the child. Assume a Cobb-Douglas utility function

$$U_i = (1-\alpha)\log C_{i,t-1} + \alpha \log Y_{it} \tag{2.3}$$

where α lies between 0 and 1 and represents the relative preferences between consumption and the child's lifetime earnings.

Human capital of the child is given by:

$$h_{it} = \theta \log(I_{i,t-1} + G_{i,t-1}) + e_{it} \tag{2.4}$$

where $G_{i,t-1}$ is the governmental investment in the child and e_{it} is the child's initial endowment of earning capacity. The government can invest in the child for instant through publicly financed education or providing health care services. The earning capacity, e_{it}, does not take into account the parent's investment, $I_{i,t-1}$ and governmental investment, $G_{i,t-1}$, but can be attributed to many factors, both genetic and environmental. For instance family values, influence from the culture the child grows up, learning skills, goals, etc. A positive θ indicates a positive marginal product of investing in human capital, the semi-log specification

[2] In appendix A.1 the model will be solved step-by-step.

[3] Which seems like reasonable assumption since few lenders would be willing to lend money against a child's potential earnings.

of (2.4) makes the marginal product of investment decreasing. In the special case where $\theta = 0$, no investment will be done and human capital of the child then only depend on the child's endowment. This can be interpreted as a purely meritocratic educational system in the sense that all that matters for human capital accumulation is the child's underling ability's, e_{it} (Bratsberg et al. 2007).

The child inherit some of the earning capacity from their parents, e.g. cognitive abilities. It is therefore natural to assume that the endowment, e_{it}, of the child is positively correlated with the parent endowment, $e_{i,t-1}$. The relationship can be described as first-order autoregressive process

$$e_{it} = \delta + \lambda e_{i,t-1} + v_{it} \tag{2.5}$$

where δ is a constant, $0 < \lambda < 1$ is the degree of heritability between the child and parent endowment and v_{it} is white noise, this follows Becker & Tomes (1979). The child's lifetime earning is given by:

$$\log Y_{it} = \mu + rh_{it}. \tag{2.6}$$

So the child's lifetime earnings depends on human capital given in (2.4), the investment I and G the parent and government made in the child, the initial endowment, e_{it}, the return rate on one unit human capital, r and finally μ which is a constant.

Assuming that the parent has knowledge of equation (2.1), (2.4), (2.5) and (2.6), the utility function, (2.3) can be restated as an objective function where the choice variable is $I_{i,t-1}$:

$$U_i = (1-\alpha)\log[(1-\psi)Y_{i,t-1} - I_{i,t-1}] + \alpha\mu + \alpha\theta r \log(I_{i,t-1} + G_{i,t-1}) + \alpha r e_{it}. \tag{2.7}$$

Finding the first order condition and solving for $I_{i,t-1}$ yields:

$$I_{i,t-1} = \left[\frac{\alpha\theta r}{1-\alpha(1-\theta r)}\right](1-\psi)Y_{i,t-1} - \left[\frac{1-\alpha}{1-\alpha(1-\theta r)}\right]G_{i,t-1}. \tag{2.8}$$

Note that this result is assuming some investment of the parent, i.e, assuming an interior solution. If the governmental spending is "too high" we could have a situation where no investment in the child will be optimal for the parent. Equation (2.8) has some interesting implications: *i*) holding governmental spendings constant richer parents will invest more in their childen than poorer parents, *ii*) governmental investment in the child's human capital, if taxes are held constant, will partly crowd out parent's investment, *iii*) parent's investment is increasing in the relative preferences for the child's lifetime earning over the parent's own consumption, α, *iv*) parent's investment is also increasing in θr, so if the return on investment in human capital is high the parents will invest more than if the return is low (Solon 2004).

Further, the implications for intergenerational mobility can now be derived. Substitution of the equation for human capital, (2.4), into the equation for the child's lifetime income, (2.6), yields:

$$\log Y_{it} = \mu + \theta r \log(I_{i,t-1} + G_{i,t-1}) + e_{it} \tag{2.9}$$

and then substituting for the optimum value of $I_{i,t-1}$ found in (2.8) and rearranging yields:

$$\log Y_{it} = \mu + \theta r \log\left[\frac{\alpha\theta r(1-\psi)}{1-\alpha(1-\theta r)}\right] + \theta r \log\left[Y_{i,t-1}\left(1 + \frac{G_{i,1-t}}{(1-\psi)Y_{i,t-1}}\right)\right] + re_{it}. \tag{2.10}$$

An approximation of (2.10) can be made if the ratio $G_{i,1-t}/(1-\psi)Y_{i,t-1}$ is small:

$$\log Y_{it} \cong \mu + \theta r \log\left[\frac{\alpha\theta r(1-\psi)}{1-\alpha(1-\theta r)}\right] + \theta r \log Y_{i,t-1} + \theta r\left[\frac{G_{i,1-t}}{(1-\psi)Y_{i,t-1}}\right] + re_{it}. \tag{2.11}$$

In the equation above, the government's policy to invest in the child will influence intergenerational mobility. Solon (2004) uses the following parameterisation of such policy:

$$\frac{G_{i,1-t}}{(1-\psi)Y_{i,t-1}} \cong \zeta - \gamma \log Y_{i,t-1} \tag{2.12}$$

where $\gamma > 0$ is the ratio of public spending to parents net earnings, and is decreasing with income. Higher γ means that the policy is more progressive By substituting equation (2.12) into (2.11) one obtains

$$\log Y_{it} \cong \mu^{\star} + \underbrace{[(1-\gamma)\theta r]}_{\equiv\beta} \log Y_{i,t-1} + re_{it}. \tag{2.13}$$

where $\mu^{\star}$ is the intercept equal to: $\mu+\zeta\theta r+\theta r\log\{\alpha\theta r(1-\psi)/[1-\alpha(1-\theta r)]\}$. Equation (2.13) takes the form of a typical intergenerational elasticity (IGE) regression, where $1-\beta$ is the degree of mobility. In steady state where $\mathrm{var}(Y_{i,t-1}) = \mathrm{var}(Y_{it})$, which imply that inequality is the same for the two generations, the probability limit of the ordinary least squares (OLS) estimator of the coefficient $Y_{i,t-1}$ is equal to:

$$\frac{(1-\gamma)\theta r + \lambda}{1+(1-\gamma)\theta r\lambda} \tag{2.14}$$

and is increasing in λ, θ, r and $1-\gamma$. So if heritability represented by λ is high, i.e, the correlation of ability between generations is higher, then the intergenerational mobility is low. The size of lambda has a direct effect on the child's lifetime earnings. Also note that the parent's endowment is affecting the parents earnings, y_{t-1}, so it indirectly affect the child's lifetime earning as given by equation (2.6). Holding investment constant, $\lambda \to 1$ suggest that there is a close relationship between human capital and lifetime earnings of the generations, hence the income mobility is low. If θ is higher, which means that the human capital investment is more productive, then mobility also will be lower. The same will be the case when the rate of return on human capital, r, is higher, and when public investment in the child is less progressive, i.e., γ is smaller (Solon 2004). Observing no persistence between parent's and child's earnings would imply no return to investment in human capital. But some returns to investment in human capital seems likely in a market economy - there will be some reward for higher human capital. For instance higher wage as a result of completed higher education. So in a market economy there tend to be some intergenerational dependence in earnings as a result of differences in ability and human capital (Black & Devereux 2011).

The special case mentioned above where $\theta = 0$ would imply the estimator to be equal to λ. This means that only heritability of the endowment that is affecting mobility, i.e. ability, and the way ability is passed down determines intergenerational income mobility.

Bratsberg et al. (2007) show two scenarios that could lead to non-linear outcomes. One such outcome is if there is credit constraints. Credit constraints would probably have more impact on investment in the child in low earning families than in high earning families. This leads to concavity. To see why, compare two groups of parents, one group R, with high income and one group P, with low income. For P the slope would be $\beta > \lambda$. This is because they are facing credit constraints which would not apply for R. R's slope will be $\beta = \lambda$. This is more relevant in a society where education is to a larger degree paid by the parents, but not so relevant for the Nordic countries where education is mostly free. The second outcome that can lead to a non-linear outcome is if all families are facing credit-constrains, this might be because higher investment is optimal for highly gifted children. In this case the default slope of the line would be the one of $\beta > \lambda$, but as a result of education institutions etc. are designed in such a way that there is access for all and equality of opportunity in the lower segments of human capital, the slope is given by λ. This would apply for the group P rather than R and would lead to convexity. This convexity might be a better illustration of the Nordic countries since they have strong redistributive policies that could effect schooling quality in poorer areas.

2.2 A statistical model

The main problem with estimating a model like the one presented above, is that there is no satisfactory way to measure the endowments and the transmission of endowments over generations. A possible solution is to use IQ and test scores as a proxy (Black & Devereux 2011). There are several problems with such an approach; firstly, data that measures this most be available,[4] secondly, it is not granted that such proxies are good proxies of endowments. This is however beyond the scope of this thesis, instead a more basic statistical model that explores the empirical relationship between parent's and children's log lifetime earnings, y,

[4]The dataset utilised in this thesis does not contain such data.

without directly measuring endowments, will be used. This model is a reduced form of equation (2.13) in the theoretical model presented above, and can be stated as

$$y_{it} = \alpha + \beta y_{i,t-1} + \epsilon_i. \tag{2.15}$$

Subscript $t-1$ refers to the parent, t to the child and i to the family. ϵ is an error term which captures earnings of the child that are not explained by the earnings of the parent, and is assumed normally distributed with mean zero and variance σ_ϵ^2. The intergenerational elasticity is measured by the parameter β. Since both $y_{i,t-1}$ and y_{it} are measured in log, an increase of $y_{i,t-1}$ of one percent gives a β percentage increase in y_{it}. Whereas β is the *elasticity* of the child's lifetime log earnings with regard to parent's lifetime log earnings, $1-\beta$ measures intergenerational income mobility between the generations. In a society where the mobility is low, i.e. where children's income are highly dependent on their parents income, the elasticity will be close to one and intergenerational mobility close to zero. An extreme case being a caste-system where your parents position in society determine your place. The opposite extreme your parents position does not matter at all, hence the intergenerational elasticity will be zero and mobility one. Another measure that is commonly used is intergenerational correlation,[5] $\text{corr}(y_{t-1i}, y_{ti}) \equiv \varphi$:

$$\varphi = \beta \frac{\sqrt{\text{var}_{y_{i,t-1}}}}{\sqrt{\text{var}_{y_i t}}} = \beta \frac{\text{sd}_{y_{i,t-1}}}{\text{sd}_{y_{it}}}. \tag{2.16}$$

Where sd is the standard deviation and var is variance of $y_{i,t-1}$ and y_{it} respectively. So in the case where the standard deviation is equal for y_t and y_{t-1} then $\varphi = \beta$. If this is not the case then

$$\begin{aligned} \text{sd}_{y_{i,t-1}} > \text{sd}_{y_{it}} &\Rightarrow \beta < \varphi \\ \text{sd}_{y_{i,t-1}} < \text{sd}_{y_{it}} &\Rightarrow \beta > \varphi. \end{aligned} \tag{2.17}$$

Intergenerational income elasticity will be approximately the same as income correlation between the generations when the standard errors for parents and children are close to each other, i.e. when $\text{sd}_{y_{i,t-1}}/\text{sd}_{y_{it}} \to 1$. So when income distribution is the same between two generations, the IGE and intergenerational income corre-

[5] See for instance Solon (1992)

lation will be the same, however if the society change for instance so there is larger inequalities in the child's generation ($\text{var}_{y_{it}}$ goes up) this would no longer be true.

2.3 Estimation problems

When trying to estimate intergenerational income mobility, researches are facing several problems. A main concern is the lack of data on permanent income that leaves the alternative of using short run proxies. Early research tended to use one year earnings as proxies for lifetime income, but this approach gave considerable biases (Solon 1992, Zimmerman 1992, Mazumder 2005). The bias can be reduced by using an average over several years, as will be shown in section 2.3.1. Is there a particular age that is better suited for a proxy than others? In practice data limitations often makes for parents earnings to be measured quite late in the lifecycle while the son's earnings are measured relatively early in their lifecycle[6]. Lifecycle bias will be discussed in section 2.3.2.

2.3.1 Short run proxy for lifetime earnings

To illustrate the problem of short run proxy, consider the true model given in equation (2.15). If we do not have data on permanent income, but use a short period of life, the observed income may be decomposed as

$$\tilde{y}_{i,t-1} = y_{i,t-1} + v_i \tag{2.18}$$

for the parent, and in the same manner for the child:

$$\tilde{y}_{it} = y_{it} + e_i. \tag{2.19}$$

, where the error terms, v and e, are the deviation between permanent earnings and the earning measured in a single period $\tilde{y}$. Both v and e are assumed to be normally distributed with variance $\sigma^2_{v_i}$ and $\sigma^2_{e_i}$. Substitution of permanent income

[6]This is the case in this thesis data, which I will come back to in chapter 4

for the child in (2.15) with the observed income in one period, as given in (2.19), yields:

$$\tilde{y}_{it} = \beta y_{i,t-1} + (\epsilon_i - e_i). \tag{2.20}$$

If e_i is not a permanent shock and is assumed uncorrelated with y_{t-1}, then this implies that the OLS estimate of β is consistent and unbiased. I.e. if measurement errors in our dependent variable are random and uncorrelated with our independent variables, they will not cause any biases to the estimated β (Wooldridge 2013). But it will effect the efficiency of our estimate, because the estimated variance is larger. However, the assumption of no correlation between the error terms and lifetime earning is a strong one. For instance, parent's and child's career path could be similar, which might lead the assumption to be wrong.

For the independent variable, the parents income, measurement errors will cause the estimate of β to be inconsistent and biased. To see why this happens, consider a model where parent's income is measured in a single period, substituting (2.18) for y_{t-1i} in equation (2.15):

$$y_{it} = \beta \tilde{y}_{i,t-1} + \underbrace{\epsilon_i - \beta v_i}_{\equiv \tilde{\epsilon}_i}. \tag{2.21}$$

In this model $y_{i,t-1s}$ is correlating with ϵ_i so that $\text{cov}(y_{t-1}, \tilde{\epsilon}_i) = -\beta\sigma^2_{v_i}$. Since there is a correlation between the independent variable and the error term, the expected value of error term is not zero for any given value of $\tilde{y}_{i,t-1}$, i.e. it violates the assumption of zero conditional mean[7]. Hence, the estimate $\hat{\beta}$ will be biased and inconsistent in the OLS regression. Expressed by probability limit:

$$p\lim \hat{\beta} = \left(\frac{\text{var}(\tilde{y}_{i,t-1})}{\text{var}(\tilde{y}_{i,t-1}) + \text{var}(v_i)} \right) \beta < \beta. \tag{2.22}$$

$\hat{\beta}$ is underestimating the true β. This is what is called an attenuation bias. If we

[7]This is one of the Gauss-Markov assumptions, and is a standard assumption in OLS. See for instance Wooldridge (2013).

replace the estimate of $y_{i,t-1s}$ with an average over T years

$$\bar{y}_{i,t-1} = \sum_{s=1}^{T} \frac{\tilde{y}_{i,t-1}}{T}, \tag{2.23}$$

the attenuation factor becomes

$$\frac{\text{var}(\tilde{y}_{i,t-1})}{\text{var}(\tilde{y}_{i,t-1}) + \text{var}(v_i)/T} < \frac{\text{var}(\tilde{y}_{i,t-1})}{\text{var}(\tilde{y}_{i,t-1}) + \text{var}(v_i)}. \tag{2.24}$$

This means that by averaging over more years the underestimating will be reduced, but there is still a downward bias. Solon (1992) estimated that the income correlation in the United States is about 0.4 when averaging fathers income over 5 years, which was higher than previous studies. A considerable rise in the estimate for income elasticity in the United States is also found by Mazumder (2005) when using averages over as long as 16 years. However, for Norwegian data Nilsen et al. (2012) finds that increasing number of year, T, have relatively small effects on the estimated intergenerational income elasticity compared to the United States case.

A different approach to solving the problem, as suggested by Solon (1992), is to apply instrument variable (IV) for the single period earning. Solon (1992) uses education, Edu_{t-1}, as an example of instrument for single year earnings. In order to be a good instrument the variable needs to be uncorrelated with the error term and correlated with the single year earnings:

$$\begin{aligned} \text{corr}(Edu_{i,t-1}, \tilde{y}_{i,t-1}) &\neq 0 \\ \text{corr}(Edu_{i,t-1}, \tilde{\epsilon}_i - \beta v_i) &= 0. \end{aligned} \tag{2.25}$$

If education satisfies the two conditions above, the probability limit of the IV estimator will be:

$$p\lim \hat{\beta}_{IV} = \beta + \frac{\text{corr}(Edu_{i,t-1}, \tilde{\epsilon}_i)}{\text{corr}(Edu_{i,t-1}, \tilde{y}_{i,t-1})} \cdot \frac{\text{sd}_{\tilde{\epsilon}_i}}{\text{sd}_{\tilde{y}_{i,t-1}}} > \beta. \tag{2.26}$$

This implies that the IV estimator will be bias and inconsistent and the bias would cause an overestimation of the true β. If the intergenerational income elasticity is estimated with both OLS and IV, OLS will represent the lower and IV the upper bound of β (Solon 1992). However, finding a good instrument is not an easy task, for instance education, as used above, could be correlated with endowments. For instance, take the suggested instrument education; if individuals with higher endowments tend to have more education, then education is not a good instrument.

2.3.2 Lifecycle bias

Over the lifecycle, a profile of earnings is assumed to be concave; people tend to have less income early and late in life. Individuals also have different lifecycle earning profiles i.e. heterogeneity in lifecycle earning. For instance two individuals might start off their carrier at the same earnings, but, for reasons such as difference in education, develop differently. Such variations in income through the lifetime can be a source for measurement error, both in the dependent and the independent variable. As a model for this association, one can consider a simple model following Haider & Solon (2006), where the parent's and child's income are measured at age a and b, respectively:

$$\begin{aligned} y_{i,t-1,a} &= \kappa_{t-1,a} y_{i,t-1} + v_{i,t-1a} \\ y_{itb} &= \kappa_{tb} y_{it} + u_{itb}. \end{aligned} \tag{2.27}$$

The two error terms $v_{i,t-1a}$ and u_{itb} are assumed uncorrelated with lifetime earnings and the error term, ϵ_i. This model allows for parent's and child's proxy to be a better proxy at some ages. For now, assume that we have a good measure of the parent lifetime earnings, i.e., $\kappa_{t-1,a} = 1$ in the equation over, but that y_{tb} is used as a proxy for the child's lifetime earnings, y_t, yielding the following IGE regression:

$$y_{itb} = \kappa_{tb}(\beta y_{i,t-1} + \epsilon_i) - u_{itb}. \tag{2.28}$$

Now the probability limit of the estimated coefficient $\hat{\beta}$ is $\beta\kappa_{tb}$ instead of β. This implies bias in the OLS estimate, if $\kappa_{tb} \neq 1$. The inconsistency in the OLS estimator will vary with the age, b, at which earnings are observed. This contradicts the argument made in 2.3.1, namely that measurement error in the dependent variable does not inflict any bias.

Looking at the opposite situation, the case where a perfect measure for the child's lifetime income is available, but there is a measurement error in the parent's lifetime earning due to use of a short run proxy, the probability limit would be:

$$p\lim \hat{\beta} = \frac{\text{cov}(y_{i,t-1,a}, y_{it})}{\text{var}(y_{i,t-1,a})} = \Theta_a \beta \tag{2.29}$$

where

$$\Theta_a = \frac{\kappa_{t-1,a}\text{var}(y_{i,t-1,a})}{\kappa^2_{t-1,a}\text{var}(y_{i,t-1}) + \text{var}(v_{i,t-1})} = \frac{\kappa_{t-1,a}\text{var}(y_{i,t-1,a})}{\kappa^2_{t-1,a} + \text{var}(v_{i,t-1})/\text{var}(y_{i,t-1})} \tag{2.30}$$

If $\kappa_{t-1,a} = 1$, then Θ_a is equal to the attenuation bias showed in section 2.3.1, which again can be dependent on parent's age since $\text{var}(v_{i,t-1a})$ can be varying with parent's age, a.[8] Under certain conditions the bias could be an amplification bias rather then an attenuation bias, as when $\text{var}(v_{i,t-1})/\text{var}(y_{i,t-1})$ is being small and $\kappa < 1$ (Haider & Solon 2006).

In practice it is easier to construct proxies for lifetime earnings for parents, since data for income is often available for a longer period of time for the parent than for the child. In most research proxies will be needed for both. If both parent and child's income are proxied, probability limit becomes:

$$p\lim \hat{\beta}_{a,b} = \kappa_{tb}\Theta_a\beta. \tag{2.31}$$

To correct for life-cycle one would like to use a year were $\kappa_{t-1,a}$ and κ_{tb} is close to one, which will be an optimal age to measure. However, it is not given that this is the same for each generation or for each gender. Estimations done of κ_{tb} for several countries shows that it is low when sons are in their twenties, rising to the region of one in the thirties and remain stable to late forties (Haider & Solon 2006, Böhlmark & Lindquist 2006, Nilsen et al. 2012)[9] Estimations of κ_{tb} for daughters in Sweden and Norway on the other hand seem to follow a steeper, inverse U-shape (Böhlmark & Lindquist 2006, Nilsen et al. 2012). This makes it

[8]See for instance Mazumder (2005), who concludes that $\text{var}(v_{i,t-1})$ is at a minimum at around 40 years

[9]Nilsen et al. (2012) follows the sons until they are 46 years old, while Haider & Solon (2006) and Böhlmark & Lindquist (2006) are following the sons until they are 60 years old.

more problematic to use a short run proxy for lifetime earnings for daughters than for sons (Böhlmark & Lindquist 2006).

2.4 Alternative measures of mobility

The OLS estimate as presented in section 2.2 above has its limitations: Firstly, it is not possible to say anything about the direction of the income mobility. The elasticity simply tell us about the degree of mobility in a society, this could be high or low. A society with low income elasticity, hence high mobility, could be a society were many children are doing better than their parents, but it could also be the case that they fall short compared to their parents. Secondly, nothing can be said about different subgroups of the sample. If you split the sample and run a regression for each subgroup, the regression would be to the subgroup mean and not the mean of the whole sample. For instance, if you would like to know if blacks are more or less mobile than whites, splitting the sample into a subsample of blacks and a subsample of whites and running a regression of both subsamples would be of no use, since you then would obtain one regression result for black children's income on black parents income and one for white children's income on white parents income. However, it is possible to check for non-linearities, which could be a problem using OLS if the transmission of economic resources is not the same over the entire income distribution.[10] One could estimate IGE at different points of the income distribution, for instance by using non-parametric regression technics. See Bratberg et al. (2007) for an example of non-parametric regression on Norwegian data. Another method is to split the parents into percentiles and report the mean of earnings for parent and child for each percentile of parent's earning besides the regression line. Bratsberg et al. (2007) shows an example of this comparing mobility patterns over the income distribution in United States, United Kingdom, Denmark, Finland and Norway. However, the problem with establishing the direction of mobility remains. The measures presented in the following sections are mainly motivated by the need to indicate the direction of mobility, comparing

[10] A brief discussion of possible causes for non-linearities can be found at the end of section 2.1 above.

subgroups and comparing them at different points of the income distribution.

2.4.1 Transition matrices and transition probabilities

Transition matrices show the probability of the child being at a given percentile in her cohort given the parent's position in their cohort. In practice it is common to split the income distribution into quartiles or quintiles and study the mobility across them; splitting the parents into equally sized ρ_p percentiles, and the children into equally sized ρ_c percentiles and then compute the probability for all pairs of ρ_p, ρ_c and present it in a matrix. In addition to giving us information about mobility in different areas of the income distribution, such transition matrices also allow us to compare mobility between subgroups across the entire income distribution, and not only over the distribution of the subgroup in question, using one matrix for each group, referring to the entire income distribution. (Having two or more matrixes that refers to a common income distribution can lead to the the sum of probabilities for each line in a single matrix, not to sum to one.)

