

The logo for Ludwig-Maximilians-Universität München (LMU) features the letters 'LMU' in a bold, white, sans-serif font centered within a dark green square.

LMU

The text 'LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN' is written in a white, sans-serif font, stacked in four lines, within a dark green square.

**LUDWIG-
MAXIMILIANS-
UNIVERSITÄT
MÜNCHEN**

Intergenerational Mobility in Income, Consumption and Wealth

Referent: Prof. Dr. Dominik Sachs

Semester: Summer Semester 2020

Betreuer: Paul Schüle

Name: Berrin Sena Karaman

Matriculation Number: 12006655

Number of Semester: 4

Table of Content

Tables.....	II
1 Introduction.....	1
2 Intergenerational Mobility Measures	3
2.1 Intergenerational Elasticity.....	3
2.2 Log-Linear Correlation (Pearson Correlation)	4
2.3 The Rank Correlation (Spearman Correlation)	5
2.4 Transition Matrices.....	6
3 Biases in Mobility Measures.....	7
3.1 Biases in Intergenerational Elasticity	8
3.2 Biases in Log-Linear Correlation (Pearson Correlation).....	9
3.3 Biases in the Rank Correlation (Spearman Correlation)	10
3.4 Biases in Transition Matrices	12
4 Data Sources	13
5 Comparison of Studies on Intergenerational Mobility.....	15
5.1 Intergenerational Income Mobility.....	16
5.1.1 Intergenerational Elasticity Estimates (IGE).....	16
5.1.2 Log-Linear Correlation (Pearson Correlation) Estimates	21
5.1.3 The Rank Correlation (Spearman Correlation) Estimates.....	24
5.2 Intergenerational Wealth Mobility	27
5.3 Intergenerational Consumption Mobility	30
6 Discussions	31
7 Conclusion	34
References.....	35

Tables

Table I. Selected Literature on the Estimates of the IGE in Different Countries.....20

Table II. Selected Literature on the Estimates of the Log-Linear Correlation in Different Countries.....23

Table III. Selected Literature on the Estimates of the Rank Correlation in Different Countries.....25

Table IV. Selected Literature on the Estimates of the Intergenerational Wealth Mobility in Different Countries.....29



1 Introduction

Intergenerational mobility is interested in the degree to which socioeconomic status is transmitted across generations. The motive for investigating intergenerational mobility is to understand the degree of inequality. In recent decades, the increase in inequality observed in some industrialized countries has highlighted the issue as it is discussed in the literature that the increase in inequality might be tolerated if there is sufficient intergenerational mobility (Corak et al., 2014). However, if most children's socioeconomic outcomes are highly dependent on their parents' socioeconomic status, inequality will persist across generations. In other words, children with poor family backgrounds are less likely to become rich in their adulthood. This inequality of opportunity leads to not being able to reach full productive potential of people which in turn results in economic inefficiency.

The socioeconomic status of people can be associated with various material well-being indicators such as income, wealth and consumption. The majority of the research on intergenerational mobility has concentrated on intergenerational income mobility (see Solon, 1999; Black and Devereux, 2011; and, Jännti and Jenkins, 2015; for surveys) while relatively less attention has been paid to the intergenerational mobility in wealth and consumption. One reason is the lack of appropriate datasets that contain wealth and consumption data for both parent and offspring generations. Yet, arguably wealth and consumption might be better indicators of long-term material well-being than income; given that convenient datasets are provided.¹

The most commonly used intergenerational mobility measures in the literature are the intergenerational elasticity, the log-linear correlation (Pearson correlation), the rank correlation (Spearman correlation), and transition matrices. Each of these four measures considers mobility from different angles; therefore, it is important to understand the conceptual differences and approximation biases of these complementary measures. The most commonly used mobility measure, the intergenerational elasticity, is a measure of persistence. It is the slope coefficient where children's log income (wealth or consumption) is regressed on parents' log income (wealth or consumption). The log-linear correlation is closely related to the intergenerational elasticity. It is equal to the elasticity times the standard deviation of

¹ See arguments of Adermon et al. (2018) for wealth; Deaton and Zaidi (2002), Meyer and Sullivan (2003) for consumption.

log parental income over the standard deviation of log children's income. The main difference between these two measures is while the elasticity is affected by changes in inequality across generations; the log-linear correlation is immune to this factor. The rank correlation and transition matrices provide information about positional mobility. They capture the relative association between the children's and their parents' positions in the marginal distributions; where transition matrices focus particularly on the mobility of the richest or poorest in the population.

These four mobility measures have also differentiated in terms of their robustness to approximation biases. The two main biases concerned in the mobility literature are lifecycle and attenuation biases. Lifecycle bias arises from the fact that datasets are not being able to capture all the economic activities in a person's lifetime. Mobility estimates which are made by using a person's income (wealth or consumption) at younger ages are particularly problematic, since it does not provide a successful proxy for lifetime values and cause lower estimates of mobility. On the other hand, attenuation bias arises from transitory fluctuations or measurement error in income (wealth or consumption). In studies, it is minimized by averaging observations over multiple years. Bearing the highly diverse consequences of measurement errors across mobility measures in mind, it is found that rank-based estimates are more robust to lifecycle and attenuation biases (Dahl and DeLeire, 2008; Chetty et al., 2014; Mazumder, 2015; Nybom and Stuhler, 2017).

In this study, I provided a summary of the literature on intergenerational mobility across different countries. Unlike most other surveys, in this study, not only intergenerational income mobility but also intergenerational wealth and consumption mobilities are considered. To assess the reasons for different estimations between studies; first, I explain the mobility estimation methods of the four measures. Second, I provide a deep insight into the robustness of these measures to lifecycle and attenuation biases. Third, I point out the strengths as well as limitations of administrative and survey datasets. Later on, I continue with summarizing the most recent studies in the literature and making comparisons of the intergenerational income, wealth and consumption mobility estimations across countries. Since, classifying countries as relatively weak or strong in terms of intergenerational mobility will help us figure out the optimal level of intergenerational mobility, which is the main motivation of this study.

The comparison of the income mobility studies which are using the elasticity and log-linear correlation suggests that Scandinavian countries are the most mobile countries. These

countries are followed by Canada; whereas, the United Kingdom and the United States are less mobile than the others. On the contrary, intergenerational income mobility studies that are utilizing rank correlation report different estimation results among Scandinavian countries. That is, Sweden is found to be even less mobile than the United States. The same estimation results as income rank mobility studies are also observed in intergenerational wealth mobility studies. Whereas, the estimates of intergenerational consumption mobility studies do not support the results of intergenerational income and wealth mobility studies. Since, the consumption mobility studies report that the United States is more mobile than Denmark, which is seen as one of the countries that has the highest intergenerational mobility according to intergenerational income and wealth mobility studies.

The paper proceeds as follows. The next section describes the four intergenerational mobility measures. Section 3 examines the robustness of these measures to lifecycle and attenuation biases. Section 4 presents the strengths and limitations of datasets. Section 5 summarizes the literature on intergenerational income, wealth and consumption mobility. Section 6 provides discussions related to studies summarized in the previous section. Lastly, Section 7 concludes.

2 Intergenerational Mobility Measures

In economics, intergenerational mobility of income, consumption and wealth is measured by the empirical works which mostly characterize the joint distributions of children and their parents' lifetime activities on these three different aspects. In large samples, it is possible to analyse the joint distributions nonparametrically; yet, for being able to make comparisons between studies, numerous mobility measures are used. Each measure has a distinct perspective on the nature and the extent of intergenerational mobility. Therefore, it might be useful to focus on the conceptual differences of literature's most commonly used four measures, which are the intergenerational elasticity, the log-linear correlation, the rank correlation, and transition matrices. In section 2 and 3, I explain and examine these four mobility measures in detail by addressing their utilization in intergenerational income mobility literature.

2.1 The Intergenerational Elasticity

The most commonly used international mobility measure is Intergenerational Elasticity (IGE), which shows the expected percentage change in offspring income (or earnings) for a 1%

change in parents' income (or earnings) (D'Addio, 2007). It is the slope coefficient of the simple linear regression model which is constructed by regressing the log children's income on log parent income. The benchmark regression is²:

$$y_{1i} = \alpha + \beta y_{0i} + \varepsilon_i \quad (1)$$

Where y_{1i} is the logarithm of children's mean income and y_{0i} is the logarithm of parents' mean income. The regression coefficient β is the intergenerational elasticity and $1 - \beta$ can be used as a measure of intergenerational mobility, ε_i is the error term which indicates the influences that are not related to parental income.

IGE shows to what extent the parents' income affects children's income. According to empirical estimates β generally lies between 0 and 1, but it can take values more than 1. The high values of β indicate higher economic persistence between generations and therefore lower intergenerational mobility. In extreme cases, when β equals to 0, parents' income has no effect on children's income so there is perfect income mobility; when β is greater or equal to 1, economic status of parents passes to the children and the income distribution does not regress to the mean (Yuan, 2017).