When interpreting a single transition matrix, perfect mobility imply that each transition probability is the same. Take quartile transition matrix as an example: perfect mobility means that each transition probability is 25 percent.[11] If there is no mobility between offspring and parent, transition probability will be equal to 100 percent in the diagonal and zero everywhere else, i.e. if you parents are located at the bottom quartile you would stay in the bottom quartile, if your parents are located in the second quartile you would also be located in the second quartile, etc.

Stated in another way, transition probability is the probability that a child in a given income percentile, Y_1, moves over or under a given percentile, ρ, in her income distribution, conditionally on the parent's percentile, Y_0, being equal to or below ρ in the parent's income distribution.[12] Transition probabilities are helpful

[11] For each row and column in the matrix the probability will have to sum to one. In this case $4 \cdot 25\% = 100\%$.

[12] Using subscript 1 for the child and 0 for the parent, instead of t and $t-1$, makes notation easier.

in describing mobility in different ranges of the income distribution, e.g. how large probability has a child with parents in the bottom 10 percent of the income distribution to move upwards over the 10th percentile in her distribution? Formally upward transition probability (hereafter UTP) can be stated as

$$UTP_{\tau,\rho} = \Pr(Y_1 > \rho + \tau | Y_0 \leq \rho). \tag{2.32}$$

τ being a threshold amount that the child has to exceed in the distribution. If $\tau = 0$, then you moving past ρ conditioned that your parents were at ρ or below would be recorded as gain, i.e in the example over were $\rho = 0.1$, if the child is at the 11th percentile or higher she would be have been recorded as making gain. Rising τ for instance to $\tau = 0.1$ the UTP is the probability of the child being ten percent or more over ρ conditioned on the parent being at or below ρ. So in the example over, with $\tau = 0.1$, the child would need to move over the 20th percentile to be registered as doing gains. Note that where in the range under ρ the parent is positioned does make an impact on how much gain the child has to make for it to be registered as gains. This means that children with parents in the low end of the range need to do relatively more gain than children with parents in the high end closer to the cutoff value ρ. τ is motivated by being able to compare the gains the children are making (by comparing different values of τ for the same value of ρ): Are many of them just making it over the chosen cutoff value ρ or are they making more gain? This is also interesting when comparing different groups: Are some of the groups more prone to make bigger gains compared to their parents? Another reason to include τ in the transition probabilities is for making comparison with the directional rank measures, which will be introduced shortly. By altering the inequality signs of (2.32), a measure of the the downward transition probabilities (henceforth DTP) can be obtained:

$$DTP_{\tau,\rho} = \Pr(Y_1 \leq \rho + \tau | Y_0 > \rho). \tag{2.33}$$

Both UTP and DTP can establish the direction of mobility, and can also be used to compare mobility for subgroups in a sample. Exemplified with DTP, one could have:

$$DTP_{\tau,\rho,X_j} = \Pr(Y_1 \leq \rho + \tau | Y_0 > \rho, X_j = x) \tag{2.34}$$

were X_j could be either gender, ethnicity, region, family status, education level, test-scores, etc.[13] However, only the two first are clearly exogenously given. Ideally we would like to understand causal mechanisms that explain the observed patterns of intergenerational income mobility, but this is often difficult in terms of research design, data quality and availability. Take for instance family dissolution due to divorce: Is there some family characteristics that leads to divorce that also affect intergenerational income mobility, or are the potentially observed differences in mobility between intact and dissolved families a direct result of the divorce itself? Conditioning on explanatory variables such as test scores could give meaningful insight into which factors that could be important. Such a descriptive approach has been used in recent studies by Mazumder (2014) and Chetty et al. (2014*b*).[14] Let $X_{hs} = 1$ denote completed high-school and $X_{hs} = 0$ denotes not completed high-school, then comparison in DTP between the groups could be made by computing:

$$\begin{aligned} DTP_{\tau,\rho,X_{hs}} &= \Pr(Y_1 \leq \rho + \tau | Y_0 > \rho, X_{hs} = 1) \\ DTP_{\tau,\rho,X_{hs}} &= \Pr(Y_1 \leq \rho + \tau | Y_0 > \rho, X_{hs} = 0) \end{aligned} \tag{2.35}$$

One could further expanded to condition on several different subgroups, X_a, X_b, X_c etc.

The equations for UTP and DTP shown above can be used for cumulative samples, for instance if ρ is raised from 0.1 to 0.2 in the case of UTP, then parents in percentiles from the 10th up to the 20th are added to the sample, so that all parents $Y_0 \leq 0.2$ is included in the sample. The calculation can be repeated until all ranges of parent income is covered. In practice, however, it is common to report percentiles up to the median for UTP and down to the median for DTP

[13] Bhattacharya & Mazumder (2011) show that these measures could be estimated conditional on continuous covariates of X_j using non-parametric regressions.

[14] Mazumder (2014) controls for test-scores, education level, family status in his article comparing black and whites mobility in the United States. Chetty et al. (2014*b*) are looking at mobility in different regions in the United States, finding correlations between mobility and level of residential segregation between ethnic groups, level of inequality, quality of primary schools, social capital, and family stability.

(Bhattacharya & Mazumder 2011, Corak et al. 2014, Mazumder 2014). An alternative to using cumulative samples is to use non-overlapping percentile intervals. In this case one would first use parents $\rho \leq$ 10th percentile, then 10th percentile $< \rho \leq$ 20th percentile, and so on up to 40th percentile $< \rho \leq$50th percentile. The link between the probability found in the quartile matrix and UTP would be, for instance for staying in the bottom quartile if your parent where in the bottom quartile, $1 - UTP_{\tau=0,\rho=0.25}$, i.e. one minus the probability of moving out off the bottom quartile.

2.4.2 Directional rank mobility

Upward directional rank mobility (URM) uses the relationship between parent's rank in the parent's income distribution and child's rank in the child's income distribution, conditional on the parent being at or below a particular percentile:

$$URM_{\tau,\rho} = \Pr(Y_1 - Y_0 > \tau | Y_0 \leq \rho). \tag{2.36}$$

Analog to the UTP, τ is a threshold amount. If $\tau = 0$, then URM is simply the probability that the child ranks higher in the distribution than her parents, conditioned on the parent being at or below given percentile, ρ. Given $\tau = 0$ every small upward movement of a child is accounted for, so if the father is in the first percentile in his income distribution and the child is on the second in hers, this is recorded as gain. This is in contrast to the transition probabilities where the child needs to exceed a given percentile ρ. By altering the value for tau, one can control how large or small the gain needs to be for it to be registered as gain, i.e, how much gain relative to the parents is need for it to be meaningful to talk about gains? If, for instance, τ is set to 0.1, this means that a gain of ten percentiles or more compared to the child's parent's position in his income distribution will be recorded as gain. Using directional rank the relative movement compared to the parent the child needs to do to be recorded as making gain is the same for all children. This is in contrast to UTP, where relative gained needed to reach the cut-off value ρ varied. The choices of values for ρ and τ are of course arguable and it would depend on the setting and the objectives of the study. In the existing literature it is common to report several values of τ alongside each other (see Bhattacharya & Mazumder (2011), Mazumder (2014) and Corak et al. (2014)). I will later explain the choices of values made for this thesis.

Using the same approach as for UTP, a measure for downward rank mobility DRM can be constructed:

$$DRM_{\tau,\rho} = \Pr(Y_0 - Y_1 > \tau | Y_0 \geq \rho). \tag{2.37}$$

ρ could, as in the case of the transition probabilities, be set as non-overlapping intervals. In intervals of ten percent, this gives 100th–91th percentile, 90th–81th percentile and so on. For transition probability measures, as well as for directional rank measures, using intervals has the advantage of pinpointing mobility at different points of the distribution. Though using intervals give more precise results at different point of the income distribution, the downside is that, unless the sample is large enough, the results are more noisy than the cumulative approach (Mazumder 2014).

In the same manner as for UTP and DTP, one can compute URM and DRM for different subgroups of the sample

$$\begin{aligned} URM_{\tau,\rho,X_j} &= \Pr(Y_1 - Y_0 > \tau | Y_0 \leq \rho, X_j = x) \\ DRM_{\tau,\rho,X_j} &= \Pr(Y_0 - Y_1 > \tau | Y_0 \geq \rho, X_j = x). \end{aligned} \tag{2.38}$$

which allows for comparison between the sample subgroups.

2.4.3 Transition probabilities and directional rank mobility compared

A criticism against transition probabilities is that is uses an arbitrarily chosen cutoff percentile, for instance the 10th percentile. In comparison, directional rank mobility measure the child's rank relative to the parent's rank. The URM and DRM approach measures every small upwards or downwards movement of the child relative to the parent, whereas in the case of transition probabilities it is ignored if it does not meet the specified cutoff point (Bhattacharya & Mazumder

2011). When using URM, a son that exceeds τ but not ρ is accounted for. This property of URM is an advantage when comparing different subgroups of children. If looking at two subgroups of children (with parents in the same percentile range of income) and the two subgroups are differently distributed so that one subgroup is concentrated in the top and one in the bottom of the distribution, then children in the top end will have higher probability of moving past their parents percentile since they already are closer to the cutoff, ρ. The bottom subgroup will have to do more gain, relatively to the top subgroups, to have their gains recorded. By instead using URM while looking at the same two subgroups, the bottom subgroup would only need to surpass their parent's rank by the same value, τ, to be recorded as making gains. However, it should be noted that directional rank does not differentiate between the size of the gains, meaning that the gain of a child with a parent in the 10th percentile will be registered the same way, regardless of if the child moves to the 11th or the 99th percentile. To conclude, the way one chooses to measure mobility will affect the results. Exemplified from the literature: Bhattacharya & Mazumder (2011) finds that blacks and whites has more equal mobility when using directional rank than transitional probabilities.

2.4.4 Estimation problems

There is not much research to be found on the topic of measurement errors using directional rank mobility and transitional probabilities, and it is unclear how the estimates are affected (Corak et al. 2014). This lack of insight on measurement errors have, however, been acknowledged as a problem for a long time. In the case of transition matrixes; Zimmerman (1992) writes "It should be noted that these results are not adjusted for measurement error, [and] this could seriously alter the groupings that are reported."

All measures presented in section 2.4 are based on relative position for the individuals in their income distribution. As a result, errors in measurement of earnings will have no effect on the estimation result if the rank is preserved in the measurement of earnings utilised (Bhattacharya & Mazumder 2011). Self reported earnings could serve as an example: If reported earnings, y', can be said to be a monotone function of true earnings, y, for instance if people state their income higher than their true income, but the proportions of the overstatement is the same, this means that all relationships between individuals are preserved. If two individuals A and B with true earnings satisfying $y_A > y_B$, then reported earnings need to satisfy $y'_A > y'_B$, and the estimation results of URM, DRM, UTP and DTP will yield the same results for the true earnings, y, as for the incorrect measure of earnings, y'.

O'Neill et al. (2007) consider classical measurement error in transition matrices. By using computer simulations they conclude that classical measurement errors in the son's income might lead to an overstating of the mobility. This bias tends to be highest for the low end of income distribution (O'Neill et al. 2007). If both parent's and son's incomes are measured with error, then the correlation between the measurement errors is decisive for the bias; low correlation could lead to an overstatement of mobility while high correlation could lead to an understatement of mobility (O'Neill et al. 2007). As a result, when looking at several studies, O'Neill et al. (2007) find that observed differences in transitional probabilities across different income distributions or across different countries could be due to measurement errors rather than structural differences. When making inferences based on transition probability this should be kept in mind.

Another problem arise when comparing different groups which lifetime earnings would be best recorded at different stages in the lifecycle. Using a short run proxy could than lead to one of the groups being lower or higher in the income distribution than they would be if a perfect measure for lifetime earnings were available. Suggestions that it is "more problematic" to use current earnings as proxy for lifetime earnings for some groups are for instance made about women when comparing with men by Böhlmark & Lindquist (2006).[15]

I conclude this section on the notion that imperfect measures of lifetime income, as in the case of the intergeneration elasticity described earlier, could be a problem when utilising the measures presented in this section. However, more research

[15]The problem of measuring women's income, in a combination with poor data, has often lead to studies focusing on males, see for instance Corak et al. (2014) or Bhattacharya & Mazumder (2011) where females are left out for this reason.

is needed to make any definitive conclusions on how this could effect the estimates. The common way to obtain better proxies for lifetime earnings is to use averages over several years and use years where the lifecycle bias is low as described in section 2.3, which also is the common approach used in literature utilising directional rank measurers and transition probabilities, (see Bhattacharya & Mazumder 2011, Chetty et al. 2014*a*, Corak et al. 2014, Mazumder 2014).

Chapter 3

Literature review

This chapter will contain a overview of previous research. Literature on transitional probabilities and directional rank measurers is scarce, but a few examples of research are represented here: Bhattacharya & Mazumder (2011), Mazumder (2014), Corak et al. (2014), Chetty et al. (2014*a*), Chetty et al. (2014*b*) and Bratberg et al. (2015).[1] The chapter also contains a more general overview of the development in the literature.[2]

3.1 Teoretical background and empirical estimation

Becker & Tomes (1979, 1986)[3] developed a theoretical model for intergenerational mobility, explaining distribution between generations and the role of human capital. The model presented in section 2.1 is a version of Becker & Tomes (1979, 1986),

[1]To the best of my knowledge, directional rank measures have never been used on Norwegian data previous to this project. In fact these measurement have only to a small extent been used on data from outside of the United States, Corak et al. (2014) claiming to be the first with their comparison of Canada, Sweden and United States. However, this year Bratberg et al. (2015) are using directional rank measures on Norwegian data, comparing several countries, including Sweden, Germany and United States.

[2]For more comprehensive literature surveys, see for example Solon (1999) and Black & Devereux (2011)

[3]Becker & Tomes (1986) is a modification of Becker & Tomes (1979), and also adds a review of empirical results.

modified by Solon (2004). From their model and a review of earlier empirical results, Becker & Tomes conclude that the intergenerational income elasticity was low, i.e., intergenerational income mobility was high. The model of Becker & Tomes (and modifications) can be empirically estimated as shown in chapter 2. Solon (1992) and Zimmerman (1992) show that earlier research on intergenerational income mobility have suffered from a downward bias. This as a result of single years commonly had been used as proxies for permanent income in early research. In an attempt to obtain more accurate estimations, Solon (1992) and Zimmerman (1992) demonstrate that this bias can be greatly reduced by using an average over several years. They use up to five years, in stead of single year. This method reduces the effect of "transitory shocks", such as a single year with low income due to unemployment or sickness. The result of this approach is shown in section 2.3.1 above. Their finding implicates that mobility was lower in the United States than earlier research, such as the work by Becker & Tomes, had predicted. Later, Mazumder (2005) suggests that even longer averages are needed for an unbiased estimate of the intergenerational earnings elasticity in the United States. For Norwegian data however, Nilsen et al. (2012) find that adding extra years to father's income increases the estimated intergenerational earnings elasticity, but to a lesser extend than in the United State case.

There has been a lot of attention to estimation errors due to short-run proxies for long-term earnings in the literature. In addition to correcting for potential transitory shocks in the earnings, much literature has been devoted to where in the lifecycle lifetime earning is best captured. As discussed in more detail in section 2.3.2 above. Haider & Solon (2006) demonstrate that lifecycle variation could lead the classical error-in-variable model to be misspecified, and that using proxies for the independent or dependent variable, or both, could cause the OLS estimator to be biased. Empirical findings suggest that measuring income early or late in the lifecycle causes larges biases, and this finding seems to be valid across countries (Haider & Solon 2006, Böhlmark & Lindquist 2006, Nilsen et al. 2012). For Norwegian data Nilsen et al. (2012) suggest income measured at the age of 36-40 minimises the life-cycle bias.

When empirically estimating intergenerational income mobility, the insights from the literature on transitory shocks and lifecycle variations are now commonly used. For instance, to estimate IGE in Norway, Bratberg et al. (2005) uses averages over five years for both father and child, and the do not use the child's income before it is 30 years old, and not the father's income after the age when retirement becomes significant. Most early studies used father's and son's earnings, however it is becoming more common to report father-daughter elasticities as well, see for instance Jäntti et al. (2006), Mazumder (2005) and Bratberg et al. (2005). With the exception of Mazumder (2005), the results seem to differ between the genders. To understand why sons and daughters can differ in mobility, Raaum et al. (2007) introduce a framework with two main mechanisms: Assortative mating and labour supply responses. Assortative mating imply that daughters form low-earning families marry low-earning men, and daughters from high-earning families high-earning men. In the latter case, where a daughter from a high earning family marries a high earning man, in a combination with negative-cross wage or income elasticity of labour supply which can lead the daughter to work less hours, hence getting a lower income. Since the income of a married woman is not always reflecting her true economical status, Raaum et al. (2007) suggested to use a measure for family income. Chadwick & Solon (2002) carried out a study using family income data from United States and found that elasticity for daughters family earnings on her parents is high, i.e. mobility low. This can to a large degree be explained by assortative mating (Chadwick & Solon 2002). Another finding by Chadwick & Solon (2002) is that there is a high correlation between the individual earnings of married couples and their in-laws, similar to IGE to their own parents.

3.2 Comparing estimations from different countries and over time

Cross-countries comparison of estimates of mobility is difficult. For instance, one would like the estimates to be obtained using the same sample selection rules and data to be obtained in the same way. In practice, this is often difficult, since data might be available in a specific time period, income data might in some data set be survey based while others are based on official tax-records, etc. Moreover, are the models used for estimation suited for all countries?

When comparing estimates for different countries, a general finding is that the Nordic countries seem to have more intergeneration mobility than countries like United Kingdom and United States (Jäntti et al. 2006, Black & Devereux 2011, Bratsberg et al. 2007). Bratberg et al. (2005) find that their IGE results are close "but in the low end" compared to other Nordic countries. Finding stable IGE results for 30 year old sons over the four cohort of their study; the 1950, 1955, 1960 and 1965 cohort, but a slightly decreasing IGE for daughters of the same age, which implies increased mobility for daughters over the period.[4] Using transition matrixes for quartiles of father-child earning, Bratberg et al. (2005) find that mobility is highest in the second and third quartile, but register some persistence in the first and fourth quartile. The persistence seems to be stronger in the top quartile. Asymmetrical results from the transition matrix can imply non-linearities data.

3.2.1 Does the linear model fit data?

The simple linear regression model, like the one presented in 2.2, assume that the IGE is the same over the entire income distribution. Which *a priori* is a strong assumption, as it is not certain that function form is the same over time or in different countries. This is the motivation for the article by Bratsberg et al. (2007) which shows how the linear function form of IGE is misspecified for the Nordic countries. They find that it is a convex relationship between son's and father's earnings in Norway, Denmark and Finland, in contrast to a more linear relationship for United Kingdom and United States. For the left-tail of the income distribution they find that the relationship is quite flat for the Nordic countries, meaning that what the father earnings has little influence on the child's income. Explanation for this, as pointed out by Bratsberg et al. (2007), could be that education provided is strong in providing foundation in skills, for the bottom of

[4]IGE were: 0.980, 0.091, 0.090 and 0.102 for sons, and 0.192, 0.156, 0.125, 0.114 for daughter in 1950, 1955, 1960 and 1965, respectively.

parent income distribution, resulting in adult earnings and parent earnings are independent of each other. A second possibility could the existence of strong wage-setting organisations, rising wages in the left-tail of the income distribution. Thirdly, the strong welfare state could have implications on labour supply to low wages. Bratsberg et al. (2007) are highlighting that differences in the function form in different countries could make cross-country comparison misleading, especially in the tails of the distribution. It should however be noted that Bratsberg et al. (2007) finds, despite their results, the intergenerational mobility to be higher in the Nordic countries than United Kingdom and United States. Non-linearity in Norwegian data is also found by Bratberg et al. (2005, 2007) using non-linear regression techniques. Bratberg et al. (2007) run quantile regressions on the same cohorts used by the same authors in 2005, and the results shows higher IGE for the low end of the income distribution, compared to the high end, for both sons and daughters.

3.2.2 Does intergenerational mobility change over time?

There are few studies of time trends in intergenerational mobility, mainly due to lack of data over long periods of time. In the United Kingdom, Blanden et al. (2004) find that mobility seem to have fallen comparing the 1958 cohort to 1970 cohort. For Norway the opposite seems to be the case: Mobility seems to be increasing from 1950 to 1965, especially for women. This pattern is found by Bratberg et al. (2005), and later supported by finding by the same authors (2007). Bratberg et al. (2007) point out that this might be as a result of different linking of parent and child in the 1950 cohort than the later cohorts, but that it also coincides with increased education and labour force participation for women. Results from the 1960 and 1970 cohort by Rieck (2008) also seem to confirm such a trend in father-daughter mobility.

3.3 Disrupted families

Findings from United States also suggest that children of divorced families are socioeconomically disadvantaged compered to children of intact families. Couch & Lillard (1997) find that sons from divorced families are less mobile than sons of intact families, but tend to come from families in the lower third of the income distribution in the first place, hence they disproportionally represented in the lower third of the income distribution for their cohort. For Norway, Rieck (2008) finds differences between the IGE for disrupted and intact families, using data from the 1960 and 1970 cohort. Using transition matrixes he observes higher downward mobility for children with divorced parents. This is later confirmed by Bratberg et al. (2014). The effect of fathers present is explored by Björklund & Chadwick (2003) on Swedish data which enables them to distinguish between four "types" of fathers and compute the IGE for each pair. The four types of fathers are biological fathers which have lived with their sons all their childhood, biological fathers that sometimes lived with their sons, biological fathers that never lived with their sons and non-biological fathers and sons. The elasticity is highest between biological fathers that have lived with their sons, sometimes and always, and lowest for biological fathers that never lived together with their sons. Nonbiological father-son elasticity lies in between. Low father-son elasticity for biological fathers that never lived with their sons, suggest that genetic effects only explain some of the child's income. On the other hand the IGE for non-biological father-son relations are lower than father-son IGE for biological fathers that lived sometimes or always with their sons, suggesting that transmission mechanisms do not solely relay on social factors.

3.4 Directional rank

Measuring IGE is one way of measuring mobility, however it does not answer question such as what is the direction of mobility? For this one can use transition matrixes, as described in section 2.4.1, however if you are interested in a subgroups are mobility and the parents of this subgroup is concentrated in the bottom of every quantile you are looking at, they would have to make a relatively larger leap compared the other group to be recorded as doing gain. Bhattacharya & Mazumder (2011) developed the measure for directional rank mobility and further developed the measurement of transition probabilities, which is described in detail in section 2.4, and applied it on the differences between blacks and whites in the United States. Bhattacharya & Mazumder show that there are less black-white gap using URM instead of UTP; more blacks do relatively better than their parents. This pattern is not registered when using upward transition probability. This is because their gain is not large enough to reach the cutoff value used in transition probabilities, ρ (see equation (2.32)). Bhattacharya & Mazumder's (2011) results are supported by Mazumder (2014). Mazumder (2014) use the same measurements to further study black-white differences in intergenerational mobility in the United States.

When controlling for education, Mazumder (2014) finds that more years of schooling is associated with higher probability of moving out of the bottom quintile. For people with more than 16 years of schooling there is virtually no gap between blacks and whites. When controlling for test scores,[5] Mazumder (2014) finds that the effect of test scores are quite similar for both blacks and whites. He concludes that cognitive skills measured in adolescence can account for much of black and white differences in upward and downward mobility. That being said, he also stresses that he interprets this finding as reflecting a broad range of family background influence, rather than reflecting innate differences. For upward mobility the black-white gap is declining when controlling for family structure; however, Mazumder (2014) finds no such difference for downwards mobility.

3.4.1 Compering countries and regions

Corak et al. (2014) uses directional rank mobility and transition probabilities to compare mobility between United States, Canada and Sweden. They find that the upward transition probability is higher for Canada than for Sweden and United

[5] Mazumder (2014) uses the Armed Forces Qualifications Test (AFQT).

states, which are more or less equal. It is unexpected that the difference between Sweden and United States is not larger, given the big differences found in transition matrixes, see for instance Jäntti et al. (2006). Corak et al. (2014) concludes that the differences found when comparing their study with other studies done on upward mobility for the bottom quintile can be attributed to differences in how the income data used are measured. Corak et al. (2014) use father as a proxy for family income as opposed to family income, and this alters the selection in the samples, which they in turn conclude could lead to an underestimation of the cross-country differences observed.

DTP found by Corak et al. (2014) is highest for Canada, and almost identical for Sweden and United States. Again the directional rank shows small differences in the case where they simply measures the probability for the child falling down compared to their parents place in their income distribution, i.e., $\tau = 0$. But there are larger differences to be found in the top of the distribution when the value of τ is increased. Canada stands out as the country with the largest downward mobility, whereas Sweden and United States have about the similar rate. Corak et al. (2014) stresses the point that even though their results show a similar degree of mobility between countries, the consequences of falling or rising are not the same in the three countries, but depend on absolute differences in the income distributions. It is not only countries that varies in mobility; Chetty et al. (2014*b*) shows great divergence in mobility in different geographical areas in the United States. However, the most mobile parts of United States are still less mobile than the least mobile regions in the Nordic countries (Bratberg et al. 2015).

Chetty et al. (2014*a*) explore the trends in intergenerational income mobility for the United states, and finding that rank mobility is stable over time, but that inequality has increased. A consequence of this is that the impact of moving up or down is bigger than it used to be. Chetty et al. (2014*a*) find the rank-rank relationship between parent and children to be almost perfectly linear. They also find that rank-rank slope estimates are robust when using parent and child income at different ages, leading them to the conclusion that measure does not suffer form significant life cycle bias or attenuation bias. Similar conclusions about the robustness of the rank measures are also reached by Corak et al. (2014). They conclude that "[i]n practice, we generally find that these issues do not appear to have much of an effect on our findings". However, it is not certain if this is due to the quality of the measures themselves or if the effect is due to good proxies for lifetime earning being used

Bratberg et al. (2015) are comparing mobility in Germany, Sweden, Norway and the United States by using rank mobility and a newly constructed measure "income share mobility". Their results seem to correspond to previous mentioned studies of IGE that concludes that United States has less intergenerational mobility than the Nordic countries. But when using the new "income share mobility" measure, United States are more equal to the Germany, Sweden and Norway. The income share mobility measures income changes normalised with the average income in an economy. While an absolute change in income in a generation would lead a child to do large gain in rank in a equal society, the rank gain for the same absolute change would be smaller in a society with large inequalities. But an identical absolute change in income would lead to identical results for income share mobility in both societies. As Chetty et al. (2014*a*) they find that rank mobility is almost linear over most part of the income distribution, however bending slightly up for the top end for Norway and Sweden, and slightly down for the bottom of the distribution for all countries. However, this is also most present for the two nordic countries. This suggest that there is some persistence in the bottom and top of the income distribution.

3.5 Isolating different effects and finding causal relations

Understanding the underlying causes and determinants for why there could be persistence in income and education between generations, have important policy implications, and has been a focus area of intergenerational mobility research in recent years (Black & Devereux 2011). For instance if parents with more wealth invests more in their children human capital and this is the cause of their success, one could argue for public financing of education as a mean to equal opportunities would work. On the other hand, if there are some characteristics of wealthy parents, for instance genetic endowment, that is transmitted to the child and contributes to its success, this might suggest a more inferior role for policy. In the following a few approaches are covered.

Another difficulty when studying income mobility is how to separate different effects. For instance for divorce, is the effect observed a result of the divorce itself, or could it be that the divorce stems from family characteristic which lead to the divorce? High conflict level can be an example of such a characteristic and will probably effect the child also if divorce did *not* happen. In a attempt to identify causal effects, Bratberg et al. (2014) uses sibling data, were they identify siblings that was not effected by the divorce. Using this to control for a fixed family effect, they are not able to identify a statistical significant effect of divorce on IGE. More general, using siblings is a common approach to study how environmental and genetic factors could affect the child. For instance if there is a positive correlation to be found between siblings, this implies that environmental and genetic factors make siblings more alike than random individuals in society. Results of these studies show that family background is more important in the United States than in the Nordic countries (Black & Devereux 2011). This could be a result of privately funded education is common i the United Stats. Further, one can try to decompose different components of sibling correlation in earnings. In addition to IGE there can be other factors that are shared by siblings but uncorrelated with parents earnings, such as the neighbourhood they grow up in. Raaum et al. (2006) find some correlation between siblings in Norway, and that the effect of neighbourhood is a minimal factor in explaining sibling correlation. This is also the general result of research conducted on neighbourhood correlation (Black & Devereux 2011). However, neither sibling or neighbourhood correlations are very helpful in establishing causal relationships, since they both can stem form genetical factors and environmental factors or a mix of the two. The low finding of neighbourhood correlations suggest that geographic factors play a minor role, but the question of why family outcomes are correlated is left open. A way of separating environmental and genetical effects is to look at different types of siblings such as identical twins, fraternal twins, full siblings, half-siblings raised apart and together, to separate environmental and genetical effects. Unfortunately, such detailed dataset is hard to come by.

Another method is to use natural experiments such as reform in welfare programs or school reforms which induce exogenous "shock" in parents earnings or education. Black et al. (2005) is explores the relationship between parent's and child's education. They use data from Norway measured pre and post the reform that made schooling compulsory during the 1960s to distinguish between selection and causation. The findings suggest that the correlation between parent's and child's education is mostly due to selection. Reforming the school system, making nine, instead of seven, years of schooling compulsory have greatest implications for children of parents with low income.

The literature that tries to establish causal relations is still in a early stage, and even though one can draw some insights from the results, they are, as shown by Black & Devereux (2011), far from conclusive. It should also be noted that it is not just intergenerational persistence in earnings and education that is being studied: Studies also explore intergenerational relationships between IQ/ability, job and occupation, health, attitudes and social behaviour (Black & Devereux 2011).

3.6 Summary

Much attention has been given to obtaining better estimates of mobility. Biases due to transitory shocks in income can be reduced by using income averaged over several years, and measuring income should not be done early and late in lifecycle as this can induce bias. Issues has also been raised over how to compare mobility between countries. A simple linear model seem to fit the United States and the United Kingdom it seem to be less fitted for the Nordic countries. Mobility does not only seem to vary between countries, but also between regions and population subgroups, and genders and family structures. New descriptive measurements that capture different aspects of mobility, such as direction, have been developed in an attempt to obtain better estimates for mobility. Chetty et al. (2014*a*) show just how important how we define and measure mobility are for results, as three different definitions applied to the United States in their data yield three different results.

A general trend in findings from different countries suggest that the Nordic countries are more mobile than United States and United Kingdom. In addition to measuring mobility, much of the newer literature tries to separate different effects and establishing causal relationship. Understanding the mechanisms behind the observed patterns of mobility can help forming better policies, which in turn can enhance equality of opportunity.

Chapter 4

Data, design and methods

This chapter will start with a description of the data material used for this thesis. Then focus will be on the design of the samples and descriptive statistics, before, at the end of the chapter, attention will be turned to how the rank mobility and transition probabilities were computed.

4.1 Data

Data used for this thesis are extracted from the Norwegian Database of Generation (DBG) provided by Norwegian Social Science Data Services (NSD). DBG contains data about children born every fifth year from $1950-1990$ linked with information about their biological parents and grandparents.

DBG is divided into three parts. The first and second parts are data obtained from the National Population and Housing Censuses. Part one contains information about type of housing, number of siblings, parents' and grandparents' occupations etc. The second part contains information about changes, such as changes in citizenship, changes in marital status, etc. The third part consists of gross income data that are available in annual series from $1967-1995$ based on tax reports. Income series based on tax reports have the advantage of being less prone to measurement errors than self-reported incomes. There are no censuring of incomes in the low or high end of the income distribution. The income series were originally used to calculate state pension, so all incomes that qualify for pension are included. This includes labour incomes, unemployment benefits, disability benefits and sick-leave payments; however, the data do not include means-tested benefits and capital gains. Merging of the different sources of data were done by Statistics Norway (SSB).

To ensure anonymity, SSB has replaced all personal identification numbers with another unique number for each child. There is no connection between the personal identification number and the number the child is given in the data. To further secure the anonymousness of the individuals, information about birth place and residential municipality have been replaced by birth- and residential county. In the linking of parents and children, personal identifications numbers were used for the cohort from 1955 onwards. However, the 1950 cohort is linked to their parents by the 1970 census, based on whether they were living at home at that time. This may have resulted in poorer matching for this cohort since many children would have moved out before the age of 20, hence are not linked to their parents, resulting in them being excluded from data. Especially among daughters this could be a problem, since they tend to move out from their parents earlier than sons (Statistics Norway 1977, figure 2.2, page 59).

4.2 Design of data samples

This thesis utilises a sample that consists of four birth cohorts; 1950, 1955, 1960 and 1965 cohort. The main reason not to include cohorts born later than 1965 is that earnings measured in the twenties tend to underestimate the gap in lifetime earnings between low and high earners (Haider & Solon 2006), thus it is a poor proxy for lifetime earnings. Children born in 1965 are 30 years old in 1995 when the income series concludes. Main focus of this thesis will be on the 1950, 1955 and 1960 cohort where income data are available for a longer timespan after the age of 30. But for some purposes the 1965 cohort is used, to get an as long as possible time span for observations. A summary of the birth cohorts' sizes and exclusions is given in table B.3.

Fathers' income is used as a proxy for parents' earnings in this thesis. This is not a realistic assumption for the cohorts studie, as it was normally the father who engaged in paid employment whilst the mother bore the child care responsibilities. The samples are limited to individuals whose father were younger than 40 at the time the child was born. This specific age restriction is applied due to the income series start in 1967 when a father of the 1950 cohort would be maximum 57 years of age. This is in line with previous research by Bratberg et al. (2005, 2007) using data from the same source. Official retirement age in Norway is 67 years, but many wage earners from period of this sample had the opportunity to retire at the age of 65.[1] As a consequence the upper age limit is set to 65 when retirement starts to become significant. There is no need for a lower limit for the age of fathers, since the youngest ones would be around thirty when the earning series starts in 1967.

All earnings reported in this thesis has been adjusted using a consumer price index with 1995 as a base year and then converted into log earnings. Using a short run proxy for lifetime earning this thesis follow the approach of Solon (1992) using an average over several years to reduce the errors in variables bias which could accrue from using single years of earning. This averages out transitory shocks, as for instance a single year with low earnings due to unemployment or sickness.[2] In choosing the number of years used in the average, there is a balance between wanting to observe as many years as possible and wishing to measure the earnings in the same stage in the lifecycle for both generations. Following Bratberg et al. (2005, 2007), this thesis is using five-years averages of fathers' (log) earnings from $1967-1971$ for the 1950 cohort, $1972-1976$ for the 1955 cohort, $1977-81$ for the 1960 cohort and $1982-1986$ for the 1965 cohort. In computing the log averages, years with zero earnings are excluded, but not individuals without complete series. If three or more years are missing or recorded with zero income the individual would be removed from the sample. For instance if two out of five years are missing or equal to zero, the average is computed of the remaining three years. This is in line

[1] Official retirement age is still 67 years, but today many wage earners has the opportunity to retire at 62.

[2] See section 2.3.1 where short term proxies for lifetime earnings are discussed in more detail.

with the approach used by Bratberg et al. (2005).[3] Observations where the father died in the period the income was measured, has been excluded. Using subsequent five year periods for the averages (the same spacing as for the cohorts), the father's income are measured at the same age of the child, 17-21 years old, and also the mean age of the fathers are about the same, making comparisons between the cohort less ambiguous.

For making the proxy of lifetime earnings more accurate for sons and daughters, averages over five years of log earnings are used: averages from $1981 - 85$ for the 1950 cohort, $1986 - 90$ for the 1955 cohort and $1991 - 95$ for the 1960 cohort. This should reduce the effect of random shocks in income. Using these averages over five years means that they are all $31 - 35$ years of age when the incomes are measured, which allow for easy comparison between the cohorts. If earning series are incomplete for an individual, the averages are computed in the same way as for the fathers; allowing up to two years with missing or zero income, and averaging over the remaining years. Using a five year average follows several studies from Norway: Bratberg et al. (2005, 2007) and Bratberg et al. (2014). The age range over which the averages of sons is computed, also corresponds to the first mentioned studies, and deviates one year from the last, making comparison to the these studies later in this thesis more relevant. The age range used is however lower than average from 36-40 suggested by Nilsen et al. (2012) which they find best suited to minimise lifecycle bias. There are two reasons for not following this advice: Firstly and most important, since the income series conclude in 1995, following Nilsen et al. (2012) would lead to an exclusion of the 1960 cohort. This would have left only the 1950 and the 1955 cohort, which would leave little indication of trends over time. Secondly, using similar sample criteria to Bratberg et al. (2005, 2007) and Bratberg et al. (2014) provides a better foundation to compare their results with the ones obtained in this thesis using different methodology.

The 1965 sample contains more observations than those of the 1950, 1955 and 1960

[3]When first receiving the data set from NSD, this thesis set out to reproduce the results from Bratberg et al. (2005). Some large deviations were found and with closer inspection these found to be due to errors in the income data for some years, and lead to income series for sons and daughters to be replaced by corrected income data from SSB. When this was corrected, the results from Bratberg et al. (2005) were successfully replicated.

cohort. One reason being that averages of child's income were not computed, hence no exclusions due to child's missing income data where made. After exclusions, the main sample of the three birth cohorts 1950, 1955 and 1960 contain of 113,190 children. As noted above, the matching of data were done differently for the 1950 cohort, which could explain why it contains significantly fewer individuals than the 1955 and 1960 cohort. Fewer daughters than sons are represented in all cohorts, this is mostly due to missing income data. (Missing income data for the years used in the child's averages are summarised in table B.1 in appendix B.) Again, females taking on child caring responsibilities in the home rather than paid employment can explain why there are more observations with missing income amongst females than men. Over the time period studied, the children log average earnings at age 31-35 have risen for each cohort of daughters. For sons, on the other hand, the earnings are at the highest for the 1955 cohort. A possible explanation of 1960 cohort sons average earning to go down could be the recession Norway experienced in the late 1980 to early 1990, since males to a larger extent than females were working in sectors affected by the recession. It is also worth noting that there is a considerably larger spread in the incomes observed for daughters than for sons. Descriptive statistics is found in 4.1.

Table 4.1: Descriptive statistics

	1950 cohort		1955 cohort		1960 cohort		1965 cohort	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sons' fathers								
Five-year earning average	11.97	0.51	12.12	0.59	12.25	0.56	12.22	0.62
Age	48.14	4.90	47.50	5.03	47.15	5.28	46.02	5.38
Sons								
Average earnings age 31-35	12.20	0.52	12.24	0.58	12.21	0.66		
N	18,732		23,048		22,922		26,897	
Daughters' fathers								
Five-year earning average	12.05	0.49	12.11	0.60	12.26	0.56	12.23	0.61
Age	48.19	4.78	47.50	5.05	47.16	5.33	45.94	5.40
Daughters								
Average earnings age 31-35	11.04	1.22	11.43	0.88	11.59	0.86		
N	8,414		19,797		20,227		25,546	

Notes: Earnings in log of 1995 NOK. Five year averages of fathers' earnings: 1967-71, 1972-76, 1977-81 and 1982-86. Fathers' age is recorded in 1967/72/77/82

4.2.1 Additional sample used to study effects of differences in family structure

The 1960 cohort sample was chosen as a base for studying effects of different family structure. The 1960 cohort is the latest cohort of the sample data where five years earnings averages for children over 30 are available. Data on family structure are available in time series taken every tenth year, in 1960, 1970, 1980 etc. Due to this limitation in the data material it is only possible to identify the structure when the child is 10 and 20 years old. However, the data on family structure is only telling if the child lived in family containing a married couple or if he or she lived alone with one of the parents. Observations with missing data were removed. If the child is registered with family type "married couple with children" in the data in both 1970 and 1980, the family is defined as intact, if not it is defined as disrupted. The downside to this definition is that it leaves out any parents that were living together without being married.

4.3 Methods

This section gives a caption of how the different measures described in section 2.4 were computed and the different values of ρ and τ utilised.

4.3.1 Computing *UTP*, *DTP*, *URM* and *DRM*

To compute UTP, DTP, URM and DRM, the log income of the children's five year averages were converted into distribution of percentiles, denoted Y_1.[4] This was also done for single years of the child's income. Similarly, parents were sorted by their rank in their income distribution, after the five year log income averages and percentiles were defined. The percentile distribution for a parent is denoted Y_0. When transforming the distribution into percentiles, the shape of the original income distribution becomes irrelevant, since absolute differences do not affect the

[4] By using log income years with zero income are in practice treated as missing.

new distribution. Furthermore, the percentile distribution allows for comparisons of the position of the child in her distribution relative to the position of the parent's in his distribution, so $Y_1 > Y_0$ implies that the child is doing better in her income distribution than her parent in his income distribution.

Offspring were separated by gender, and the 1960 cohort applied in studying the differences in family structure was further split into disrupted and intact families, so that UTP, DTP, URM and DRM could be computed for each of the different groups.

In computing the UTP, the percentile ρ that the child needed to exceed conditioned on the parent being in that percentile to be varied cumulatively in increments of 0.1. This was done for the bottom half of the distribution. In the simple case where threshold value τ was set to zero, the chances of getting out of the bottom 10 percent, given that the parent was in the bottom 10 percent was observed. By this definition, moving up to the 11th percentile would be recorded as gain for a child. Then the parents from the 11th–20th percentile were added to the sample, and the probability of escaping the bottom 20 percent conditional on the parent being in the bottom 20 percent was computed. This process was repeated up to the median. (Descriptive statistics of the cumulative samples is presented in tables B.4 – B.11.)

In order to be recorded as gain, the child has to do strictly better than the percentile range that the parents is in: If the parent is in the 30 percentile, and $\tau = 0$, then the child has to be in 31 or higher in order to be recorded as gaining. Rising τ with 0.1 would mean that the child has to do ten percentiles better than the percentile range of the parent. This would mean that the child needed to be at 41th percentile or higher, since the parent is being located in the third decile, furthermore for $\tau = 0.2$ the child has to be on the 51 percentile or higher to be recorded as making gains, lastly $\tau = 0.3$ would imply that the child has to be on the 61 percentile or higher to be recorded as making gains.

One important issue is the choice of percentile cut-off points, ρ, and the spacing between them is arbitrary, but by selecting 0.1, a reasonable amount of observations are insured in both the study of gender differences and in the study of the impact of family structure for the 1960 cohort. The chosen level of ρ is used in other research, such as Mazumder (2014), however, there are also articles that utilise other values, see for instance Corak et al. (2014). Further in the empirical analysis, τ was varied from $0 - 0.3$ in increments of 0.1. Throughout this thesis, $\tau = 0$ is used as a benchmark value, unless tau is explicitly said to take on another value. Using deciles spacing for ρ and a value of τ of ten percentiles is also based on it being a "significant" gain or loss, something would matter for the individuals that are moving up or down in their income distribution. Thereby adjusting the value of τ, it is possible to record everything from a marginal movement compared to the parent, with the DRM and URM, to a rather significant movement of 30 percentiles up or down compared to the parents percentile in their distribution.

For DTP, conditioning was started on the top 10 percent of the income distribution for parents, and probability for the child in the simple case there $\tau = 0$ to fall below the top 10 percent in their distribution was computed. Next adding the ten percentiles of parents' income (from the 90th–81th percentile) to the sample, and when conditioned on this sample, the probability for the child to fall below the top 20 percent is computed. The process was repeated adding lower percentile ranges of parents income to the sample in increment of 0.1, until the sample used for conditioning consisted of the parents of the top 50 percentiles. Afterwards the process was repeated for $\tau = 0.1$, $\tau = 0.2$ and $\tau = 0.3$. To estimate the transition probabilities and the directional rank measures for different values of τ is interesting when comparing groups. This can be illustrated using UTP in an example: if two groups both have a high probability of moving past ρ, does one have higher probabilities of making larger gains, $\rho + \tau$? In respect to this thesis, do sons have greater probability of making larger gains compared to their parents, than daughters? And the other way around, for the downward measures; are there some groups that are more prone to fall further down the income distribution, compared to their parents?

The directional rank measures URM and DRM utilise the relationship between the parent's and child's rank in their respective income distributions. For URM that is the probability of Y_1 being greater than Y_0 conditioned on the parent being on or below a certain percentile, ρ, in his income distribution. Similarly for DRM:

what is the probability of Y_0 being greater than Y_1, conditioned on the parent being on or above a certain percentile, ρ, in his income distribution. The chosen values for ρ are identical with the values used for UTP in the case of URM and DTP for DRM. τ are also varied in the same way and cumulative sample were used. The reason for using the same values for ρ and τ is that it enables easier comparisons between the different measures.

The decision to use cumulative samples is two folded: Firstly, it reduces noise around the estimates (Mazumder 2014). If the sample size is small, and is divided up into intervals containing certain percentiles, then large or no movement by few individuals in the percentile will greatly affect the mobility estimate. This will result in the estimate to "jump around" from percentile to percentile; one percentile could for instance have very high UTP, the next interval very low, before being very high again in the third interval. By using cumulative samples this will average out. Estimating UTP, DTP, URM and DRM for the two genders will not be a problem, samples are large enough for all measures to be computed for intervals for all values of τ.[5] However, for family status there were so few observations of disrupted families that making interval sample resulted in them some of the intervals containing a very small number of observation, so estimating UTP, DTP, URM and DRM for intervals would not yield any meaningful results. This is in line with Mazumder's (2014) approach to deal with the same problem in his research. The second reason to use the cumulative samples, is that when estimated the same way, the results presented in this thesis are easy to compare. Cumulative samples is commonly used in the existing literature, see for instance Bhattacharya & Mazumder (2011), Mazumder (2014) and Corak et al. (2014), however the two latter also report transition probabilities and directional rank mobility for intervals.[6]

[5] The conditional expectation of children's rank on their parent's for $\rho = 1, 2, 3...100$, is plotted in figure 5.5 and 5.6 which is presented in chapter 5.

[6] Mazumder (2014) shows results for URM and UTP for intervals, while as Corak et al. (2014) shows both interval and cumulative samples for all measures.

Chapter 5

Results

5.1 Priors

Norway and the other Nordic countries are found to have a relatively high degree of intergenerational income mobility compared to other countries such as the United States or Britain (Black & Devereux 2011). The main reasons for this phenomenon is accredited to low inequality and/or social and educational policies (Black & Devereux 2011). In Norway several reforms of educational systems, including kindergarten, aims to reduce social inequality and the earnings distribution is compressed, i.e the return to skills is low. All this suggest a low intergenerational elasticity, in other words high mobility and this is supported by the empirical findings (Bratberg et al. 2005, Bratberg et al. 2007). This should be reflected in this thesis' estimation results as well.

Bratberg et al. (2005) found that daughters had lower intergenerational mobility than sons, which suggest a gap between men and women using rank mobility and transition probability measures. Daughters are measured up against fathers' income rank in this thesis. A gender divided labour market where women are most present in the public services, such as healthcare which are lower payed than sectors dominated by men. This would imply a lower upward mobility and higher downward mobility for daughters than for sons. A larger number of women not participating in the labour market or working part time, when caring for children could also leave to higher mobility downward and lower mobility upward than for sons. Social policies that aim to make it easier to work while raising children, for instance childcare, have gradually improved over the time period studied and should suggest that gaps between sons and daughters decreased. It should be noted that a ten year period is not sufficient as a clear reflection of time trends, but it could serve as an indication.

From the model presented in chapter 2 the child would benefit from having the investment of two parents, as opposed to one, therefore it is expected to be some differences in the rank mobility and transition probability measures between disrupted and intact families. Norwegian data suggests that there are some differences between intact and disrupted families. Children from disrupted families seem to have a socioeconomic disadvantage compared to those of intact families (Bratberg et al. 2014, Rieck 2008). Bratberg et al. (2014) use transition matrixes and find that children of divorced families move downward in the income distribution with higher probabilities than children from intact families. This would imply that children of disrupted families have lower UTP and URM and higher DTP and DRM than those of intact families.

In the following chapter the estimation results are presented. A discussion of the results will follow in chapter 6. In the first section the transition probability and directional rank mobility estimates by gender are presented, and in the second section the results for the transition probability and rank estimated by gender and family structure are presented. For all results there is a graphical representation showing the minimum and maximum value of τ is used illustrating the results and the difference between different groups.[1] A separate graph for a high value of τ shows how probabilities for different groups of making larger gains/losses differs. At the end of the chapter a summary of the main trends and findings will be given.

[1]Minimum and maximum value is $\tau = 0$ and $\tau = 0.3$ receptively.