2.2 The Log-Linear Correlation (Pearson Correlation)

The Pearson Correlation is closely related to the intergenerational elasticity. The intergenerational correlation equals intergenerational elasticity given that the standard deviations of log incomes of parents and children are equal. Therefore, the Pearson correlation can be shown as:

$$\rho = (\sigma_0/\sigma_1)\beta \quad (2)$$

where σ_0 is the standard deviation of the log income of parents and σ_1 is the standard deviation of the log income of children. This equation indicates that the changes in the standard deviations of log incomes between parents and children have mechanical effects on elasticity but not on the correlation (Nybohm and Stuhler, 2017). In other words, the cross-sectional dispersion of log incomes between the two generations is factored out by the correlation. Therefore, the IGE can be higher in society A than in society B simply because of the variance of log parents' income is lower in society A. Accordingly, while the correlation

² It is often in the literature to include age controls to the regression yet few other control variables. Since β reflects all the factors that are correlated with parental income, rather than giving a causal interpretation.

could only take values between 0 and 1, the elasticity could be greater than one. Regarding this difference between the two measures, some studies prefer the Pearson correlation, while the others use IGE because it incorporates the changes in income inequality³.

2.3 The Rank Correlation (Spearman Correlation)

The Spearman rank correlation measures the association between the children's positions in the lifetime income distribution and their parents' positions in the lifetime income distribution. Children's incomes are ranked relative to other children's incomes from the same cohort; likewise, their parents' incomes are ranked relative to other parents' from the same cohort. Then, the slope of the rank-rank regression between the children and their parents gives the mobility. The benchmark regression is:

$$R_i^{child} = \beta_0 + \beta_1 R_i^{parent} + \epsilon_i \quad (3)$$

where R_i^{child} is the percentile rank of child i in the lifetime income distribution of children, R_i^{parent} is the percentile rank of child i 's parent in the parental distribution of lifetime income, β_0 stands for the absolute mobility of ranks across generations, β_1 stands for the relative mobility of ranks across generations and ϵ_i is the random error component that captures the factors which might affect children's distributional positions independently from their parents' ranks.

The intercept coefficient, β_0 , shows the expected rank of a child when his or her parent is at the bottom of the income distribution. The slope coefficient, β_1 , shows the percentage point change in the child's rank for a percentage point change in his or her parent's rank. The degree of mobility is negatively related to the value of the slope. A zero value for the β_1 means that the expected rank of the child in the distribution of income does not depend on the parent's rank, which signifies that there is complete intergenerational mobility. Meanwhile, when β_1 is 1, the expected rank of the child in the distribution of income fully depends on the parent's rank, which signifies that there is complete intergenerational immobility.

³ See Mitnik et al. (2014).

2.4 Transition Matrices

A transition matrix demonstrates the probability of the child's being in a given quintile, quartile, or decile of the income distribution; conditional on the parent's position in the income distribution. It provides greater information across the distribution and also makes it possible to compare mobility rates of subgroups across the whole income distribution rather than just across the income distribution for that group. Interest is often centred on specific elements; such as the mobility in the very top or bottom classes ("poverty traps") or the probability to rise from the lowest class to the highest class ("rags to riches") (Nybom and Stuhler, 2017). To construct a transition matrix, the values of the variables are divided into bins in order that each value p_{ij} of the matrix's cell (i, j) gives the relative conditional frequency. This is the conditional frequency of given that the value of the variable for the parent being in the bin i , the value of the same variable for the child being in the bin j . Therefore, a transition matrix with all its cell values concentrated around the diagonal signals immobility. A transition matrix can give information about the degree of immobility within each quintile as well as across different quintiles (Caballé, 2016).

One of the most important aspects of transition matrices is the main diagonal. It shows the children that stayed at the same quantile as their parents. The other one is corner probabilities. In this way, the upward mobilities of the poorest or downward mobilities of the richest can be calculated. Lastly, the shape of the transition matrix. The observed asymmetry implies that mobility may be different across distribution and the bivariate log normal distribution not likely to fit the data well (Jäntti and Jenkins, 2015).

In order to compare the mobilities of different transition matrices easily, all the data in the transition matrices can be summarized in a single number which results in severe loss of information. Since, this single number cannot give information about whether there is strong mobility which is observed across distant quantiles or weak mobility that is observed across near quantiles. Moreover, it cannot give information about whether the immobility within each quantile is low or high.