5.2 Transition probability and directional rank mobility estimated by gender

Estimation results for transition probability and rank mobility for the 1950, 1955 and 1960 cohort by gender are presented in table C.1 – C.12. Graphical presentation is also provided for chosen values of τ, zero and thirty percent respectively, in figure 5.1 – 5.4. All probabilities and differences reported are significant on a one percent level. Estimates show that males have a higher probability of moving upwards and have a lower probability of moving downwards than females for all cohorts, both for rank mobility and transition probabilities measures. Differences between the genders seem to be declining over time, but remains substantial.

5.2.1 Upward transition probabilities

The upward transition probability (see figure 5.1) for males seems to be quite stable over the time period of this study, decreasing as new percentile ranges of their fathers' income are added. Probability of making a larger leap compared to their fathers increases for sons over the period of the study. Overall sons have a higher probability of surpassing their fathers' percentile range with 30 percentiles or more in the 1955 and 1960 than in the 1950 cohorts. Daughters have a lower UTP than sons for all percentile ranges of fathers' income, e.g., in 1950 daughters with fathers in 1 to 30 percentile had a 29 percent probability of surpassing their fathers' percentile range, versus a 81 percent probability in sons with fathers in the same percentile range. The gender gap in this example is a sizeable 52 percent. In general relatively few daughters surpass their fathers' percentile range (ρ) by 30 percentiles or more compared to sons. For fathers' percentile range 1 to 50 the probability for a daughter to move beyond the 80 percentile is only a few percent. Daughters' probabilities do however increase over time, upward mobility being most prominent in the low end of fathers' percentile range.

5.2.2 Downward transition probabilities

Probability of moving downwards depending on fathers' income percentile is highest in those who have fathers in the top ten percent of the income distribution, declining as we add fathers from lower percentiles to the sample (see figure 5.2). The estimation results show a gradually decreasing trend in sons of all cohorts, with DTP being quite stable over the time period studied. Daughters are more downward mobile measured with DTP than sons. There is however, a tendency of DTP decreasing somewhat in daughters from the 1950 cohort compared to those in the 1960 cohort. There is no clear trend that the gender gap is declining over time as there is no significant difference in the gap between the 1950 and 1955 cohorts.

When increasing the threshold value, τ, the differences between sons and daughters increase. Estimating probabilities for $\tau = 0.3$ the sons probability for DTP is quite stable over the time period. Daughters have high DTP for the high end of the fathers' percentile range of income, but this it is rapidly declining as fathers with lower income percentiles are added. This trajectory is repeated for all cohorts when $\tau = 0.3$, but the probability of downwards transition is declining for all percentiles of fathers' income in each of the three cohorts. The gender gap is also declining for all cohorts over the period of this study.

5.2.3 Upward rank mobility

URM is generally higher than UTP. By construction URM measures all small upward movements for sons and daughters relative to their fathers' rank in the income distribution, whereas for UTP these children to reach the chosen cut-off percentile value, ρ (see figure 5.3), which means that the relative gain they have to achieve would differ. URM decreases monotonically as fathers from higher percentiles are added for both genders. For sons it is relatively monotonous compared to daughters; URM only varies by a couple of percentage points.

Daughters' probability of surpassing their fathers' position in the income distribution is decreasing more rapidly than for sons, when adding fathers from higher income percentile ranges to the sample. The 1950 cohort has the highest gaps between genders, the gap is least significant when looking at children with fathers in the first decile, and steadily grow as fathers in higher ranges of income percentiles are added to the sample.

As for the UTP increasing the threshold value, τ, this has a larger effect on daughters than sons, especially in the low end of the fathers' income percentile. E.g. for the 1950 cohort the probability of a daughter surpassing her father in his income distribution with 10 percentiles or more is only 57.7 percent if the father is located in the first decile. This is a decline of 25.2 percent from just surpassing her father. On the other hand a son under the same circumstances would have a 90 percent probability of making a leap of 10 percentiles or more past their fathers, which is down 7.6 percent from just surpassing their father. However, over the period URM for $\tau = 0.3$ is steadily rising for each cohort of daughters, most of the gain is done for those with fathers in the low end of the income-distribution. For sons the trend is less obvious, with highest URM for $\tau = 0.3$ in 1955, with lower URM for the 1960 cohort and lowest for the 1950 cohort. The gender gap does not differ significantly in 1950 and 1955, but is declining for the 1960 cohort.

5.2.4 Downward rank mobility

In the same manner as URM probabilities are higher than UTP. The measure of DRM is higher than the DTP; since by construction the DRM uses the child's own father as a yardstick instead of a chosen percentile cut-off value. Daughters have very high probability of moving down in their income distribution compared to their fathers' placement in his income distribution for all percentiles ranges of the is fathers income used. In sons the probability of downward movement in income distribution is starting at lower and decreasing at a higher rate than for the daughters. The gender gap seems to be stable over time. A decrease in DRM can be observed over time for daughters when τ is increased.

5.2.5 Rank-rank relationships

Another way to illustrate rank-rank relationships in the income distribution is to draw a figure plotting of the expected income rank of children versus their fathers income rank for the entire distribution and the OLS regression line for sons and daughters respectively.[2] Figures 5.5 and 5.6 indicates an almost linear relationship. There is however a small tendency of an upward bend in the top end of the income distribution in both genders, indicating that there are somewhat more persistence in rank than the linear relationship would suggest. For sons, though fairly linear, there seem to be a slight curve downwards at the low end of fathers' income percentiles and a slight curve upwards in the top end, resembling an inverted "s" shape around the linear fit. For daughters there seem to be higher upwards rank mobility than the linear prediction in the top and low end of fathers' income distribution. Whereas in the middle of the distribution downward mobility seems to be greater than the linear fit predicts. Overall my results indicates that the linear prediction is close to a non-parametric one in all cohorts.

5.3 Transition probability and rank mobility estimated by intact/disrupted families

Estimation results for transition probability and rank mobility for sons and daughters of the 1960 cohort by intact/disrupted families are presented in table C.13 – C.20. A graphical presentation of $\tau = 0$ and $\tau = 0.3$ are given in figure 5.7 – 5.10. In general children of intact families have a lower probability of moving downwards and higher probability of moving upwards than children of disrupted families. Though the differences are quite small and in some cases not statistically significant of a five percent level.[3] Differences seem to be larger between sons

[2] This plot is showing the conditional expectations (CE) of the child, conditional on fathers' income percentile: $CE(\rho) = E(Y_1|Y_0 = \rho), \quad \rho = 1, 2, 3, ..., 100$. In addition to the plots and the linear regression line the locally weighted regression line where added to the plot using the lowess function in STATA.

[3] Not statistically significant differences between intact and disrupted families are mostly found for sons. Significance levels are marked in the tables.

in disrupted and intact families for the downward mobility measures. Regarding daughters the tendency is less clear. Overall the findings in these groups was as expected; that children of disrupted families were doing slightly worse than children of intact families. Note that these results are not to be interpreted as a causal relationship between family structure and the child's outcome.

5.3.1 Upward transition probabilities

Sons of intact families do have some higher UTP than those of disrupted families. When increasing the threshold value, τ, differences in sons decreases. In $\tau = 0.2$ and $\tau = 0.3$ the difference between sons from disrupted and intact families is insignificant for most percentile ranges of fathers' income. Daughters have slightly higher UTP for intact families, but in contrast to sons the gap between intact and disrupted families are growing in the lowest decile of fathers' income when τ is increased, and converging when fathers from higher deciles are added. The differences between daughters from disrupted and intact families stays significant on a five percent level for all levels of τ used.

5.3.2 Downwards transition probabilities

Downward transition probabilities are highest in daughters of disrupted families, 4–7.9 percent higher than daughters of intact families. This also applies in sons. When increasing τ sons' transition probabilities seem to converge when fathers from lower ranges are added to the sample. For daughters, the gap between those from intact and those from disrupted families seem to be quite persistent.

5.3.3 Upward rank mobility

There are only small differences in URM between disrupted and intact families in both sons and daughters. However the general pattern is that sons and daughters of intact families are doing slightly better than those in disrupted families. For $\tau = 0.3$ there are no significant differences between sons, but there is a notable gap between daughters of intact and disrupted families when their fathers are in the bottom ten percentiles of the income distribution. The gap declines gradually as fathers from higher percentile ranges of income are added to the sample.

5.3.4 Downward rank mobility

Only small differences can be found in the downwards rank mobility between daughters of intact and disrupted families. The differences are slightly larger for sons, with gaps ranging from 3.8–8.3 percent. When increasing τ the difference between daughters also increases, and for $\tau = 0.3$ the gaps between intact and disrupted families are close to equal in both sons and daughters.

5.4 Main findings and trends

This section summarises the main findings from the material presented above. The most distinct result is that sons do have larger probabilities of moving upwards and lower probabilities of moving downwards than daughters in all cohorts. Sons are also more likely to make larger upward movements, relative to their fathers than daughters. Daughters on the other hand are more prone to larger downward movements.

5.4.1 Gender

Regarding gender differences there are some points to be noted: Firstly, for both upward and downward transition probabilities, the gap between the genders seem to grow for $\tau = 0$, as we move along fathers income distribution. The opposite seems to be the case when $\tau = 0.3$. The UTP figure clearly reveals that for $\tau = 0$, the gap in UTP for sons and daughters is lowest in children with fathers in the bottom ten percent of their income distribution, for $\tau = 0$. However, looking at the probability that a child with fathers in this decile moves up into the fourth decile in their income distribution, i.e $\tau = 0.3$, the gap between the genders is largest in the bottom distribution. Even though both daughters and sons with fathers in the bottom decile of the income distribution have a relatively high probability of leaving the bottom decile, sons have a higher probability of making a major leap. The reverse relationship is found in DTP; daughters have higher probability of moving further down their income distribution than sons.

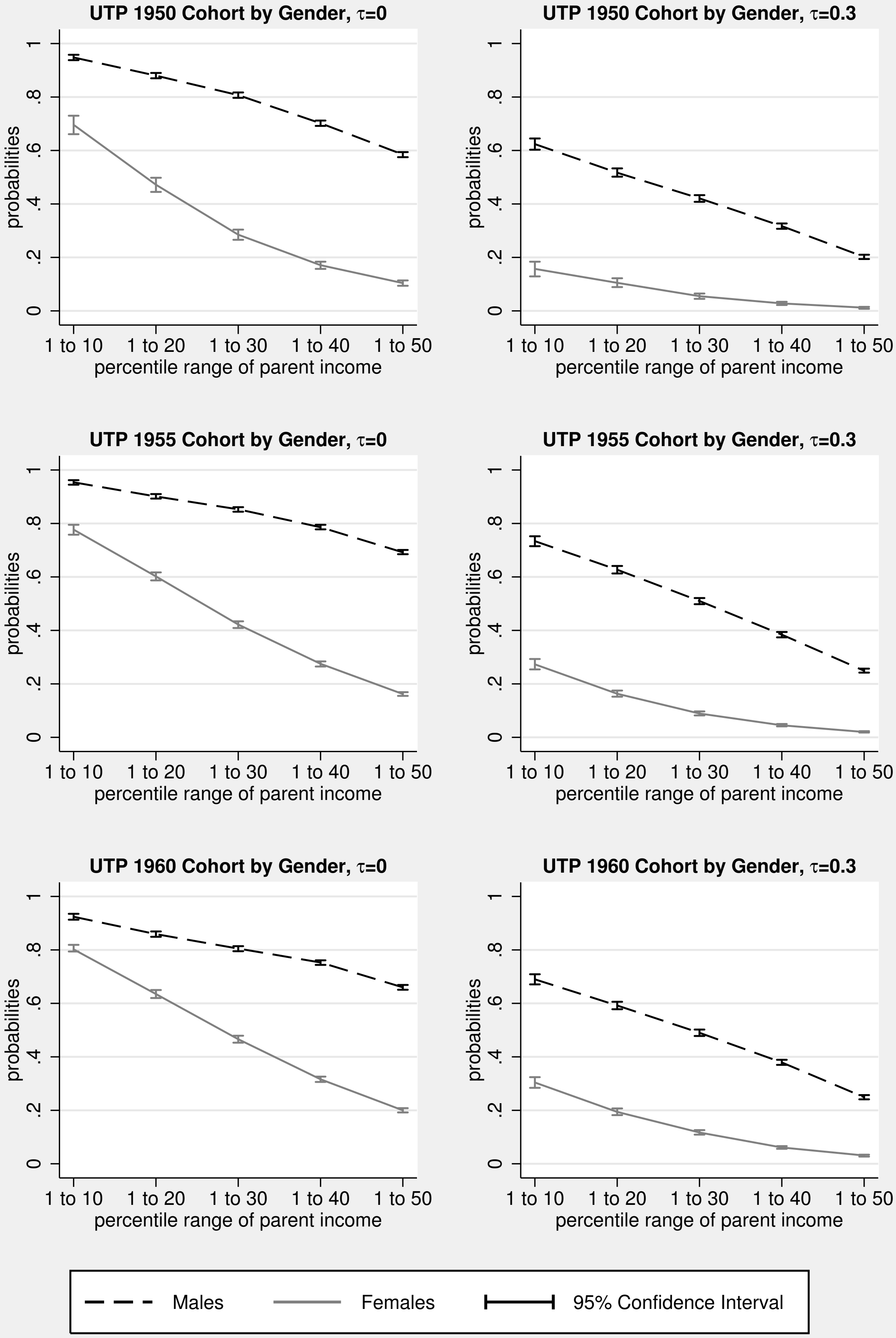
Secondly, the same pattern as for transition probabilities is found using directional rank. The gender gap is least significant at the top and bottom end of fathers' income distribution, but increase when τ is raised. In contrast to transition probabilities, the gender gap stays almost constant over all ranges of fathers' income. Thirdly, if $\tau = 0$ there are smaller differences in the gender gap if one uses the directional rank measures than transition probabilities, and the results are more equal over all ranges of fathers' income. Fourthly, there seems to be some decline in the gaps between the genders during the time period of this study, but the overall pattern seems to remain the same. Fifthly, it seems as though there is an almost linear rank-rank relationship for both sons and daughters in figure 5.5 and 5.6.

5.4.2 Intact and disrupted families

In children of disrupted families downward mobility is higher than in children of intact families, in both sons and daughters. The difference between disrupted and intact families seems to be quite stable for daughters, but decreasing in sons when fathers from lower percentile ranges are added to the sample. There are small differences in DRM for daughters, but when increasing τ the differences between intact and disrupted families are getting bigger, i.e. more daughters are falling to a position in their income distribution considerably below their father's placement in his income distribution. For sons the differences are smaller.

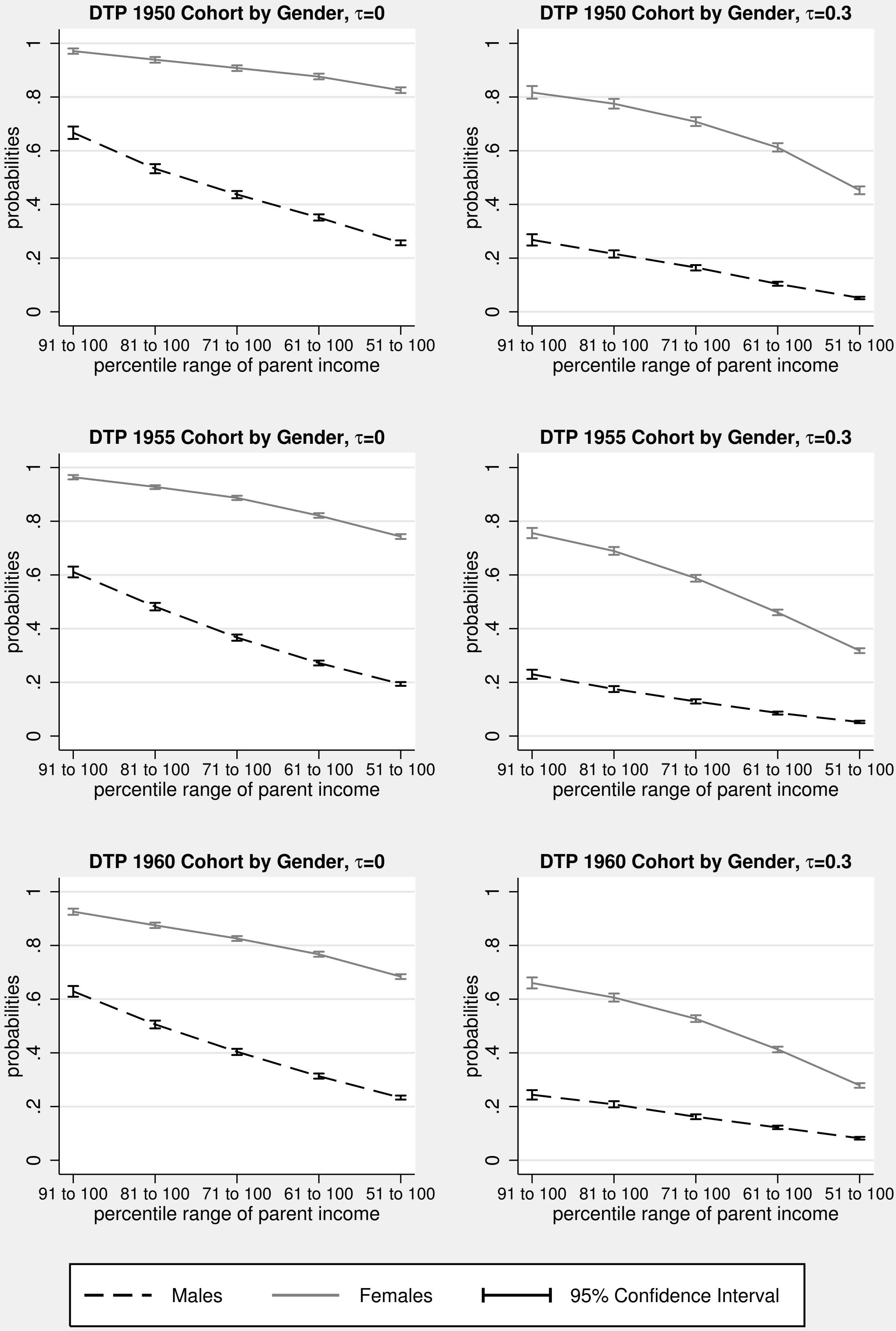
URM seems to be fairly equal in both disrupted and intact families, with one exception; there is a larger gap between disrupted and intact families in daughters with fathers in the lowest percentile range of income. From the estimation results it seems that a daughter from an intact family in the first decile, is more than ten percent more likely than a daughter from an intact family to surpass her father in his income distribution by thirty percent or higher. This result is reflected in UTP as well. The differences are quite stable for $\tau = 0$ in both genders up to the median of fathers' income distribution. However, when it comes to surpassing a father belonging to a certain decile with thirty percentiles or more, there is no difference between intact and disrupted families for sons, but some differences recorded for daughters with fathers in the bottom of the income distribution. The differences in daughters also seem to converge when fathers from higher percentiles are added to the sample. It should be noted that these results may not be interpreted as causal impacts of family disruption.

Figure 5.1: Upward Transition Probabilities by Gender



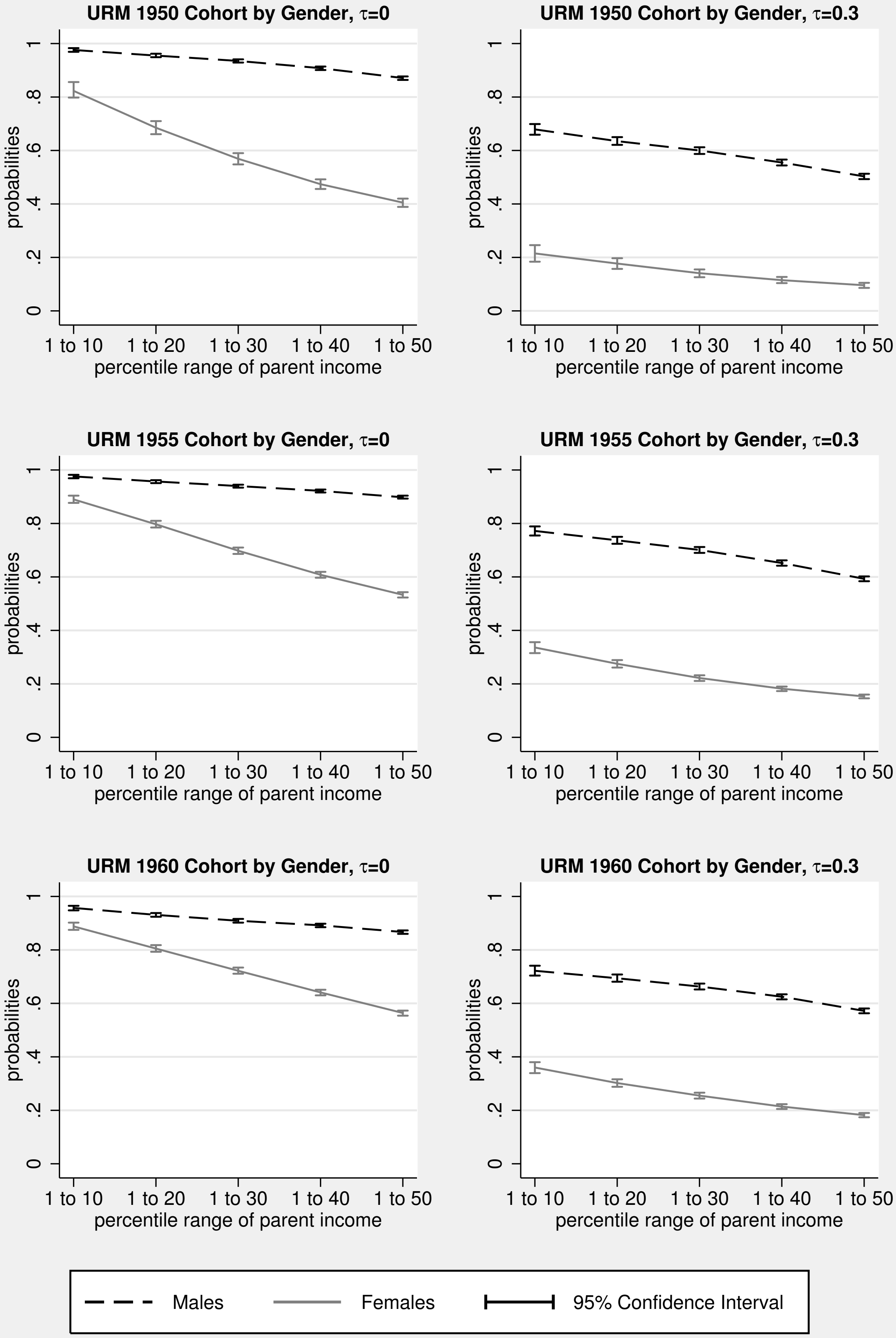
Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.2: Downward Transition Probabilities by Gender