The total value of a transition matrix's each row should be equal to 1 since it is a stochastic matrix. This implies that the transition matrix has an eigenvalue equal to 1 and its other eigenvalues should be less than or equal to 1. The distance between the identity matrix, which shows the absolute immobility across quantiles, and the transition matrix gives the degree of

mobility. One of the most popular intergenerational mobility measures is calculated by subtracting the second largest eigenvalue from 1. In this case, all the eigenvalues of the identity matrix are equal to 1. Therefore, its intergenerational mobility measure is 0. The other popular intergenerational mobility measure is, when considering a $P \times P$ matrix with its entire cell values equal to $1/P$, which implies complete mobility, has an eigenvalue of 1 and all other eigenvalues are 0. Therefore, its intergenerational mobility measure is 1 (Caballé, 2016).

3 Biases in Mobility Measures

The availability of data on lifetime income for both children and their parents is the necessary condition for obtaining robust estimates of intergenerational mobility. However, in applications, it is not easy to find such datasets that provide all the information needed. Researchers typically only observe the short-run incomes for both children and their parents. These snapshots are used as proxies for unobserved lifetime income.

Most of the studies in this field adopt Friedman (1957)'s well-known textbook errors-in-variables model in order to proxy current income variables for unobserved lifetime incomes:

$$x = x^* + u \tag{4}$$

$$y = y^* + v \tag{5}$$

where x stands for current parental income variable such as log annual income, y stands for children's current income variable, x^* be true log lifetime income of parents, y^* be true log lifetime income of children, u is the measurement error in x as a proxy for x^* and v is the measurement error in y as a proxy for y^* .

The textbook errors-in-variables model in equation 4 (or equation 5) assumes that the slope coefficient is equal to 1. One important implication of this restriction is, when x proxies for x^* as the dependent variable, ordinary least squares estimation of this regression gives consistent estimates of the slope coefficient. Another important implication is, the probability limit of the OLS estimator of the slope equals the true coefficient times the attenuation factor $Var(x^*) / [Var(x^*) + Var(u)]$ (Haider and Solon, 2006).

Letting x^* and y^* expressed as deviations from generational means, the relationship between x^* and y^* can be observed by using the intergenerational elasticity, the Pearson correlation,

the Spearman correlation, or transition matrices. However, it is suspected that the textbook errors-in-variables model characterizes this relationship incorrectly, which means that the frequently used implications of this model no longer accurate. These will be result in biases in intergenerational mobility measures.

3.1 Biases in Intergenerational Elasticity

The conditional expectation function can be used to summarize the log income relationship between children and parents. When linear regressing y^* on x^* , the coefficient $\beta_{(x^*,y^*)} = \text{Cov}(x^*,y^*)/\text{Var}(x^*)$ is the best linear approximation for the slope which is the intergenerational elasticity.⁴ Meanwhile, using the short-run approximations instead of true lifetime incomes results in the estimation of the following coefficient:

$$\beta_{(x,y)} = \frac{\text{Cov}(x,y)}{\text{Var}(x)} = \frac{\beta_{(x^*,y^*)}\text{Var}(x^*) + \text{Cov}(x^*,v) + \text{Cov}(y^*,u) + \text{Cov}(u,v)}{\text{Var}(x^*) + \text{Var}(u) + 2\text{Cov}(x^*,u)} \quad (6)$$

This coefficient might not be equal to the true intergenerational elasticity for two reasons. Firstly, classical measurement error may cause attenuation bias. According to the textbook errors-in-variables, $\beta_{(x,y)} = \frac{\beta_{(x^*,y^*)}\text{Var}(x^*)}{\text{Var}(x^*) + \text{Var}(u)}$. If credible estimates of the attenuation factor are available, then intergenerational elasticity estimates made from annual incomes can be corrected for classical error. Importantly, according to the classical measurement error model, only the random fluctuations in parental income lead attenuation bias (Atkinson, 1981b). The most common solution, which is first used by Solon (1989, 1992) and Zimmerman (1992), is to deal with the attenuation bias by diminishing it by using multiyear averages of parental income instead of single year incomes.

In addition to attenuation bias, heterogeneous income profiles may cause systematic variations over age between true values and error terms which leads to lifecycle bias (Jenkins 1987). For example, if the slope coefficient from the children's log annual income on children's true log lifetime income (equation 5) deviates from 1 in such a way that it evolves over the children's lifecycle, then intergenerational elasticity estimates will generate systematically different results at different ages. Haider and Solon (2006) suggest that the income of early in life tends to understate the true lifetime income; meanwhile, income of later in life overstates the true lifetime income. In between, there exists an age that the textbook errors-in-variables model is correct. Moreover, Grawe (2006) finds that there is an

⁴ The best approximation of the slope in terms of minimized mean squared error.

inverse relationship between father's age and intergenerational elasticity. As the father's age increases, the elasticity tends to decrease. This is consistent with the result of Nilsen et al. (2008), they show that each additional year to father's age decreases intergenerational elasticity by about 1.1%. Another result of Grawe (2006) is, for any given age of father; as son's age increases, the elasticity tends to increase. These studies prove that intergenerational elasticity is prone to lifecycle bias.

3.2 Biases in Log-Linear Correlation (Pearson Correlation)

The Pearson correlation coefficient is not affected by the fluctuations in the variance of the log incomes of the children and the parents. According to the textbook errors-in-variables

model, when proxy incomes are used, this yields $\rho_{(x,y)} = \rho_{(x^*,y^*)} \sqrt{\frac{\text{Var}(x^*)}{\text{Var}(x^*)+\text{Var}(u)} \frac{\text{Var}(y^*)}{\text{Var}(y^*)+\text{Var}(v)}}$

Therefore, while the intergenerational elasticity is attenuated by only the parental income; the Pearson correlation is attenuated by both children's and their parent's income. Nybom and Stuhler (2017) argue that under the left-side (children) measurement error, Pearson correlation estimates are much lower than intergenerational elasticity estimates; while, when both-sided measurement error is present, the two measures are attenuated more similarly. Therefore, to deal with the attenuation bias, using multiyear averages of parental income and also the offspring income instead of single year incomes are equally important.

Following Haider and Solon (2006), Nybom and Stuhler (2017) bring some new insights to the linear projection of $y = \lambda y^* + w$. Assuming w is not correlated to x^* , they come up with:

$$\rho_{(x^*,y)} = \begin{cases} -\rho_{(x^*,y^*)} \sqrt{\frac{\text{Var}(y^*)}{\text{Var}(y^*)+(\frac{1}{\lambda^2})\text{Var}(w)}} , & \text{if } \lambda < 0 \\ \rho_{(x^*,y^*)} \sqrt{\frac{\text{Var}(y^*)}{\text{Var}(y^*)+(\frac{1}{\lambda^2})\text{Var}(w)}} , & \text{if } \lambda > 0 \end{cases} \quad (7)$$

This equation means that at very early ages of lifetime when there is a negative correlation between current and lifetime income ($\lambda < 0$) exists, Pearson correlation is sensitive to the lifecycle bias. The ratio goes to 0, as $\lambda \rightarrow 0$; so, Pearson correlation is less sensitive at mid ages and late ages. And, when the ratio goes to 1, as $\lambda \rightarrow \infty$; Pearson correlation is expected to increase. Therefore, Pearson correlation is still attenuated at late ages in contrast to intergenerational elasticity.

Their results from the empirical study which uses the Swedish dataset approve these implications. They find that at early ages strong lifecycle bias effects are observed; however, the estimations get more stable after age 30 under left-side and both-side measurement errors. Moreover, since the ratio rises with λ and age, they come up with the conclusion that the textbook errors-in-variables model understates it at later ages. Lastly, even the usage of five or nine-year-long income averages, the Pearson coefficient still strongly suffers from attenuation bias.

3.3 Biases in the Rank Correlation (Spearman Correlation)

The ranks of true lifetime income of parents and the children in their respective distribution can be denoted by $\tilde{x}^* = F_x(x^*)$ and $\tilde{y}^* = F_y(y^*)$. Then the observed ranks are:

$$\tilde{x} = \tilde{x}^* + \tilde{u} \quad (8)$$

$$\tilde{y} = \tilde{y}^* + \tilde{v} \quad (9)$$

where \tilde{u} and \tilde{v} are the measurement errors in ranks.

The Spearman correlation, $\rho^S_{(x^*, y^*)} = \frac{Cov(\tilde{x}^*, \tilde{y}^*)}{\sqrt{Var(\tilde{x}^*)Var(\tilde{y}^*)}}$, shows which variable increases with the other variable without the need for a linear relationship between them.