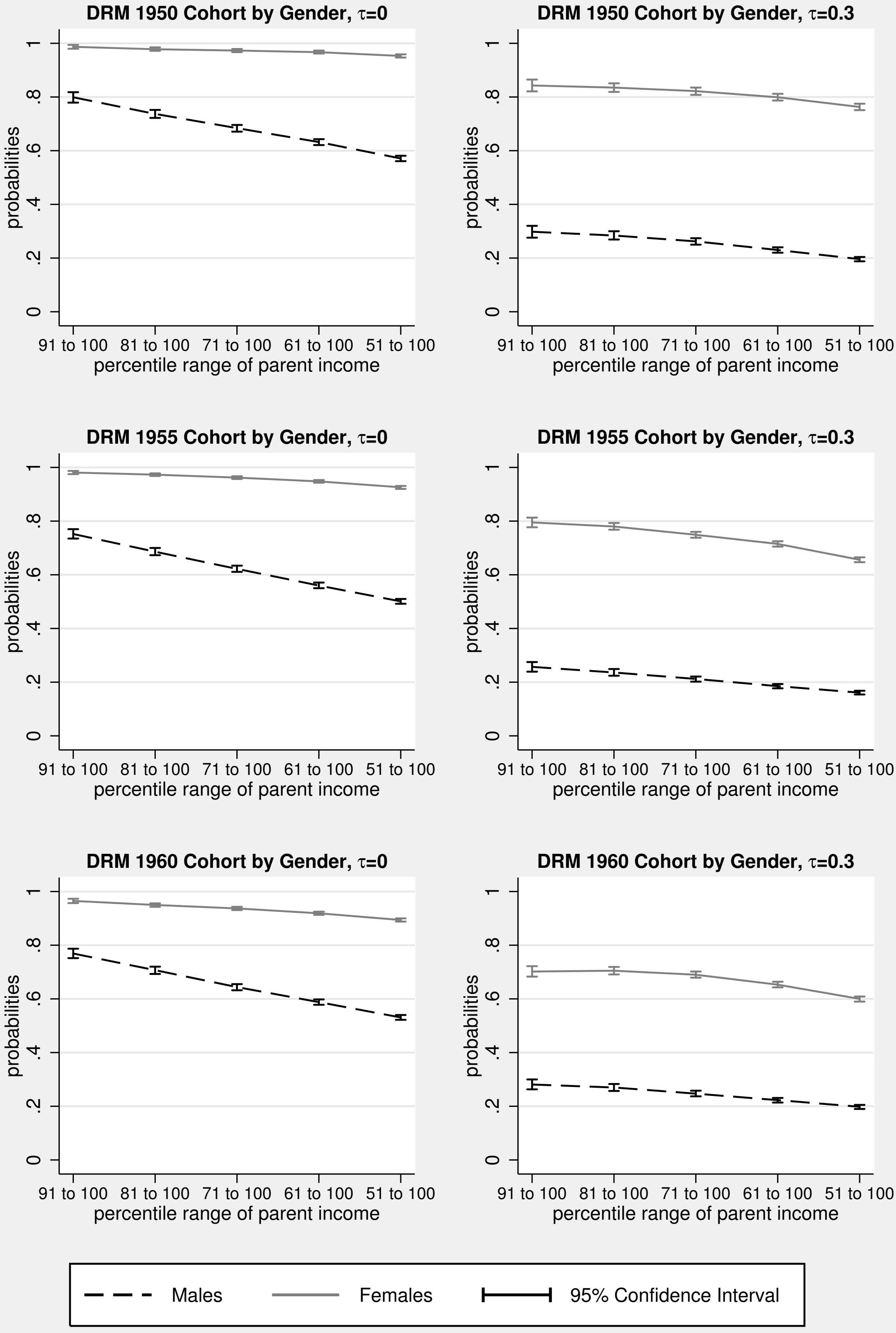
Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.3: Upward Rank Mobility by Gender



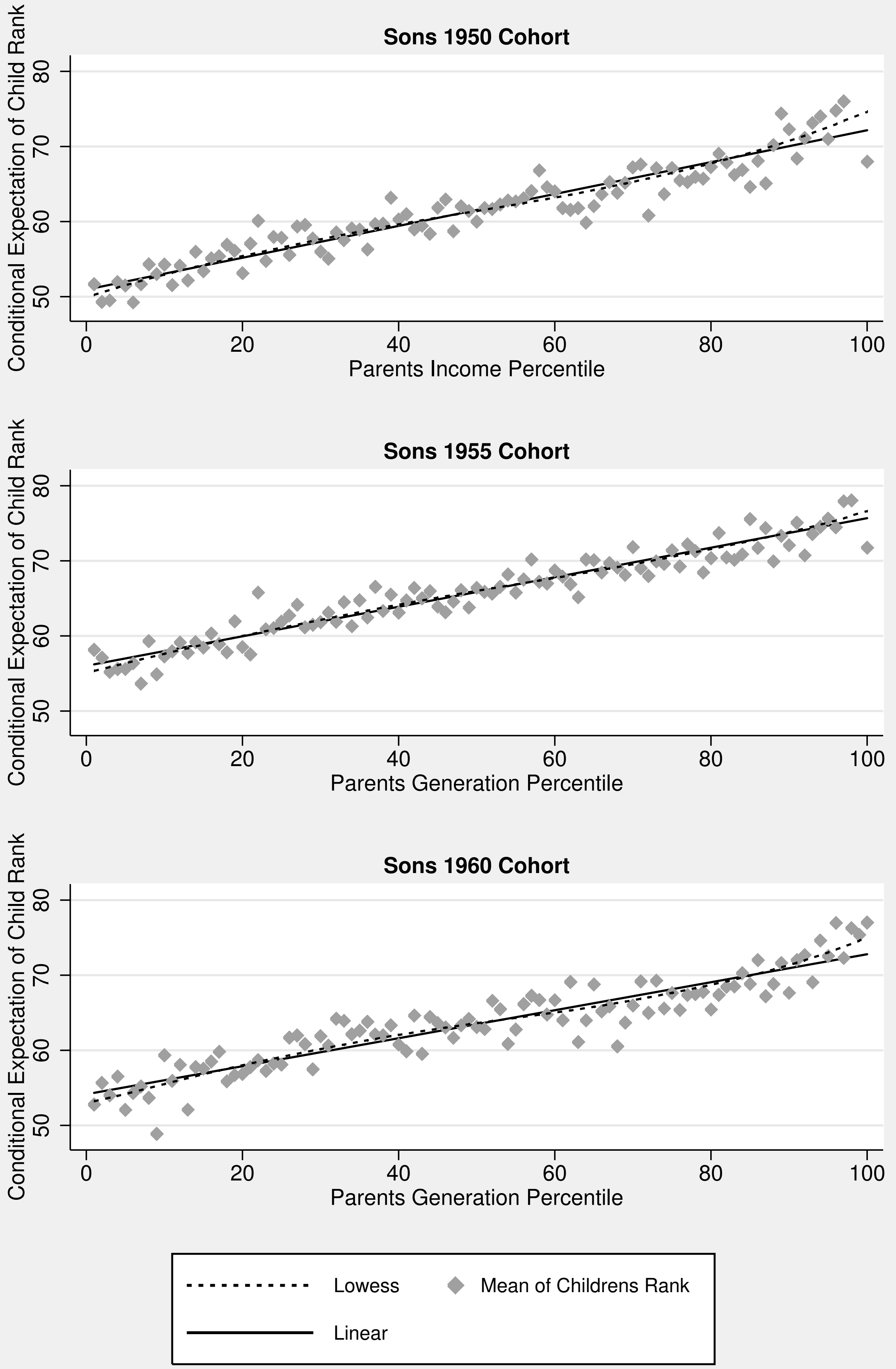
Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.4: Downward Rank Mobility by Gender



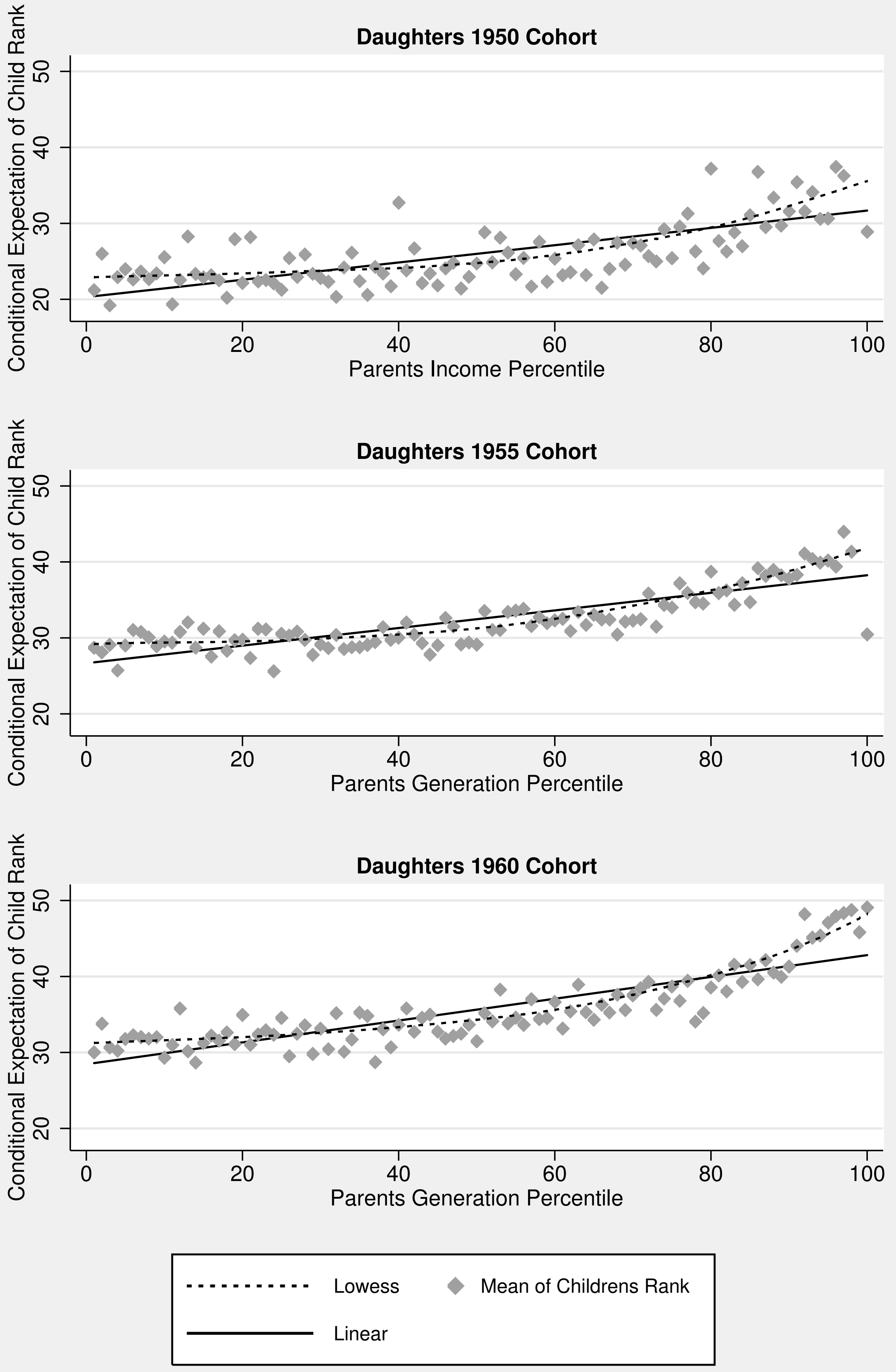
Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.5: Expectation of Sons Rank Condition on Parent Rank.



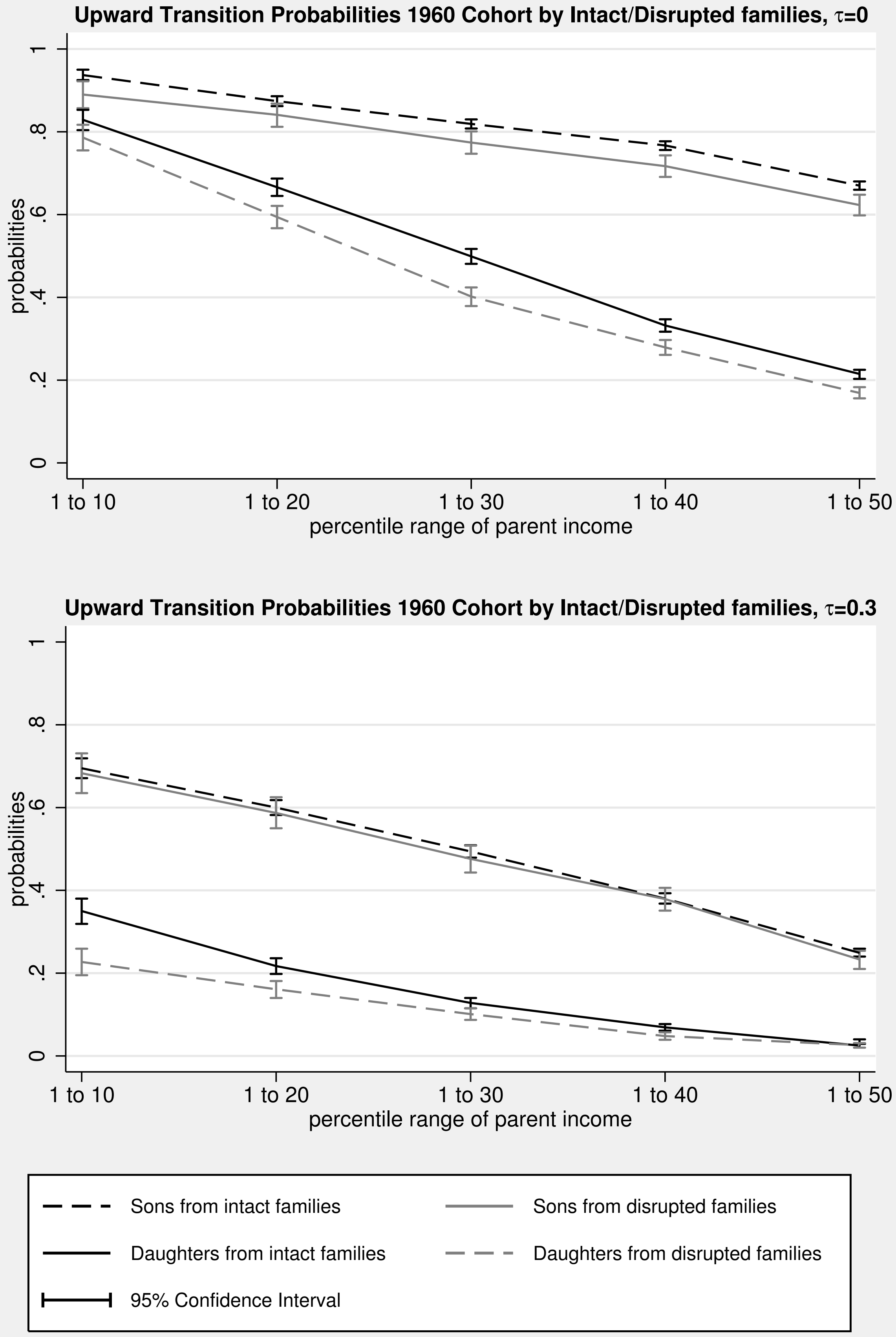
Notes: See text for a description.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.6: Expectation of Daughters Rank Condition on Parent Rank.



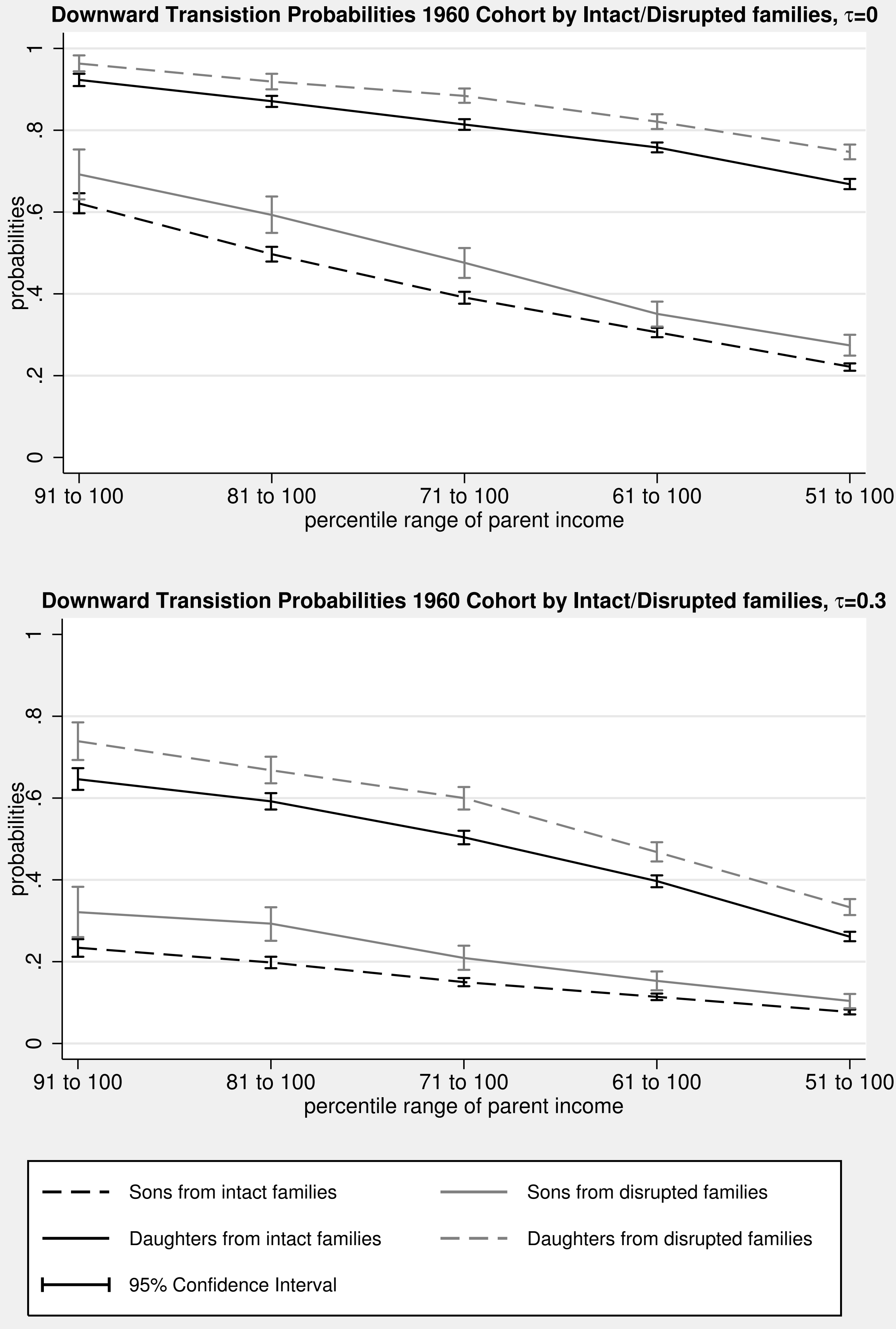
Notes: See text for a description.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.7: Upward Transition Probabilities 1960 Cohort by Intact/disrupted families



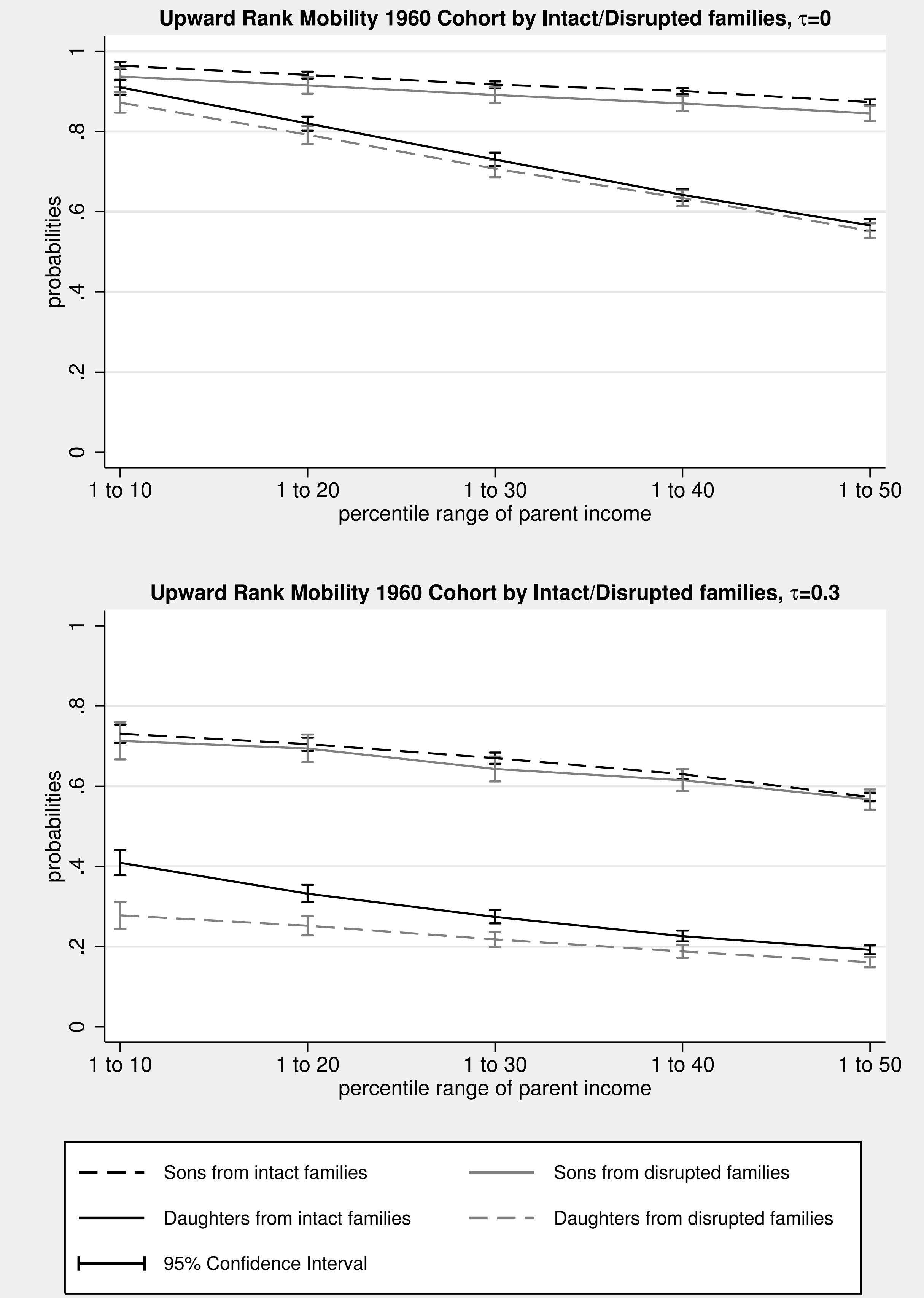
Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.8: Downward Transition Probabilities 1960 Cohort by Intact/disrupted families



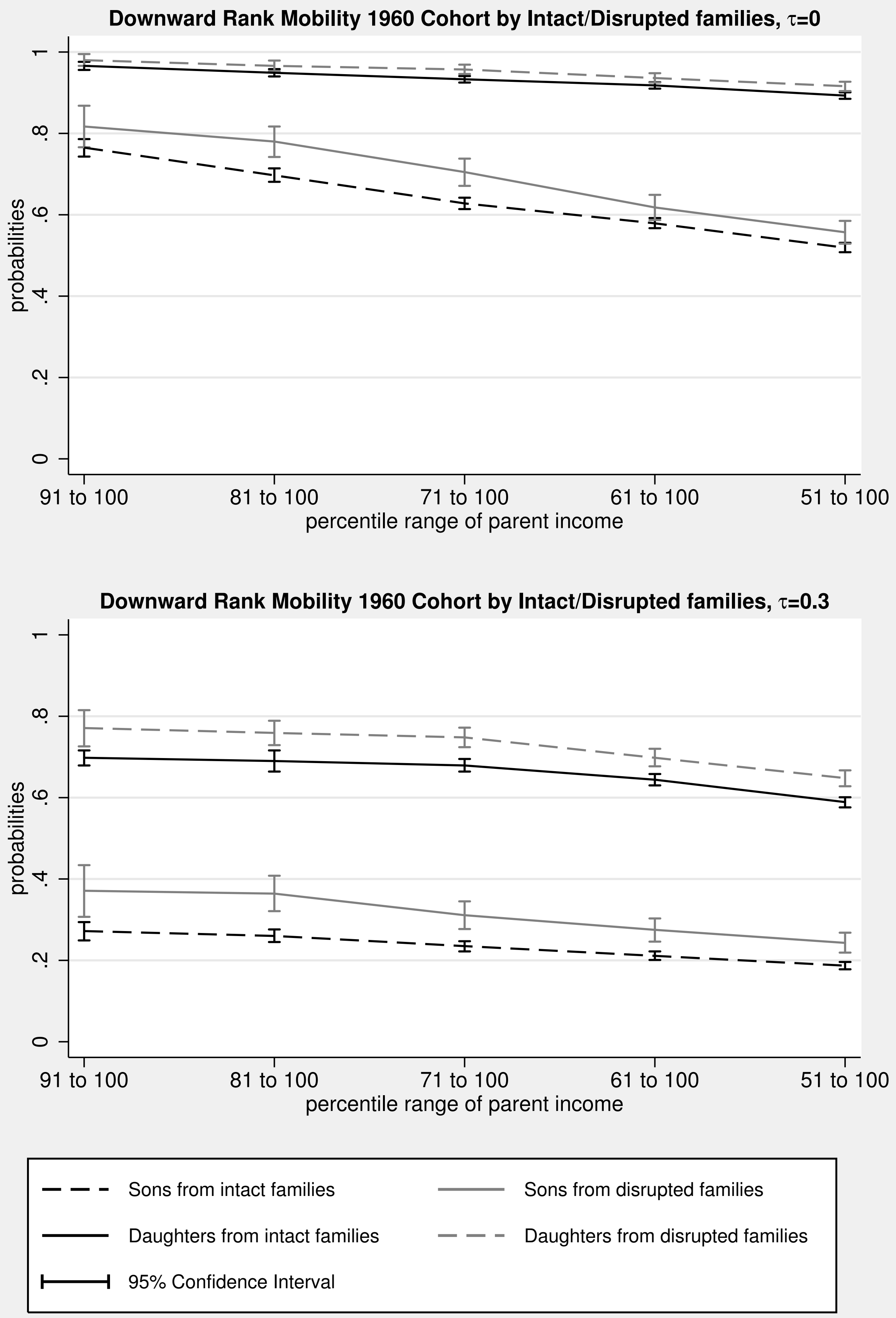
Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.9: Upward Rank Mobility 1960 Cohort by Intact/disrupted families



Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Figure 5.10: Downward Rank Mobility 1960 Cohort by Intact/disrupted families



Notes: See text for a description of the estimator.
Sources: Author's calculations based on data from Norwegian Database of Generation provided by Norwegian Social Science Data Services.