According to classical measurement error, the variance of observed ranks is equal to true ranks. Since the distributions of the ranks are normalized to the unit interval, these rank-ordered variables' variances are equal to 1/12. However, Nybom and Stuhler (2017) argue that observed ranks are not equal to true ranks. According to the authors, there is a negative correlation between the true ranks and errors in ranks due to the fact that the bottom ranks cannot be understated; while, the top ranks cannot be overstated. Formally, they demonstrate this relation by $Var(\tilde{y}^*) = Var(\tilde{y}) = Var(\tilde{y}^*) + Var(\tilde{v}) + 2Cov(\tilde{y}^*, \tilde{v})$. Thus, $Cov(\tilde{y}^*, \tilde{v}) = (-1/2)Var(\tilde{v})$.

After proving that textbook errors-in-variables model is not appropriated for ranks, following Haider and Solon (2006), Nybom and Stuhler (2017) formulate a generalized errors-in-variables model:

$$\tilde{y} = \alpha + \lambda_y \tilde{y}^* + \tilde{w} \quad (10)$$

where the slope coefficient is λ_y . They assume that \tilde{w} is not correlated to \tilde{y}^* and \tilde{x}^* . The slope coefficient is smaller or equal to 1 and, it is the representation of expected measurement error. Such that, when λ_y is close to 0, it means that \tilde{y} does not carry information about \tilde{y}^* ; whereas, when λ_y is close to 1, it means that there is very little measurement error. It should be noted that, in this model, for any form of measurement error ($Var(\tilde{v}) > 0$), the slope coefficient (λ_y) will be less than 1.

Let λ_x be the slope coefficient of regressing \tilde{x} on \tilde{x}^* . Including the errors on both sides, gives the Spearman correlation equation:

$$\rho^S_{(x,y)} = \frac{Cov(\tilde{x},\tilde{y})}{\sqrt{Var(\tilde{x})Var(\tilde{y})}} = \lambda_x\lambda_y \frac{Cov(\tilde{x}^*,\tilde{y}^*)}{1/12} = \lambda_x\lambda_y\rho^S_{(x^*,y^*)} \quad (11)$$

Since λ_y and λ_x are smaller than 1, the Spearman correlation is understated. It has attenuation bias because of the errors in both children and parents' incomes. However, the authors find that ranks are less sensitive to outliers at the tails of the distribution. Therefore, the size of the attenuation bias in rank correlation is smaller than in log-linear measures (Dahl and DeLeire, 2008; Chetty et al., 2014; Mazumder, 2015). Nevertheless, since attenuation bias in rank correlations can still be observed, in order to decrease the bias to a negligible level, long averages of income around mid-ages can be used.

The Spearman correlation also suffers from lifecycle bias. Haider and Solon (2006) and Grawe (2006) have shown that the earnings profile of children with high lifetime incomes is steeper at young ages; therefore, measuring the income at the beginning of their careers underestimate intergenerational mobility. Therefore, the Spearman correlation is strongly affected by lifecycle bias at young ages while this effect is less observed at later ages.

Dahl and DeLeire (2008), Chetty et al. (2014), and Nybom and Stuhler (2017) find that the rank correlation stabilizes around age 30. Moreover, Chetty et al. (2014) test whether measuring the parental income at very young or very old ages causes an analogous lifecycle bias or not. They use the income variables of mothers when they are between 41 to 55 years old and their result suggests that the rank-rank estimate exhibits almost no variation when this range of parental income is used. Lastly, when compared to intergenerational elasticity, estimates of rank correlation are found to be more robust to lifecycle bias (Dahl and DeLeire, 2008; Chetty et al., 2014; Mazumder, 2015; Nybom and Stuhler, 2017). Since the Spearman correlation does not vary with the rank-preserving spreads.

3.4 Biases in Transition Matrices

Researchers commonly rely on transition matrices instead of regression-based models when analysing intergenerational mobility patterns over the distribution (Zimmerman, 1992; Dearden et al., 1997). However, there can be biases in transition matrices while using short-run income data.

Allowing for classical error in log children income; conditional on the parent's true rank j , the probability of children's rank i can be written as:

$$P(\tilde{y} = i \mid \tilde{x}^* = j) = P(\tilde{y}^* = i \mid \tilde{x}^* = j) + \sum_{r \neq i} P(\tilde{y} = i \mid \tilde{y}^* = r) [P(\tilde{y}^* = r \mid \tilde{x}^* = j) - P(\tilde{y}^* = i \mid \tilde{x}^* = j)] \quad (12)$$