Chapter 6

Discussion

In this chapter follows a discussion of the empirical findings. The discussion focuses on the essence of the results. Potential sources of error are pointed out and the results of the empirical findings are compared to previous findings. Potential explanations for those findings are presented.

6.1 Gender differences

In accordance with earlier finding for the Nordic countries, see for instance Bratberg et al. (2005, 2007, 2014), Jäntti et al. (2006), Raaum et al. (2007) and Nilsen et al. (2012), differences in mobility between genders are also found in this analysis. Why are there gender differences in mobility? Two primary mechanisms are put forward: Assortative mating and labor supply choices (Raaum et al. 2007, Chadwick & Solon 2002). For instance, it is found in this thesis that daughters are more downward mobile than sons. One possible explanation is assortative mating; explanation being that assortative mating would lead women from high-earning families to be more likely to marry high-earning men. If there is negative cross-wage or income elasticity of labour supply, women will choose to work less hours, hence ending up with lower personal income. It is likely that labour supply decisions of married women and women with partners differs from the labour supply of married women (Chadwick & Solon 2002). Raaum et al. (2007) find evidence of some marital sorting in Norway, but it is generally weaker in the Nordic countries than in United States and the United Kingdom. In light of this finding, a combined measure of family income would be preferable, both for children and parents with partners. This would give a better perception of the rank and transition mobility actually experienced by both genders and better reflects women's economic status. However there would be other data issues, such as how to define and identify a family in data, problems with family dissolutions, etc..[1] Exclusions done in my sample as a result of missing income data (see table B.1) might suggest that mobility for daughters alone are even lower than the estimated results suggest, as a higher percentage than sons are recorded with no income and the directional rank and transition probabilities over a life time would be affected.

Factors affecting labour supply decisions could help to explain why intergenerational mobility for the two genders differs between countries, but also why it could, as the presented results suggest, change over time. Incentives to allocate time between the labour market and the household could have changed over time. For instance a change in rules regarding benefits, such as right to take out a longer maternity leave could affect labour supply. Raaum et al. (2007) point out that working part time in the Nordic countries involves a marginal wage penalty compared to the United States and the United Kingdom. This would imply more individuals choosing to work part time in Norway. If more women than men work part-time this would imply a gender gap in mobility, which is the case in Norway (Statistics Norway 2014). Another factor could be the tax-system: are couples taxed as individuals or together? The degree to which individuals are taxed together could affect a household's labour decisions, since the returns from the second household member working could be lower if taxed together. Services such as kindergarten and their price and quality would probably have effect on the labour supply of parents, especially mothers. Cultural and social factors, including values, attitudes and norms, could also play a part in understanding why labour supply decisions are varying over time and place. For instance: Attitudes toward

[1] Linking on children's souses and their income data was not available in in the dataset, so I am unable to utilise family income for the generation of children. For the generation of the parents the father would in most cases be the breadwinner in the family, which make him suited as a proxy for family income.

women working have changed over time and differ between cultures. This might help explain differences in men's and women's mobility in different countries, but also trends over time.

Despite the differences in IGE estimates found between sons and daughters, the overall trend is the same for father-son elasticities as for father-daughter elasticities: smaller IGE for the Nordic countries and higher for the United Kingdom and the United States (Jäntti et al. 2006). Using different measures I do not have any directly comparable results for the directional rank and transition measures on gender, but the relatively high probabilities for both upwards and downwards movements in the income distribution could serve as support for earlier findings of high mobility in Norway. Comparing the results for sons found in this analysis to the findings of Corak et al. (2014), who also used directional rank mobility and transition probability, my findings for upward rank mobility are higher and downward mobility lower than in Canada, the United States and Sweden. However, the cohorts used are younger and sampling methods differ somewhat, so it should not be taken as anything more than possible indication. Comparing countries is at any rate a difficult task, as countries differ in many ways. When comparing rank measures a pit-fall is that moving, for instance, ten percentiles could have very different implications in different countries. The impact would depend on the absolute difference in inequality: A drop in a relatively equal society would mean less than a drop in a society with high inequality. So a drop in Norway would mean less then the same drop in rank in the United States.

6.1.1 Changes in mobility over time

As we have seen in chapter 5 estimation results for both transitional probabilities and directional rank showed a large and lasting difference in mobility for the two genders. The differences between sons and daughters seem however to be getting smaller from 1950 to the 1960 cohort, but remains substantial. For the 1950 cohort it should be pointed out that data are linked differently than for the 1955 and 1960 cohort, and this difference resulted in lower number of females than men in the 1950 cohort. The children that are present are those who where still living at home at the age of 20, which was more common for sons than daughters.[2] If those who stayed home have different characteristics than those that left home earlier, comparison with the 1955 and 1960 cohort could be flawed. One possible characteristic is that daughters being registered to live at home to a higher degree were taking higher education, than the ones that left home, which could inflict a selection bias.[3] Difference in linking could explain some of the differences between the 1950 cohort and the 1955 and 1960 cohort, especially among daughters.

A reason for the larger movement in the directional rank and transition probability measurers observed for females compared to men in the period could be due to their increased labour force participation and more females working full time over the period. In the 1980's and early 1990's when daughters from the different cohorts in this study were in their early thirties, there was an increase in the number of women joining the labour force (Statistics Norway 2014). On the other hand, a disproportionate share of the daughters in this study are likely to have worked part time, hence having lower incomes compared to the sons. This would help explain the large gender gap observed.[4] There are several explanations for a higher percentage of women working in the period. The considerable increase in kindergarten coverage could be one; the coverage rose from 19,3 percent in 1980 to 52,3 percent in in 1995 (Statistics Norway 2014). Moreover, the average level of education among women has increased over time. In 1995, 42,3 percent of Norwegian women had at least twelve years of education, as opposed to 38,3 percent in 1980 (Statistics Norway 2014). This enhances "equality of opportunity" and could be a factor of why woman have become upwardly mobile over the study period.

Several school reforms have also taken place over the period of study, and may have affected the cohorts differently. For instance the increase in compulsory schooling from seven to nine years was carried out from 1960 and was fully implemented in 1972 (Aakvik, Salvanes & Vaage 2010). This would benefit only a small number of the 1950 cohort but would apply to all of 1960 cohort. The reform was implemented

[2]See Statistics Norway (1977), figure 2.2 on page 59.

[3]Students are allowed to stay residents in the municipality of their parents during studies.

[4]The proportion of employees working full time was 47.5 percent for woman compared to 90.2 percent for men in 1980. (Statistics Norway 2014)

at different times in different municipalities, so there would also be some variance in how the earlier cohort was affected.[5] In this period regional collages were opened and Norway founded its fourth university, increasing access to higher education.[6] Affecting the cohorts differently the reforms could help to explain some of the differences found from the 1950 to the 1960 cohort. It is, as put forward by Bratberg et al. (2007), reasonable to assume that compulsory schooling had the strongest impact on the families with the lowest income.[7] This effect might be reflected in the higher probabilities for women to do gain relative to their fathers for the 1960 cohort, than for the 1950 cohort, and the probability of them making larger leaps have increased. This also corresponds well with the Bratberg et al. (2007) finding of lower elasticities over time for daughters with parents at the lower end of the income distribution.

With only ten years between the oldest and youngest cohort it is too short a period to say anything definitive about trend, but there seems to be a decrease in the gap between the genders. The intergenerational income elasticity estimate for the same period by Bratberg et al. (2005) shows a rise in mobility for daughters from the 1950 to the 1960 cohort, and the mobility of daughters is getting closer to the mobility of sons. This thesis suggests that this pattern is fuelled by higher upward mobility and to a smaller degree countered by lower downward mobility for daughters in the period. Bratberg et al. (2005) also found higher mobility among sons from the 1950 to the 1960 cohort. In my results this seems to be reflected in some higher upwards mobility, especially in the middle of the income distribution and stable downward mobility for the same cohorts. This pattern of increased mobility over time in Norway is also supported in findings using data for the 1960 and 1970 cohort by Rieck (2008).

The IGE estimate for the children of the 1960 cohort to their fathers' earnings could

[5] Due to lacking data on which municipalities children compulsory schooling found place, it is not possible for me to directly test for the effect of reform on intergenerational income mobility. If data were available it would have been a candidate for doing a natural experiment to test the effects of the reform.

[6] University of Tromsø officially opened in 1972. This was a step in reforms intending to decentralising education, and increasing access to higher education.

[7] See also Aakvik et al. (2010) for corresponding finding of higher educational attainment in low earning families for this time period.

illustrate one of the IGE estimate weaknesses; The estimate is 0.126 for daughters and 0.129 for sons (Bratberg et al. 2005), so not too far apart. However, using directional rank and transition probabilities, one can see that sons enjoy more mobility upwards and less downwards than the daughters, but the effects cancel each other out, which could explain why the IGE estimates are similar for the two groups.

One of the motivations for using directional rank and transition probability measures, is to be able to explore mobility for different parts of the income distribution. URM estimates show that children with parents whose income is in the lowest ten percentiles of their distribution, have high probability of surpassing them. However, as higher percentile ranges of parents income are added to the sample, daughters' probabilities of surpassing their parents drop at a much higher rate than sons, see figure 5.3. As the probability of surpassing their parents is quite high for both sons and daughters for those who come from families where the father was in the bottom ten percent of his income distribution, it is interesting that daughters are much less likely than sons to make major income leaps (see 5.3 right panel). A possible explanation could be that women tend to go into lower paid sectors than men, such as public health care.[8] Another possible explanation could be that many women in their early thirties work part time in their children's first years, and this had a somewhat negative effect on the averages of income used for the estimation.

6.1.2 Specifications and measurement issues

In addition to the already discussed possible sampling problem due to the different linking of cohort, it is here raised a couple of other issues. In general, this thesis finds that the directional rank measures are quite robust compared to IGE, and which is in line with the findings of Chetty et al. (2014*b*) and Corak et al. (2014).[9]

[8]There are variety of explanation for segregation into sectors: Difference in taste (see for instance Bertrand (2011)), or discrimination in the labour marked towards a group, in this context gender, could serve as to examples. For a textbook crowding model see for instance Boeri & van Ours (2013, chapter 4.).

[9]For instance if I measure income at a older age for the 1955 cohort, it does not give any significant changes in the probabilities and differences observed. The same is true for a longer

As Chetty et al. (2014*b*) suggest, this might be due to rank relationship between parent and child being created quite early in life. However, this theisis find that the bias from measuring the child's income at a "too young" age seems to persist longer in the Norwegian data than what Chetty et al. (2014*a*) found for the United States. Their findings suggest that rank-rank relationships can be determined from quite early in the career of the child, e.g., they find that earnings at age 26 is a good predictor for trends of mobility at age 30 (Chetty et al. 2014*a*). Table C.21 suggest that for Norwegian data the bias will persist. It should be noted that Chetty et al. (2014*a*) is using data material from a different time period than that used in this thesis. Even though lifecycle bias and transitory fluctuations in earning seem to be less of an issue using directional rank measures and transition probabilities than IGE, it is hard to make any definitive judgement of the effects, and future research should address this more thoroughly.

6.1.3 Rank-rank relationships

The rank-rank slope, which can be understood as the difference in the mean income rank for children from the poorest compared to the wealthiest families (Chetty et al. 2014*a*), is steeper for sons than for daughters in all three cohorts. The general pattern observed in this thesis seems to be persistent over the period studied. Linear results are found in studies from United States by Chetty et al. (2014*a*) and Chetty et al. (2014*b*). However, the results found here seem to be more linear than findings of Bratberg et al. (2015) for Norway and Sweden, which shows sharper curves downwards and upwards in the bottom and top end, respectively, than I observed in this thesis's sample. A possible explanation for this could be that Bratberg et al. (2015) are using children of both genders together while this thesis has separated the two, and also family income is used, whereas this thesis uses fathers' income as an approximation for family income. There is, however, for both genders in all cohorts a slight tendency that rank of children with parents in the top end of the income distribution has higher persistence, which corresponds to the findings of Bratberg et al. (2015).

income average period. Log-log specification, as used here, or utilising ordinary income, seems to have only minor effects on the overall results.

Another indication of the rank relationship to be stabile over time, is found comparing correlations between fathers and offspring rank at age thirty; with father-daughter correlation rising slightly from the 1950 cohort, until being more or less equal to the father-son correlation from 1960 and onwards, see figure C.1. The low correlation rank is also an indication of high mobility in Norway.

6.2 Impact of family dissolutions

The estimations of this thesis show some differences in mobility between intact and disrupted families. Higher upward mobility, UTP and URM, and lower downward mobility, DTP and DRM, for intact families than for disrupted families seem to be the general outcome for both sons and daughters. Rieck (2008) and Bratberg et al. (2014) uses transition matrixes to study the same, and their results are in line with my findings. Looking back to the model from chapter 2 this seems reasonable: a family with only one parent, and hence one income, will probably have less investment capital. Moreover, more responsibility on one parent can lead to less time spent with the child, which also could affect the human capital of the child.[10] Both seem realistic: The non-custodial parent would be likely to spend less time with the child and the capital investment would probably also go down. The prior claim is supported by the data contained within this thesis that suggests that fathers of disrupted families earn less than the fathers of intact families. Another point to be made in this context, is that if the parent that has custodial rights, which in most cases will be the mother, would like to continue investing as much as before the disruption, this would probably lead to her spending less time with the child which could affect the child's outcome. There are, however, findings in this work without obvious explanations, such as why daughters of intact families with parents at the bottom of the income distribution have significantly higher probability of moving up 30 percentiles compered to their fathers, while there is virtually no difference in the probability between sons of intact and sons of disrupted families to do the same.

[10]Represented by endowment, e_{it}, in the model.

As noted earlier we would like to know if there is a causal relationship or if the effects we observe of divorce are due to selection. This can however not be decided in the framework used here. Work by Rieck (2008) and Bratberg et al. (2014) that tried to determine causality for Norwegian data has been inconclusive. And further work on this subject is warranted for.

Chapter 7

Concluding remarks

In this study, transitional probabilities and directional rank measures were used on Norwegian data to explore the probability of upward and downward mobility for children in their income distribution relative to their parent's position in the parents' income distribution. Fathers' income were used as a proxy for parents' income. This was done in three pairs of groups; sons and daughters, sons of intact and disrupted families, and lastly daughters of intact and disrupted families.

Results revealed that daughters were less upward mobile and more downward mobile than sons, both measured by transitional probabilities and directional rank measures. Daughters also had lower probabilities of larger gains compared to their fathers, than sons had. Daughters were more prone to a decline in income distribution compared to fathers' position than sons were. It does however seem as though the gender-gap decreased somewhat over the period studied. The differences between the genders remained substantial. The results for sons were more stable over the period, while there were more substantial movements in the daughters. This coincides with increased education and labour force participation among women, which might be two explanatory factors. However, there are possible sample selection problems due to different linking between parents and children in the 1950 cohort which might have affected daughters to a higher degree than sons. This data problem could possibly be reflected in the thesis results.

An important question is how many of the observed gender differences can be attributed to, in the words of Roemer (2004), "different objectives" and how many are due to other causes? As we have seen, common explanations for the gender gap are assortative mating, and labour supply decisions. A source of improvement in research design could be to use family income, as it might better reflect women's true economic status. A comparison between families and single women could also be informative.

Using the same methods as for genders on a subsample of the 1960 cohort, this thesis found that there seemed to be some small differences between intact and disrupted families. The general pattern being that sons and daughters of intact families did slightly better than those of disrupted families, having higher upward and lower downward probabilities. This coincides with earlier findings of Rieck (2008) and Bratberg et al. (2014) on Norwegian data, which indicates that children of disrupted families are somewhat socioeconomic disadvantaged later in life. In a society where increasingly more children are experiencing a family dissolution due to divorce this could imply that differences in mobility observed between intact and disrupted families could affect the general mobility patterns observed.

Exploring the rank-rank relationship between the parent and sons/daughters over time, it seems to be quite stable over time for both genders. The relationship is quite linear, with some persistence for both genders in the top end of the fathers income distribution. The rank-rank results found are more linear than results found by Bratberg et al. (2015). The reason for this could be that this thesis has separated the genders, and uses fathers' income as an approximation for family income while Bratberg et al. (2015) uses both gender together and family income.

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Appendix A

The Theoretical Framework

A.1 The Theoretical Model

The utility function is assumed to be a Cobb-Douglas function:

$$U = (1-\alpha)\log C_{t-1} + \alpha \log Y_t. \tag{A.1}$$

The parents budget constraint is given by:

$$(1-\psi)Y_{i,t-1} = C_{i,t-1} + I_{i,t-1} \Rightarrow C_{i,t-1} = (1-\psi)Y_{i,t-1} - I_{i,t-1}. \tag{A.2}$$

Human capital of the child is given by:

$$h_{it} = \theta \log(I_{i,t-1} + G_{i,t-1}) + e_{it} \tag{A.3}$$

The child's lifetime earning is given by:

$$\log Y_{it} = \mu + rh_{it}. \tag{A.4}$$

Substituting in the expression for human capital (A.3) into the child's lifetime earnings (A.4) yields:

$$\log Y_{it} = \mu + \theta r \log(I_{i,t-1} + G_{i,t-1}) + e_{it}. \tag{A.5}$$

Reformulating the utility function as a objective function of the choice variable I_{t-1} by substituting for $C_{i,t-1}$ and $\log Y_{it}$ in (2.3):

$$U_i = (1-\alpha)\log[(1-\psi)Y_{i,t-1} - I_{i,t-1}] + \alpha\mu + \alpha\theta r \log(I_{i,t-1} + G_{i,t-1}) + \alpha r e_{it}. \tag{A.6}$$

Finding the first order condition for maximum utility:

$$\frac{\partial U_i}{\partial I_{i,t-1}} = -\frac{(1-\alpha)}{(1-\psi)Y_{i,t-1} - I_{i,t-1}} + \frac{\alpha\theta r}{I_{i,t-1} + G_{i,t-1}} = 0 \tag{A.7}$$

Solving for $I_{i,t-1}$

$$\begin{aligned}
(1-\alpha)(I_{i,t-1} + G_{i,t-1}) &= \alpha\theta r[(1-\psi)Y_{i,t-1} - I_{i,t-1}] \\
I_{i,t} - \alpha I_{i,t-1} + \alpha\theta r I_{i,t-1} &= Y_{i,t-1}\alpha\theta r(1-\psi) - G_{i,t-1} + \alpha G_{i,t-1} \\
I_{i,t-1}[1-\alpha(1-\theta r)] &= \alpha\theta r(1-\psi)Y_{i,t-1} - (1-\alpha)G_{i,t-1} \\
I^{\star}_{i,t-1} = \left[\frac{\alpha\theta r}{1-\alpha(1-\theta r)}\right](1-\psi)Y_{i,t-1} &- \left[\frac{1-\alpha}{1-\alpha(1-\theta r)}\right]G_{i,t-1}.
\end{aligned} \tag{A.8}$$

And then substitute in for the optimal investment: $I^{\star}_{t-1}$ in (A.5):

$$\log Y_{it} = \mu + \theta r \log(\left\{\left[\frac{\alpha\theta r}{1-\alpha(1-\theta r)}\right](1-\psi)Y_{i,t-1} - \left[\frac{1-\alpha}{1-\alpha(1-\theta r)}\right]G_{i,t-1}\right\} + G_{i,t-1}) + e_{it}. \tag{A.9}$$

Rearranging, yields:

$$\log Y_{it} = \mu + \theta r \log \left[\frac{\alpha\theta r(1-\psi)}{1-\alpha(1-\theta r)} \right] + \theta r \log \left[Y_{i,t-1} \left(1 + \frac{G_{i,1-t}}{(1-\psi)Y_{i,t-1}} \right) \right] + re_{it}. \tag{A.10}$$

If the ration of government investment and parent income after taxes is small (A.10) can be approximated as:

$$\log Y_{it} \cong \mu + \theta r \log \left[\frac{\alpha\theta r(1-\psi)}{1-\alpha(1-\theta r)} \right] + \theta r \log Y_{i,t-1} + \theta r \left[\frac{G_{i,1-t}}{(1-\psi)Y_{i,t-1}} \right] + re_{it}. \tag{A.11}$$

Parameterisation of policy as suggested by Solon (2004):

$$\frac{G_{i,1-t}}{(1-\psi)Y_{i,t-1}} \cong \zeta - \gamma \log Y_{i,t-1} \tag{A.12}$$

By substituting equation (A.12) into (A.11) one obtains

$$\log Y_{it} \cong \mu + \theta r \log \left[\frac{\alpha\theta r(1-\psi)}{1-\alpha(1-\theta r)} \right] + \theta r \log Y_{i,t-1} + \theta r[\zeta - \gamma \log Y_{i,t-1}] + re_{it}$$

$$\log Y_{it} \cong \mu + \theta r\zeta + \theta r \log \left[\frac{\alpha\theta r(1-\psi)}{1-\alpha(1-\theta r)} \right] + \theta r \log Y_{i,t-1} - \gamma\theta r \log Y_{i,t-1} + re_{it}$$

$$\log Y_{it} \cong \mu^\star + [\underbrace{(1-\gamma)\theta r}_{=\beta}] \log Y_{i,t-1} + re_{it}. \tag{A.13}$$

where $\mu^\star$ is the intercept equal to: $\mu + \zeta\theta r + \theta r \log\{\alpha\theta r(1-\psi)/[1-\alpha(1-\theta r)]\}$. Which is the familiar linear regression.

Appendix B

Data descriptions

In this appendix more details about the data set are presented.

Table B.1: Summary statistics of missing income data for children of each cohort

	Sons		Daughters		Total	
	***N* missing**	**Percent**	***N* missing**	**Percent**	***N* missing**	**Percent**
1950 cohort						
Income '81	762	3.83	2,812	25.44	3,574	11.56
Income '82	832	4.19	2,730	24.70	3,562	11.52
Income '83	869	4.37	2,678	24.23	3,547	11.47
Income '84	971	4.89	2,548	23.05	3,519	11.38
Income '85	862	4.34	2,239	20.26	3,101	10.03
N	25,345		24,356		49,701	
1955 cohort						
Income '86	1,152	4.60	4,206	17.58	5,358	10.95
Income '87	1,108	4.43	3,718	15.54	4,826	9.86
Income '88	1,235	4.94	3,592	15.01	4,827	9.86
Income '89	1,370	5.47	3,687	15.41	5,057	10.33
Income '90	1,509	6.03	3,586	14.99	5,095	10.41
N	25,023		23,930		48,953	
1960 cohort						
Income '91	1,604	6.33	3,742	15.36	5,346	10.76
Income '92	1,721	6.79	3,783	15.53	5,504	11.07
Income '93	1,789	7.06	3,680	15.11	5,469	11.00
Income '94	1,768	6.98	3,488	14.32	5,256	10.58
Income '95	1,781	7.03	3,360	13.80	5,141	10.34
N	19,877		11,052		30,929	

Table B.2: Summary statistics of missing income data for fathers of each cohort

	***N* missing**	**Percent**
Fathers of children in the 1950 cohort		
Income '67	1214	3.93
Income '68	930	3.01
Income '69	995	3.22
Income '70	1040	3.36
Income '71	1241	4.01
N	30929	
Fathers of children in the 1955 cohort		
Income '72	1778	3.63
Income '73	1998	4.08
Income '74	2202	4.50
Income '75	2485	5.08
Income '76	2741	5.60
N	48953	
Fathers of children in the 1960 cohort		
Income '77	2001	4.03
Income '78	2201	4.43
Income '79	2439	4.91
Income '80	2605	5.24
Income '81	3137	6.31
N	49701	
Fathers of children in the 1965 cohort		
Income '82	3288	5.90
Income '83	3617	6.49
Income '84	4074	7.31
Income '85	4081	7.32
Income '86	4588	8.23
N	55726	

Table B.3: Descriptive statistics of birth cohorts' size.

	1950 Cohort			1955 Cohort		
	Sons	**Daughters**	**Total**	**Sons**	**Daughters**	**Total**
Total cohort size	35,924	33,490	69,414	36,815	34,634	71,449
Excluded due to fathers age	15,512	22,263	37,775	10,065	9,314	19,379
Excluded due to own death	256	49	305	447	121	568
Excluded due to fathers death	279	126	405	1,280	1,269	2,549
Excluded due to missing income data	1,145	2,638	3,783	1,975	4,133	6,108
Final cohort size	18,732	8,414	27,146	23,048	19,797	42,845
	1960 Cohort			**1965 Cohort**		
	Sons	**Daughters**	**Total**	**Sons**	**Daughters**	**Total**
Total cohort size	37,226	34,982	72,208	40,085	37,827	77,912
Excluded due to fathers age	10,042	9,182	19,224	8,999	8,812	17,811
Excluded due to own death	477	162	639	1,071	625	1,696
Excluded due to fathers death	1,362	1,282	2,644	1,434	1,245	2,679
Excluded due to missing income data	2,423	4,129	6,552	3,349	4,663	8,012
Final cohort size	22,922	20,227	43,149	25,232	22,482	47,714
Marital status 1960 cohort						
Parents not married in 1960	4,847	4,316	9,163			
Missing information on family type	172	166	338			
Cohort size disrupted/intact families	17,903	15,745	33,648			

Table B.4: Descriptive statistics: 1950 cohort cumulative samples for ranges of parent income I

	Percentile range of parent income:									
	1 to 10		1 to 20		1 to 30		1 to 40		1 to 50	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sons' fathers										
Five-year earning average	10.87	0.50	11.22	0.51	11.41	0.50	11.54	0.49	11.63	0.48
Age	49.80	5.00	49.29	4.98	48.96	4.99	48.74	5.00	48.54	5.01
Sons										
Average earnings age 31-35	12.02	0.61	12.05	0.57	12.09	0.54	12.11	0.53	12.13	0.52
N	2,045		4,035		5,946		7,863		9,805	
Daughters' fathers										
Five-year earning average	10.86	0.55	11.23	0.53	11.45	0.51	11.58	0.48	11.67	0.47
Age	49.83	4.88	49.44	4.93	49.16	4.91	48.85	4.99	48.65	5.01
Daughters										
Average earnings age 31-35	11.12	1.05	11.12	1.05	11.14	1.02	11.15	1.01	11.15	1.01
N	670		1,345		2,198		2,996		3,768	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings 1967-71. Fathers' age in 1967.

Table B.5: Descriptic statistics 1950 cohort cumulative samples for ranges of parent income II.

	Percentile range of parent income:									
	91 to 100		81 to 100		71 to 100		61 to 100		51 to 100	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sons' fathers										
Five-year earning average	12.62	0.05	12.55	0.09	12.47	0.13	12.40	0.16	12.34	0.19
Age	48.71	4.29	48.22	4.52	47.91	4.63	47.72	4.71	47.70	4.75
Sons										
Average earnings age 31-35	12.38	0.55	12.34	0.54	12.32	0.52	12.29	0.51	12.28	0.50
N	1,669		3,400		5,190		7,033		8,927	
Daughters' fathers										
Five-year earning average	12.62	0.05	12.56	0.09	12.48	0.13	12.42	0.17	12.36	0.19
Age	48.76	4.10	48.46	4.31	48.14	4.44	47.93	4.52	47.82	4.56
Daughters										
Average earnings age 31-35	11.50	0.94	11.42	0.98	11.40	0.97	11.36	0.97	11.34	0.98
N	1,045		2,029		2,953		3,825		4,646	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings 1967-71. Fathers' age in 1967.

Table B.6: Descriptive statistics 1955 cohort cumulative samples for ranges of parent income I

	Percentile range of parent income:									
	1 to 10		1 to 20		1 to 30		1 to 40		1 to 50	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sons' fathers										
Five-year earning average	10.80	0.77	11.27	0.72	11.50	0.67	11.64	0.63	11.74	0.60
Age	49.01	5.18	48.57	5.18	48.28	5.20	48.04	5.19	47.91	5.14
Sons										
Average earnings age 31-35	12.04	0.67	12.08	0.63	12.11	0.61	12.13	0.60	12.15	0.58
N	2,288		4,598		6,885		9,174		11,513	
Daughters' fathers										
Five-year earning average	10.77	0.80	11.25	0.75	11.49	0.70	11.63	0.65	11.74	0.62
Age	48.92	5.20	48.53	5.21	48.24	5.23	48.04	5.21	47.83	5.21
Daughters										
Average earnings age 31-35	11.33	0.89	11.34	0.89	11.34	0.89	11.35	0.89	11.34	0.89
N	1,997		3,971		5,969		7,964		9,910	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings: 1972-76. Fathers' age in 1972.

Table B.7: Descriptic statistics 1955 cohort cumulative samples for ranges of parent income II

	Percentile range of parent income:									
	91 to 100		81 to 100		71 to 100		61 to 100		51 to 100	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sons' fathers										
Five-year earning average	12.89	0.11	12.74	0.17	12.64	0.20	12.56	0.22	12.50	0.23
Age	47.87	4.47	47.57	4.67	47.24	4.77	47.14	4.84	47.10	4.87
Sons										
Average earnings age 31-35	12.43	0.63	12.39	0.59	12.36	0.57	12.34	0.56	12.33	0.55
N	2,312		4,516		6,899		9,208		11,535	
Daughters' fathers										
Five-year earning average	12.88	0.11	12.73	0.17	12.63	0.20	12.56	0.22	12.50	0.23
Age	48.01	4.51	47.63	4.66	47.29	4.77	47.19	4.82	47.17	4.86
Daughters										
Average earnings age 31-35	11.63	0.88	11.60	0.86	11.57	0.86	11.53	0.86	11.52	0.87
N	1,972		3,953		5,954		7,930		9,887	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings: 1972-76. Fathers' age in 1972.

Table B.8: Descriptive statistics 1960 cohort cumulative samples for ranges of parent income I

	Percentile range of parent income:									
	1 to 10		1 to 20		1 to 30		1 to 40		1 to 50	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sons' fathers										
Five-year earning average	11.05	0.89	11.50	0.77	11.71	0.69	11.83	0.63	11.92	0.59
Age	48.30	5.52	47.95	5.48	47.87	5.44	47.65	5.40	47.48	5.41
Sons										
Average earnings age 31-35	12.01	0.76	12.05	0.71	12.08	0.71	12.11	0.69	12.12	0.68
N	2,263		4,596		6,914		9,243		11,547	
Daughters' fathers										
Five-year earning average	11.07	0.87	11.50	0.76	11.70	0.69	11.83	0.63	11.92	0.59
Age	48.39	5.64	48.08	.5.60	47.82	5.53	47.64	5.51	47.51	5.50
Daughters										
Average earnings age 31-35	11.45	0.93	11.48	0.90	11.48	0.89	11.50	0.87	11.51	0.87
N	2,052		4,034		6,013		8,017		10,028	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings: 1977-81. Fathers' age in 1977

Table B.9: Descriptic statistics 1960 cohort cumulative samples for ranges of parent income I

	Percentile range of parent income:									
	91 to 100		81 to 100		71 to 100		61 to 100		51 to 100	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sons' fathers										
Five-year earning average	12.97	0.17	12.82	0.20	12.72	0.21	12.65	0.22	12.59	0.23
Age	47.32	4.89	47.12	4.98	46.99	5.07	46.88	5.11	46.82	5.14
Sons										
Average earnings age 31-35	12.43	0.66	12.38	0.65	12.34	0.64	12.31	0.65	12.30	0.64
N	2,257		4,510		6,804		9,070		11,375	
Daughters' fathers										
Five-year earning average	12.98	0.17	12.82	0.20	12.73	0.21	12.65	0.22	12.59	0.23
Age	47.45	4.88	47.24	4.94	46.95	5.05	46.87	5.08	46.81	5.13
Daughters										
Average earnings age 31-35	11.86	0.81	11.79	0.82	11.74	0.83	11.71	0.84	11.69	6.55
N	2,057		4,119		6,140		8,189		10,199	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings: 1977-81. Fathers' age in 1977

Table B.10: Descriptive statistics for intact and disrupted families in the 1960 cohort, cumulative samples by range of parent income

	Percentile range of parent income:									
	1 to 10		1 to 20		1 to 30		1 to 40		1 to 50	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Intact families										
Sons' fathers										
Five-year earning average	11.07	0.87	11.52	0.75	11.73	0.67	11.85	0.61	11.94	0.57
Age	49.13	5.32	48.74	5.22	48.57	5.19	48.27	5.18	48.07	5.20
Sons										
Average earnings age 31-35	12.05	0.71	12.09	0.67	12.11	0.66	12.14	0.65	12.15	0.64
N	1,405		2,915		4,474		6,038		7,594	
Daughters' fathers										
Five-year earning average	11.08	0.90	11.52	0.77	11.72	0.69	11.85	0.63	11.94	0.58
Age	49.01	5.36	48.72	5.27	48.39	5.30	48.22	5.26	48.07	5.28
Daughters										
Average earnings age 31-35	11.55	0.91	11.55	0.87	11.54	0.87	11.54	0.86	11.56	0.84
N	935		1,881		2,877		3,886		4,920	
Disrupted families										
Sons' fathers										
Five-year earning average	11.00	0.94	11.43	0.84	11.62	0.78	11.75	0.73	11.83	0.69
Age	46.78	5.66	46.58	5.60	46.64	5.54	46.57	5.50	46.44	5.55
Sons										
Average earnings age 31-35	11.94	0.91	12.00	0.84	12.01	0.81	12.04	0.79	12.06	0.78
N	363		671		925		1,191		1,427	
Daughters' fathers										
Five-year earning average	11.07	0.83	11.49	0.75	11.68	0.69	11.80	0.64	11.89	0.61
Age	48.07	5.74	47.76	5.75	47.54	5.65	47.39	5.59	47.25	5.55
Daughters										
Average earnings age 31-35	11.35	0.96	11.40	0.93	11.42	0.91	11.44	0.89	11.44	0.90
N	665		1,271		1,833		2,369		2,914	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings: 1977-81. Fathers' age in 1977. Family structure based on data from 1970 and 1980.

Table B.11: Descriptic statistics for intact and disrupted families in the 1960 cohort, cumulative samples by range of parent income

	Percentile range of parent income:									
	91 to 100		81 to 100		71 to 100		61 to 100		51 to 100	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Intact families										
Sons' fathers										
Five-year earning average	12.96	0.16	12.81	0.19	12.72	0.21	12.64	0.22	12.58	0.23
Age	47.62	4.80	47.50	4.88	47.39	4.93	47.29	4.97	47.25	4.99
Sons										
Average earnings age 31-35	12.45	0.66	12.39	0.65	12.36	0.64	12.33	0.64	12.32	0.62
N	1,510		3,017		4,585		6,116		7,686	
Daughters' fathers										
Five-year earning average	12.97	0.17	12.82	0.20	12.66	0.23	12.66	0.23	12.60	0.24
Age	48.18	4.58	47.90	4.68	47.57	4.81	47.47	4.85	47.44	4.91
Daughters										
Average earnings age 31-35	11.90	0.78	11.82	0.81	11.77	0.82	11.75	0.81	11.73	0.82
N	1,241		2,400		3,500		4,617		5,695	
Disrupted families										
Sons' fathers										
Five-year earning average	12.97	0.18	12.81	0.20	12.71	0.21	12.64	0.22	12.58	0.23
Age	46.77	4.90	46.46	5.03	46.30	5.09	46.13	5.18	46.04	5.19
Sons										
Average earnings age 31-35	12.34	0.67	12.26	0.68	12.26	0.64	12.26	0.67	12.24	0.68
N	224		472		721		947		1,196	
Daughters' fathers										
Five-year earning average	12.97	0.17	12.80	0.20	12.70	0.20	12.62	0.21	12.56	0.22
Age	46.44	5.10	46.54	5.14	46.30	5.14	46.25	5.15	46.22	5.18
Daughters										
Average earnings age 31-35	11.71	0.85	11.67	0.83	11.62	0.87	11.59	0.87	11.57	0.87
N	353		793		1,245		1,740		2,216	

Notes: Earnings in log of 1995 NOK. Five-year averages of fathers' earnings: 1977-81. Fathers' age in 1977. Family structure based on data from 1970 and 1980.

Appendix C

Results

Table C.1: Upward Transtition Probability for the 1950 Cohort Estimated by Gender

Parent percentile range	Percent of children exceeding their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
1 to 10	.948	.696	-.252	.858	.479	-.379	.752	.276	-.476	.624	.157	-.467
$N_m = 2,045, N_f = 670$	(.005)	(.018)	(.019)	(.008)	(.019)	(.021)	(.010)	(.017)	(.020)	(.011)	(.014)	(.018)
1 to 20	.880	.472	-.408	.782	.284	-.498	.649	.163	-.486	.517	.105	-.412
$N_m = 4,035, N_f = 1,395$	(.005)	(.013)	(.014)	(.007)	(.012)	(.014)	(.008)	(.010)	(.013)	(.008)	(.008)	(.011)
1 to 30	.807	.285	-.522	.680	.170	-.510	.545	.105	-.440	.421	.055	-.366
$N_m = 5,946, N_f = 2,198$	(.005)	(.010)	(.011)	(.006)	(.008)	(.010)	(.006)	(.007)	(.009)	(.006)	(.005)	(.008)
1 to 40	.702	.171	-.531	.565	.104	-.461	.437	.058	-.379	.317	.028	-.289
$N_m = 7,863, N_f = 2,996$	(.005)	(.007)	(.009)	(.006)	(.006)	(.008)	(.006)	(.004)	(.007)	(.005)	(.003)	(.006)
1 to 50	.585	.104	-.481	.454	.057	-.397	.326	.028	-.298	.202	.012	-.190
$N_m 9,805 =, N_f = 3,768$	(.005)	(.005)	(.007)	(.005)	(.004)	(.006)	(.005)	(.003)	(.006)	(.004)	(.002)	(.004)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1967-71. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.2: Downward Transition Probability for the 1950 Cohort Estimated by Gender

Parent percentile range	Percent of children at or below the bottom of their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
91 to 100	.667	.971	.304	.473	.923	.450	.350	.874	.524	.268	.817	.549
$N_m = 1,669, N_f = 1,045$	(.012)	(.005)	(.013)	(.012)	(.008)	(.014)	(.012)	(.010)	(.016)	(.011)	(.012)	(.016)
81 to 100	.533	.939	.406	.395	.890	.495	.298	.835	.537	.216	.775	.559
$N_m = 3,400, N_f = 2,029$	(.009)	(.005)	(.010)	(.008)	(.007)	(.011)	(.008)	(.008)	(.011)	(.007)	(.009)	(.011)
71 to 100	.437	.908	.471	.327	.858	.531	.235	.795	.560	.165	.708	.543
$N_m = 5,190, N_f = 2,953$	(.007)	(.005)	(.009)	(.007)	(.006)	(.009)	(.006)	(.007)	(.009)	(.005)	(.008)	(.009)
61 to 100	.351	.876	.525	.249	.816	.567	.171	.731	.560	.104	.612	.508
$N_m = 7,033, N_f = 3,825$	(.006)	(.005)	(.008)	(.005)	(.006)	(.008)	(.004)	(.007)	(.008)	(.004)	(.008)	(.009)
51 to 100	.257	.825	.568	.172	.742	.570	.102	.624	.522	.052	.453	.402
$N_m = 8,927, N_f = 4,646$	(.005)	(.006)	(.008)	(.004)	(.006)	(.007)	(.003)	(.007)	(.008)	(.002)	(.007)	(.007)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1967-71. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.3: Upward Rank Mobility for the 1950 Cohort Estimated by Gender

Parent percentile range	Percent of children exceeding their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
1 to 10	.976	.827	-.149	.900	.575	-.325	.804	.355	-.449	.679	.215	-.464
$N_m = 2,045, N_f = 670$	(.003)	(.015)	(.015)	(.007)	(.019)	(.020)	(.009)	(.019)	(.021)	(.010)	(.016)	(.019)
1 to 20	.955	.685	-.270	.880	.458	-.422	.771	.282	-.489	.635	.177	-.458
$N_m = 4,035, N_f = 1,345$	(.003)	(.012)	(.012)	(.005)	(.013)	(.014)	(.007)	(.012)	(.014)	(.008)	(.010)	(.013)
1 to 30	.935	.569	-.366	.853	.376	-.477	.738	.232	-.506	.600	.141	-.459
$N_m = 5,946, N_f = 2,198$	(.003)	(.011)	(.011)	(.005)	(.010)	(.011)	(.006)	(.009)	(.011)	(.006)	(.007)	(.009)
1 to 40	.908	.474	-.434	.815	.312	-.503	.693	.192	-.501	.555	.115	-.440
$N_m = 7,863, N_f = 2,996$	(.003)	(.009)	(.009)	(.004)	(.008)	(.009)	(.005)	(.007)	(.009)	(.006)	(.006)	(.008)
1 to 50	.871	.405	-.466	.771	.263	-.508	.643	.161	-.482	.503	.096	-.408
$N_m = 9,805, N_f = 3,768$	(.003)	(.008)	(.009)	(.004)	(.007)	(.008)	(.005)	(.006)	(.008)	(.005)	(.005)	(.007)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1967-71. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.4: Downward Rank Mobility for the 1950 Cohort Estimated by Gender

Parent percentile range	Percent of children below their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
91 to 100	.799	.987	.188	.546	.946	.400	.389	.894	.505	.298	.843	.545
$N_m = 1,669, N_f = 1,045$	(.010)	(.004)	(.011)	(.012)	(.007)	(.014)	(.011)	(.010)	(.016)	(.011)	(.011)	(.016)
81 to 100	.737	.978	.241	.523	.939	.416	.385	.889	.504	.284	.835	.551
$N_m = 3,400, N_f = 2,029$	(.008)	(.003)	(.009)	(.009)	(.005)	(.010)	(.008)	(.007)	(.011)	(.008)	(.008)	(.011)
71 to 100	.684	.973	.289	.496	.936	.440	.360	.885	.525	.262	.822	.560
$N_m = 5,190, N_f = 2,953$	(.006)	(.003)	(.007)	(.007)	(.005)	(.009)	(.007)	(.006)	(.009)	(.006)	(.007)	(.009)
61 to 100	.632	.967	.335	.455	.931	.476	.324	.878	.554	.230	.799	.569
$N_m = 7,033, N_f = 3,825$	(.006)	(.003)	(.007)	(.006)	(.004)	(.007)	(.006)	(.005)	(.008)	(.005)	(.006)	(.008)
51 to 100	.571	.953	.382	.406	.913	.507	.282	.851	.569	.196	.763	.567
$N_m = 8,927, N_f = 4,646$	(.005)	(.003)	(.006)	(.005)	(.004)	(.006)	(.005)	(.005)	(.007)	(.004)	(.006)	(.007)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1967-71. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.5: Upward Transition Probability for the 1955 Cohort Estimated by Gender

Parent percentile range	Percent of children exceeding their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
1 to 10	.954	.777	-.177	.888	.590	-.298	.823	.422	-.401	.734	.273	-.461
$N_m = 2,288, N_f = 1,997$	(.004)	(.009)	(.010)	(.007)	(.011)	(.013)	(.008)	(.011)	(.014)	(.009)	(.010)	(.013)
1 to 20	.901	.602	-.299	.841	.425	-.416	.751	.279	-.472	.627	.163	-.464
$N_m = 4,598, N_f = 3,971$	(.004)	(.008)	(.009)	(.005)	(.008)	(.009)	(.006)	(.007)	(.009)	(.007)	(.006)	(.009)
1 to 30	.853	.422	-.431	.770	.275	-.495	.652	.161	-.491	.510	.089	-.421
$N_m = 6,885, N_f = 5,969$	(.004)	(.006)	(.007)	(.005)	(.006)	(.008)	(.006)	(.005)	(.008)	(.006)	(.004)	(.007)
1 to 40	.786	.275	-.511	.675	.159	-.516	.532	.089	-.443	.384	.045	-.339
$N_m = 9,174, N_f = 7,964$	(.004)	(.005)	(.006)	(.005)	(.004)	(.006)	(.005)	(.003)	(.006)	(.005)	(.002)	(.005)
1 to 50	.692	.167	-.531	.550	.092	-.458	.400	.047	-.354	.249	.020	-.229
$N_m = 11,513, N_f = 9,910$	(.004)	(.004)	(.006)	(.005)	(.005)	(.006)	(.005)	(.002)	(.005)	(.004)	(.001)	(.004)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1972-76. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.6: Downward Transition Probability for the 1955 Cohort Estimated by Gender

Parent percentile range	Percent of children at or below the bottom of their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
91 to 100	.611	.964	.353	.435	.911	.476	.313	.847	.534	.230	.756	.526
$N_m = 2,312, N_f = 1,972$	(.010)	(.004)	(.011)	(.010)	(.006)	(.012)	(.010)	(.008)	(.013)	(.009)	(.010)	(.013)
81 to 100	.482	.928	.446	.341	.870	.529	.246	.784	.528	.175	.689	.514
$N_m = 4,616, N_f = 3,953$	(.007)	(.004)	(.008)	(.007)	(.005)	(.009)	(.006)	(.006)	(.009)	(.006)	(.007)	(.009)
71 to 100	.367	.887	.520	.260	.804	.544	.183	.710	.527	.129	.588	.459
$N_m = 6,899, N_f = 5,954$	(.006)	(.004)	(.007)	(.005)	(.005)	(.007)	(.005)	(.006)	(.008)	(.004)	(.006)	(.007)
61 to 100	.272	.821	.549	.187	.730	.543	.128	.611	.483	.086	.460	.375
$N_m = 9,208, N_f = 7,930$	(.005)	(.004)	(.006)	(.004)	(.005)	(.006)	(.003)	(.005)	(.006)	(.003)	(.006)	(.007)
51 to 100	.194	.743	.549	.131	.623	.492	.087	.473	.386	.052	.318	.267
$N_m = 11,535, N_f = 9,887$	(.004)	(.004)	(.006)	(.003)	(.005)	(.006)	(.003)	(.005)	(.006)	(.002)	(.005)	(.005)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1972-76. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.7: Upward Rank Mobility for the 1955 Cohort Estimated by Gender

Parent percentile range	Percent of children exceeding their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
1 to 10	.976	.890	-.086	.921	.676	-.245	.852	.496	-.356	.772	.336	-.436
$N_m = 2,288, N_f = 1,997$	(.003)	(.007)	(.008)	(.006)	(.010)	(.012)	(.007)	(.011)	(.013)	(.009)	(.011)	(.014)
1 to 20	.957	.797	-.160	.904	.590	-.314	.833	.419	-.414	.737	.275	-.462
$N_m = 4,598, N_f = 3,971$	(.003)	(.006)	(.007)	(.004)	(.008)	(.009)	(.006)	(.008)	(.010)	(.006)	(.007)	(.009)
1 to 30	.940	.698	-.242	.883	.505	-.378	.806	.345	-.460	.701	.222	-.479
$N_m = 6,885, N_f = 5,969$	(.003)	(.006)	(.007)	(.004)	(.006)	(.007)	(.005)	(.006)	(.008)	(.006)	(.005)	(.008)
1 to 40	.922	.608	-.314	.858	.429	-.429	.771	.287	-.484	.652	.182	-.470
$N_m = 9,174, N_f = 7,964$	(.003)	(.005)	(.006)	(.004)	(.006)	(.007)	(.004)	(.005)	(.006)	(.005)	(.004)	(.006)
1 to 50	.898	.533	-.365	.823	.371	-.452	.724	.245	-.479	.593	.153	-.440
$N_m = 11,513, N_f = 9,910$	(.003)	(.005)	(.006)	(.004)	(.005)	(.006)	(.004)	(.004)	(.006)	(.005)	(.004)	(.006)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1972-76. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.8: Downward Rank Mobility for the 1955 Cohort Estimated by Gender