On the right-hand side, the true probability is shown by the first term is and the bias is denoted by the second term. On the main diagonal ($i = j$), if $P(\tilde{y}^* = i \mid \tilde{x}^* = i) > P(\tilde{y}^* = r \mid \tilde{x}^* = i) \forall r \neq i$, then inside of the square bracket is negative. This means that the probability of children to be at a certain rank will be the largest if their parents are at the same rank. Therefore, $P(\tilde{y} = i \mid \tilde{x}^* = j) < P(\tilde{y}^* = i \mid \tilde{x}^* = j) \forall i=j$ signifies that the terms on the main diagonal are understated when there exist classical errors. In contrast, the off-diagonal terms are generally overstated. Moreover, the bias observed in the transition matrix's corners will be larger, if $P(\tilde{y}^* = i \mid \tilde{x}^* = i)$ is large for where the ranks are bounded from above or below and; when the difference between i and r decreases, $P(\tilde{y}^* = r \mid \tilde{x}^* = i)$ decreases. Therefore, Nybom and Stuhler (2017) expect to observe significant overestimation of long-distance transitions due to the common low-income data in annual incomes.

Following the theoretical predictions, the authors make nonlinear analysis to test whether the robustness of Spearman correlation is also valid for the transition matrix as it also is a rank-based intergenerational mobility measure. They find that the slope of the conditional expectation function is lower in between the tails. Another result is that, when the conditional expectation function is approximated, the age of the children when annual income data is taken is important. The rank of the children is overstated (understated) by up to 10% in the bottom (top) in the top 5% of the parent's rank distribution. When the income data are measured around the age of 40, underestimation observed in the top is negligible. However, overestimation in the bottom does not disappear across any age. Lastly, the authors find the most possible position of the children is the same position where their parents are located.

This probability is the highest for the poorest and also the richest parents since the ranks are bounded from bottom and top. These results are in accordance with O’Neill et.al (2007), who find that the bias resulted from classical measurement error is observed most severely in the tails. In their paper, O’Neill et.al (2007) examine the biases in transition matrices which are stemmed from the omitted variable bias and measurement error. They find that the omitted variable bias has a modest effect on transition matrices. Classical measurement error in earnings of the offspring causes to overestimation of intergenerational mobility which is in contrast to OLS where elasticity remains unbiased. Meanwhile, when there is measurement error in both earnings of fathers and sons, the impact depends on the correlation between errors. When there is a low (high) correlation, mobility is overstated (understated). They thus caution that the difference in mobility estimations across studies might be stemming from data reliability rather than true differences across countries.

4 Data Sources

To study intergenerational mobility, researches use different sources including surveys, tax records, and other administrative data sources. Each source has its strengths as well as limitations. Surveys generally have rich socioeconomic status information such as consumption, wealth, hours of work, health, race, and education. Tax records are presumed to be very accurate and have high coverage since it includes tax forms from government agencies and firms. Administrative data from government benefit programs have income and consumption information which are not fully captured by the other data sources. For instance, in the US, most of the benefits given by the Department of Veterans Affairs are not included in tax data; since these are not taxable and they tend to be not reported accurately in surveys (Medalia et al., 2019). Therefore, integration of this kind of benefits’ data makes it possible for researches to do better longitudinal analysis. On the other hand, self-reported surveys tend to have attenuation bias since the responses might not be accurate. Medalia et al. (2019) state that, in the United States, more than half of the cash welfare payments and private pension payments are not reported in surveys; therefore, the income of very poor or very rich people is poorly measured. Moreover, the authors point out that tax data do not contain information about non-taxable cash transfers, in-kind benefits, and demographic characteristics. Tax variables are missing the income information of the people who fall below the tax filing income threshold. Furthermore, there might also be underreporting of self-employment income. Finally, the authors mention that administrative data from government programs have

limited information beyond the programs' administrative perspective and only the participants are available to reach these data.

The differences between survey and administrative data might have an impact on the results of the intergenerational mobility studies. Taking this into consideration, Mazumder (2018) discusses the pros and cons of the widely used Panel Study of Income Dynamics (PSID) which he believes has helped to shape intergenerational mobility literature. The PSID is the US's longest-running survey beginning in 1968 with nearly 5000 families. Until 1997, the interviews were held annually and continued biannually thereafter. The long panel length reduces the biases which occur due to the poor coverage of life course and short term measures, these problems are observable in administrative data. Moreover, the PSID collects rich information on the parents and the demographic details which are irrelevant for administrative purposes. It is also better than tax records data when identifying family relationships. Regarding the increase in the complexity of family arrangements, tax data are not ideal for tracking a child's all parental figures over the lifetime which is important for intergenerational mobility researches. Another advantage is administrative data are highly confidential, and therefore difficult to obtain; while the PSID is easy to access, and accordingly studies using it are more transparent. Finally, the PSID makes available to study other topics like wealth mobility more accurately. Related data on this topic is more difficult to find than finding income data. For example, prior to the PSID, Menchik (1979) use probate records of children and their parents in Connecticut to study wealth mobility, which do not provide a healthy representation. Nowadays, all of the modern intergenerational wealth mobility studies in the US use the PSID because it overcomes the limitation of data sources like the Internal Revenue Service (IRS), which provides information about wealth only if it is significant for tax purposes.