Parent percentile range	Percent of children below their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
91 to 100	.752	.981	.229	.501	.939	.438	.358	.874	.516	.257	.795	.538
$N_m = 2,312, N_f = 1,972$	(.009)	(.003)	(.009)	(.010)	(.005)	(.011)	(.010)	(.007)	(.012)	(.010)	(.009)	(.013)
81 to 100	.686	.973	.287	.466	.929	.463	.332	.862	.530	.236	.780	.544
$N_m = 4,616, N_f = 3,953$	(.007)	(.003)	(.008)	(.007)	(.004)	(.008)	(.007)	(.005)	(.009)	(.006)	(.007)	(.009)
71 to 100	.622	.962	.340	.424	.912	.488	.301	.838	.537	.212	.749	.537
$N_m = 6899, N_f = 5954$	(.006)	(.002)	(.006)	(.006)	(.004)	(.007)	(.006)	(.005)	(.008)	(.005)	(.006)	(.008)
61 to 100	.560	.948	.388	.379	.893	.514	.264	.811	.547	.185	.715	.530
$N_m = 9,208, N_f = 7,930$	(.005)	(.003)	(.005)	(.005)	(.003)	(.006)	(.004)	(.004)	(.006)	(.004)	(.005)	(.006)
51 to 100	.501	.926	.425	.337	.860	.523	.233	.766	.533	.161	.656	.495
$N_m = 11,535, N_f = 9,887$	(.005)	(.003)	(.006)	(.004)	(.003)	(.005)	(.004)	(.004)	(.006)	(.003)	(.005)	(.006)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1972-76. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.9: Upward Transition Probability for the 1960 Cohort Estimated by Gender

Parent percentile range	Percent of children exceeding their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
1 to 10	.924	.802	-.122	.843	.629	-.214	.768	.453	-.315	.690	.304	-.386
$N_m = 2,263, N_f = 2,052$	(.006)	(.009)	(.011)	(.008)	(.011)	(.014)	(.009)	(.011)	(.014)	(.010)	(.010)	(.014)
1 to 20	.859	.635	-.224	.788	.459	-.329	.709	.305	-.404	.592	.194	-.398
$N_m = 4,596, N_f = 4,034$	(.005)	(.008)	(.009)	(.006)	(.008)	(.010)	(.007)	(.007)	(.010)	(.007)	(.006)	(.009)
1 to 30	.805	.466	-.339	.731	.314	-.417	.619	.199	-.420	.490	.117	-.373
$N_m = 6,914, N_f = 6,031$	(.005)	(.006)	(.008)	(.005)	(.005)	(.008)	(.006)	(.005)	(.008)	(.006)	(.004)	(.007)
1 to 40	.753	.316	-.437	.645	.199	-.446	.514	.118	-.396	.379	.061	-.318
$N_m = 9,243, N_f = 8,017$	(.004)	(.005)	(.006)	(.005)	(.004)	(.006)	(.005)	(.004)	(.006)	(.005)	(.003)	(.006)
1 to 50	.660	.200	-.460	.531	.121	-.410	.393	.064	-.329	.249	.031	-.218
$N_m = 11,547, N_f = 10,028$	(.004)	(.004)	(.006)	(.005)	(.003)	(.006)	(.005)	(.002)	(.005)	(.004)	(.002)	(.004)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.10: Downward Transition Probability for the 1960 Cohort Estimated by Gender

Parent percentile range	Percent of children at or below the bottom of their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
91 to 100	.629	.926	.297	.455	.840	.385	.335	.751	.416	.244	.660	.416
$N_m = 2,227, N_f = 2,057$	(.010)	(.006)	(.012)	(.010)	(.008)	(.013)	(.010)	(.010)	(.014)	(.009)	(.010)	(.013)
81 to 100	.506	.875	.369	.379	.798	.419	.276	.714	.438	.208	.606	.398
$N_m = 4,510, N_f = 4,119$	(.007)	(.005)	(.009)	(.007)	(.006)	(.009)	(.007)	(.007)	(.010)	(.006)	(.008)	(.010)
71 to 100	.404	.826	.422	.296	.745	.449	.219	.644	.425	.162	.527	.365
$N_m = 6,804, N_f = 6,140$	(.006)	(.005)	(.008)	(.006)	(.006)	(.008)	(.005)	(.006)	(.008)	(.004)	(.006)	(.007)
61 to 100	.313	.767	.454	.227	.667	.440	.167	.550	.383	.122	.413	.291
$N_m = 9,070, N_f = 8,189$	(.005)	(.005)	(.007)	(.004)	(.005)	(.006)	(.004)	(.005)	(.006)	(.003)	(.005)	(.006)
51 to 100	.233	.684	.451	.170	.565	.395	.123	.424	.301	.082	.279	.197
$N_m = 11,375, N_f = 10,199$	(.004)	(.004)	(.006)	(.004)	(.005)	(.006)	(.003)	(.005)	(.006)	(.003)	(.004)	(.005)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.11: Upward Rank Mobility for the 1960 Cohort Estimated by Gender

Parent percentile range	Percent of children exceeding their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
1 to 10	.957	.888	-.069	.878	.707	-.171	.803	.534	-.269	.722	.360	-.362
$N_m = 2,263, N_f = 2,052$	(.004)	(.007)	(.008)	(.007)	(.010)	(.012)	(.008)	(.011)	(.014)	(.009)	(.010)	(.013)
1 to 20	.931	.805	-.126	.857	.631	-.226	.783	.455	-.328	.694	.302	-.392
$N_m = 4,596, N_f = 4,034$	(.004)	(.006)	(.007)	(.005)	(.008)	(.009)	(.006)	(.008)	(.010)	(.007)	(.007)	(.010)
1 to 30	.909	.722	-.187	.841	.552	-.289	.764	.390	-.374	.663	.255	-.408
$N_m = 6,914, N_f = 6,013$	(.003)	(.006)	(.007)	(.004)	(.006)	(.007)	(.005)	(.006)	(.008)	(.006)	(.006)	(.008)
1 to 40	.892	.641	-.251	.821	.479	-.342	.735	.331	-.404	.625	.214	-.411
$N_m = 9,243, N_f = 8,017$	(.003)	(.005)	(.006)	(.004)	(.006)	(.007)	(.005)	(.005)	(.007)	(.005)	(.005)	(.007)
1 to 50	.867	.564	-.303	.789	.415	-.374	.691	.285	-.406	.572	.182	-.390
$N_m = 11,547, N_f = 10,028$	(.003)	(.005)	(.006)	(.004)	(.005)	(.006)	(.004)	(.005)	(.006)	(.005)	(.004)	(.006)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.12: Downward Rank Mobility for the 1960 Cohort Estimated by Gender

Parent percentile range	Percent of children below their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Males	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**	**Males**	**Females**	**F-M**
91 to 100	.769	.965	.196	.526	.883	.357	.383	.794	.411	.281	.702	.421
$N_m = 2,257, N_f = 2,057$	(.009)	(.004)	(.010)	(.010)	(.007)	(.013)	(.010)	(.009)	(.013)	(.009)	(.010)	(.014)
81 to 100	.707	.950	.243	.503	.882	.379	.367	.802	.435	.270	.705	.435
$N_m = 4,510, N_f = 4,119$	(.007)	(.003)	(.008)	(.007)	(.005)	(.009)	(.007)	(.006)	(.009)	(.006)	(.007)	(.010)
71 to 100	.644	.937	.293	.460	.869	.409	.336	.789	.453	.247	.690	.443
$N_m = 6,804, N_f = 6,140$	(.006)	(.003)	(.007)	(.006)	(.004)	(.007)	(.006)	(.005)	(.008)	(.005)	(.006)	(.008)
61 to 100	.588	.919	.331	.420	.847	.427	.305	.759	.454	.223	.653	.430
$N_m = 9,070, N_f = 8,189$	(.005)	(.003)	(.006)	(.005)	(.004)	(.006)	(.005)	(.005)	(.007)	(.004)	(.005)	(.006)
51 to 100	.531	.894	.363	.378	.815	.437	.273	.717	.444	.198	.600	.402
$N_m = 11,375, N_f = 10,199$	(.005)	(.003)	(.006)	(.005)	(.004)	(.006)	(.004)	(.004)	(.006)	(.004)	(.005)	(.006)

Notes: Cumulative samples. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35. All results and differences are statistical significant at a 1 % level.

Table C.13: Upward Transition Probability for Sons in 1960 Cohort Estimated by Intact/Disrupted Families.

Parent percentile range	Percent of children exceeding their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
1 to 10	.937	.890	-.047***	.858	.821	-.037**	.779	.747	-.032	.695	.683	-.012
$N_i = 1,405, N_d = 363$	(.006)	(.016)	(.017)	(.009)	(.020)	(.022)	(.011)	(.023)	(.025)	(.012)	(.024)	(.027)
1 to 20	.874	.841	-.033**	.803	.773	-.030**	.721	.699	-.022	.600	.587	-.013
$N_i = 2,915, N_d = 363$	(.006)	(.014)	(.015)	(.007)	(.016)	(.017)	(.008)	(.018)	(.020)	(.009)	(.019)	(.021)
1 to 30	.819	.774	-.045***	.745	.701	-.044***	.630	.589	-.041***	.494	.476	-.018
$N_i = 4,474, N_d = 925$	(.006)	(.014)	(.015)	(.007)	(.015)	(.017)	(.007)	(.016)	(.017)	(.007)	(.016)	(.017)
1 to 40	.767	.717	-.050***	.656	.614	-.042***	.519	.501	-.018	.380	.379	-.002
$N_i = 6,038, N_d = 1,191$	(.005)	(.013)	(.014)	(.006)	(.014)	(.015)	(.006)	(.014)	(.015)	(.006)	(.014)	(.015)
1 to 50	.670	.622	-.047***	.535	.512	-.023*	.393	.384	-.009	.249	.233	-.016*
$N_i = 7,294, N_d = 1,427$	(.005)	(.013)	(.014)	(.006)	(.013)	(.014)	(.006)	(.013)	(.014)	(.005)	(.011)	(.012)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Family structure registered in 1970 and 1980. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.14: Downward Transition Probability for Sons in the 1960 Cohort Estimated by Intact/Disrupted Families

Parent percentile range	Percent of children at or below the bottom of their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
91 to 100	.621	.692	.071**	.452	.527	.075**	.328	.420	.092***	.234	.321	.087***
$N_i = 1,510, N_d = 224$	(.012)	(.031)	(.033)	(.013)	(.033)	(.035)	(.012)	(.033)	(.035)	(.011)	(.031)	(.033)
81 to 100	.497	.593	.096***	.370	.468	.098***	.267	.362	.095***	.198	.293	.094***
$N_i = 3,017, N_d = 472$	(.009)	(.023)	(.025)	(.009)	(.023)	(.025)	(.008)	(.022)	(.023)	(.007)	(.021)	(.022)
71 to 100	.391	.476	.085***	.285	.356	.071***	.208	.273	.065***	.150	.209	.059***
$N_i = 4,585, N_d = 721$	(.007)	(.019)	(.020)	(.007)	(.018)	(.019)	(.006)	(.017)	(.018)	(.005)	(.015)	(.016)
61 to 100	.306	.351	.045***	.217	.271	.054***	.157	.204	.047***	.114	.153	.039***
$N_i = 6,116, N_d = 947$	(.006)	(.016)	(.017)	(.005)	(.015)	(.016)	(.005)	(.013)	(.014)	(.004)	(.012)	(.013)
51 to 100	.222	.274	.052***	.159	.205	.046***	.113	.156	.043***	.077	.104	.027***
$N_i = 7,686, N_d = 1,196$	(.005)	(.013)	(.014)	(.004)	(.012)	(.013)	(.004)	(.011)	(.012)	(.003)	(.009)	(.009)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Family structure registered in 1970 and 1980. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.15: Upward Rank Mobility for Sons in the 1960 Cohort Estimated by Intact/Disrupted Families.

Parent percentile range	Percent of children exceeding their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
1 to 10	.964	.937	-.027**	.893	.856	-.036**	.811	.780	-.031*	.731	.713	-.018
$N_i = 1,405, N_d = 367$	(.005)	(.013)	(.014)	(.008)	(.018)	(.020)	(.010)	(.021)	(.023)	(.012)	(.024)	(.027)
1 to 20	.941	.915	-.026**	.872	.842	-.030**	.796	.769	-.027*	.705	.694	-.011
$N_i = 2,915, N_d = 671$	(.004)	(.011)	(.012)	(.006)	(.014)	(.015)	(.007)	(.016)	(.017)	(.008)	(.018)	(.020)
1 to 30	.917	.891	-.026***	.855	.816	-.039***	.774	.736	-.038***	.670	.643	-.027*
$N_i = 4,474, N_d = 925$	(.004)	(.010)	(.011)	(.005)	(.013)	(.014)	(.006)	(.014)	(.015)	(.007)	(.016)	(.017)
1 to 40	.901	.870	-.031***	.834	.801	-.033***	.744	.711	-.033**	.630	.615	-.015
$N_i = 6,038, N_d = 1,191$	(.004)	(.010)	(.011)	(.005)	(.012)	(.013)	(.005)	(.013)	(.014)	(.006)	(.014)	(.015)
1 to 50	.873	.845	-.028***	.798	.770	-.028**	.696	.672	-.024**	.573	.567	-.006
$N_i = 7,594, N_d = 1,427$	(.004)	(.010)	(.011)	(.005)	(.011)	(.012)	(.005)	(.012)	(.013)	(.006)	(.013)	(.014)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.16: Downward Rank Mobility for Sons in the 1960 Cohort Estimated by Intact/Disrupted Families

Parent percentile range	Percent of children exceeding their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
91 to 100	.765	.817	.052**	.521	.598	.077**	.377	.469	.092***	.272	.371	.099***
$N_i = 1,510, N_d = 224$	(.010)	(.025)	(.028)	(.012)	(.031)	(.035)	(.012)	(.032)	(.035)	(.011)	(.031)	(.034)
81 to 100	.697	.780	.083***	.494	.589	.095***	.361	.445	.084***	.260	.364	.104***
$N_i = 3,017, N_d = 472$	(.008)	(.019)	(.021)	(.009)	(.022)	(.025)	(.009)	(.022)	(.025)	(.008)	(.021)	(.023)
71 to 100	.628	.705	.077***	.449	.527	.078***	.328	.386	.058***	.235	.311	.076***
$N_i = 4,585, N_d = 721$	(.007)	(.017)	(.018)	(.007)	(.018)	(.020)	(.007)	(.018)	(.019)	(.006)	(.017)	(.018)
61 to 100	.579	.618	.039**	.409	.471	.062***	.298	.344	.046***	.211	.275	.064***
$N_i = 6,116, N_d = 947$	(.006)	(.016)	(.017)	(.006)	(.016)	(.017)	(.006)	(.015)	(.016)	(.005)	(.010)	(.016)
51 to 100	.519	.557	.038***	.366	.423	.057***	.265	.309	.044***	.187	.243	.056***
$N_i = 7,686, N_d = 1,196$	(.006)	(.014)	(.015)	(.005)	(.014)	(.015)	(.005)	(.013)	(.014)	(.004)	(.012)	(.013)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Family structure registered in 1970 and 1980. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.17: Upward Transition Probability for Daughters in the 1960 Cohort Estimated by Intact/Disrupted Families.

Parent percentile range	Percent of children exceeding their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
1 to 10	.829	.786	-.043**	.677	.577	-.100***	.512	.362	-.150***	.350	.227	-.123***
$N_i = 935, N_d = 665$	(.012)	(.016)	(.020)	(.015)	(.019)	(.024)	(.016)	(.019)	(.025)	(.016)	(.016)	(.023)
1 to 20	.666	.594	-.072***	.502	.387	-.115***	.333	.255	-.078***	.217	.161	-.056***
$N_i = 1,881, N_d = 1,271$	(.011)	(.014)	(.018)	(.012)	(.014)	(.018)	(.011)	(.012)	(.016)	(.010)	(.010)	(.014)
1 to 30	.499	.402	-.097***	.336	.271	-.065***	.217	.166	-.051***	.128	.101	-.027***
$N_i = 2,877, N_d = 1,833$	(.009)	(.011)	(.014)	(.009)	(.010)	(.013)	(.008)	(.009)	(.012)	(.006)	(.007)	(.009)
1 to 40	.332	.279	-.053***	.212	.173	-.039***	.124	.106	-.018**	.069	.048	-.021***
$N_i = 3,886, N_d = 2,369$	(.008)	(.009)	(.012)	(.007)	(.008)	(.010)	(.005)	(.006)	(.008)	(.004)	(.004)	(.006)
1 to 50	.215	.169	-.046***	.130	.104	-.025***	.074	.051	-.023***	.035	.026	-.009**
$N_i = 4,920, N_d = 2,914$	(.006)	(.007)	(.009)	(.005)	(.006)	(.007)	(.004)	(.004)	(.006)	(.003)	(.003)	(.004)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Family structure registered in 1970 and 1980. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.18: Downward Transition Probability for Daughters the 1960 Cohort Estimated by Intact/Disrupted Families

Parent percentile range	Percent of children at or below the bottom of their parents percentile range by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
91 to 100	.923	.963	.040***	.838	.890	.052***	.741	.816	.075***	.646	.739	.093***
$N_i = 1,241, N_d = 353$	(.008)	(.010)	(.013)	(.010)	(.017)	(.020)	(.012)	(.021)	(.024)	(.013)	(.023)	(.027)
81 to 100	.871	.919	.048***	.792	.858	.066***	.705	.774	.069***	.592	.668	.076***
$N_i = 2,400, N_d = 793$	(.007)	(.010)	(.012)	(.008)	(.012)	(.015)	(.009)	(.014)	(.018)	(.010)	(.017)	(.020)
71 to 100	.814	.884	.070***	.730	.807	.077***	.627	.715	.088***	.504	.600	.096***
$N_i = 3500, N_d = 1,245$	(.007)	(.009)	(.011)	(.008)	(.011)	(.013)	(.008)	(.013)	(.015)	(.008)	(.014)	(.016)
61 to 100	.758	.821	.063***	.651	.732	.081***	.529	.617	.088***	.397	.468	.071***
$N_i = 4,617, N_d = 1,740$	(.006)	(.009)	(.011)	(.007)	(.010)	(.013)	(.007)	(.012)	(.014)	(.007)	(.012)	(.014)
51 to 100	.668	.747	.079***	.543	.636	.093***	.405	.486	.081***	.261	.333	.072***
$N_i = 5,695, N_d = 2,216$	(.006)	(.009)	(.011)	(.007)	(.010)	(.012)	(.007)	(.011)	(.013)	(.006)	(.010)	(.012)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Family structure registered in 1970 and 1980. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.19: Upward Rank Mobility for Daughters in the 1960 Cohort Estimated by Intact/Disrupted Families.

Parent percentile range	Percent of children exceeding their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
1 to 10	.910	.872	-.038***	.749	.672	-.077***	.591	.462	-.129***	.409	.278	-.132***
$N_i = 935, N_d = 665$	(.009)	(.013)	(.016)	(.014)	(.018)	(.023)	(.016)	(.019)	(.025)	(.016)	(.017)	(.023)
1 to 20	.820	.792	-.028**	.657	.601	-.056***	.491	.406	-.085***	.332	.252	-.080***
$N_i = 1,881, N_d = 1,271$	(.009)	(.011)	(.014)	(.011)	(.014)	(.018)	(.012)	(.014)	(.018)	(.011)	(.012)	(.016)
1 to 30	.730	.707	-.023**	.548	.527	-.041***	.413	.351	-.062***	.274	.218	-.056***
$N_i = 2,877, N_d = 1,833$	(.008)	(.011)	(.014)	(.009)	(.012)	(.015)	(.009)	(.011)	(.014)	(.008)	(.010)	(.013)
1 to 40	.642	.634	-.008	.487	.464	-.023**	.343	.308	-.035***	.226	.188	-.038***
$N_i = 3,886, N_d = 2,369$	(.008)	(.010)	(.013)	(.008)	(.010)	(.013)	(.008)	(.009)	(.012)	(.007)	(.008)	(.010)
1 to 50	.566	.552	-.013	.423	.400	-.023**	.295	.266	-.029***	.192	.161	-.031***
$N_i = 4,920, N_d = 2,914$	(.007)	(.009)	(.012)	(.007)	(.009)	(.011)	(.007)	(.008)	(.010)	(.006)	(.007)	(.009)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Family structure registered in 1970 and 1980. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.20: Downward Rank Mobility for Daughters in the 1960 Cohort Estimated by Intact/Disrupted Families

Parent percentile range	Percent of children exceeding their parents *exact* percentile by the amount, τ											
	$\tau = 0$			$\tau = 0.1$			$\tau = 0.2$			$\tau = 0.3$		
	Intact	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**	**Intact**	**Disrupted**	**I-D**
91 to 100	.966	.980	.014	.882	.924	.042	.786	.856	.070	.690	.771	.081
$N_i = 1,241, N_d = 353$	(.005)	(.007)	(.009)	(.009)	(.014)	(.017)	(.012)	(.019)	(.022)	(.013)	(.022)	(.026)
81 to 100	.949	.966	.017*	.879	.923	.044***	.797	.854	.057***	.698	.759	.061***
$N_i = 2,400, N_d = 793$	(.005)	(.006)	(.008)	(.007)	(.010)	(.012)	(.008)	(.013)	(.015)	(.009)	(.015)	(.018)
71 to 100	.933	.957	.024**	.861	.912	.051***	.779	.846	.067***	.679	.748	.069***
$N_i = 3,500, N_d = 1,245$	(.004)	(.006)	(.007)	(.006)	(.008)	(.010)	(.007)	(.010)	(.012)	(.008)	(.012)	(.014)
61 to 100	.918	.936	.018***	.841	.884	.043***	.750	.805	.055***	.644	.698	.054***
$N_i = 4,617, N_d = 1,740$	(.004)	(.006)	(.007)	(.005)	(.008)	(.009)	(.006)	(.010)	(.011)	(.007)	(.011)	(.013)
51 to 100	.893	.916	.023***	.808	.858	.050***	.707	.766	.059***	.589	.648	.059***
$N_i = 5,695, N_d = 2,216$	(.004)	(.006)	(.007)	(.005)	(.007)	(.009)	(.006)	(.009)	(.011)	(.007)	(.010)	(.012)

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%. Cumulative samples. Family structure registered in 1970 and 1980. Fathers earnings measure: five-year income averages from 1977-81. Childs earning measures: five-year averages at age 31–35.

Table C.21: Correlation between fathers and children's rank in the income distribution, from single years and 5 years average income.

	1950 cohort	**1955 cohort**	**1960 cohort**	**1965 cohort**
Sons				
Average age 31-35	.242	.231	.202	
Age 30	.185	.189	.175	.160
Age 31	.206	.205	.187	
Age 32	.225	.218	.196	
Age 33	.233	.227	.198	
Age 34	.246	.231	.205	
Age 35	.249	.226	.209	
Age 40	.259	.222		
Age 45	.248			
Daughters				
Average age 31-35	.155	.150	.175	
Age 30	.135	.153	.174	.167
Age 31	.145	.156	.173	
Age 32	.151	.148	.176	
Age 33	.156	.146	.174	
Age 34	.166	.153	.169	
Age 35	.171	.148	.174	
Age 40	.172	.161		
Age 45	.206			

Five-year averages of fathers' earnings: 1967-71, 1972-76, 1977-81, 1982-86.

Figure C.1: Correlation between parents and 30 years olds rank in the income distribution for the 1950-65 cohorts.