The PSID's most important disadvantage is that it has a smaller sample size compared to administrative data. Thus, it is not ideal for investigating heterogeneity within a population's subgroups. Another disadvantage is the sample attrition. As the years of observation increase, the size of intergenerational samples declines significantly in the studies using this data source⁵. While Fitzgerald (2011) argues that attrition bias is not severe, Schoeni and Wiemers (2015) claim that attrition bias likely to cause underestimation of the intergenerational persistence rates. Moreover, there might be measurement errors stemming from not

⁵ See Solon (1992) and Mazumder (2016).

responding to the survey questions or not responding to the questions at all. Lastly, the PSID has limitations on consumption data. It has expenditures data on mortgage payments, rent, food at home, food away from home, property taxes, utilities, etc. However, since it successfully captures information of two generations, it is preferred to be used for intergenerational consumption mobility studies.

It is known that there are also other household surveys⁶. One of the most outstanding household surveys is the National Longitudinal Survey of Youth 1979 cohort (NLSY79). It began with a sample of more than 12,000 people aged 14 to 22 in 1979. Until 1994, the interviews were held annually and continued biannually thereafter. It follows a larger set of fixed birth cohorts than the PSID, which is NLSY79's main advantage. Its main disadvantage is it has less information about the parents' generation and this information might suffer from recall error since it is retrospective.

Since each data source has its weaknesses and strengths, it is recommended for researchers to combine the administrative and survey data sources to construct more robust estimates (Abowd and Stinson, 2013; Mazumder, 2018; Medalia et al., 2019). Another recommendation for researchers is to take the differences across surveys into consideration. These are problematic in cross-national studies since country-based surveys might not be comparable. Therefore, the cross-national researchers have to invest significant time and effort to harmonize the data and create equivalent measures (Frick et al., 2007). To deal with this problem, researchers can use data sets of standardization projects such as the Cross National Equivalent File (CNEF) which allows researchers to do longitudinal and cross-sectional analyses by harmonizing panel survey data of Australia's HILDA, Canada's SLID, Germany's SOEP, Great Britain's BHPS, Switzerland's SHP and the United States' PSID.

5 Comparison of Studies on Intergenerational Mobility

In this section, I present the most recent studies of intergenerational income, wealth and consumption mobility in different countries. Then, I compare the intergenerational mobility levels of countries according to the estimation results of these studies.

⁶ For example; The CPS Annual Social and Economic Supplement Surveys, the American Community Survey (ACS), the Survey of Income and Program Participation (SIPP), the Consumption Expenditure Surveys (CE).

5.1 Intergenerational Income Mobility

The majority of the intergenerational mobility studies concentrate on income. Therefore, the following subsections investigate intergenerational income mobility studies separately for the intergenerational elasticity, the log-linear correlation (Pearson correlation), and the rank correlation (Spearman correlation) which are the most commonly used mobility measures in the intergenerational income mobility literature.

5.1.1 Intergenerational Elasticity Estimates (IGE)

In the analyses of intergenerational elasticity studies; due to the log-log specification, zero or negative incomes and earnings of offspring and parents are excluded.

Murray et al. (2018) are the first ones to estimate intergenerational mobility in Australia by using direct observations of the incomes of parents and their children. They use a panel dataset called Household, Income and Labour Dynamics Australia Survey (HILDA). In the baseline analysis, they average offspring income over the years 2014 and 2015 when the children were around 30 years old. The parents' income is averaged over five years, from 2001 to 2005. Using household total income as the preferred income measure, the baseline IGE estimate is 0.282. Lifecycle bias is not significant in the baseline result. Meanwhile, after correcting for attenuation bias, the income elasticity estimate increases to 0.409.

Corak et al. (2014) estimate intergenerational earnings elasticities of Canada, Sweden and the US. The authors use Canadian administrative data on income tax returns of individuals who are grouped into families. They use sons' earnings in 1999 when they were 33 to 36 years old. The fathers' earnings are averaged over five years, during the early 1980s when the sons were 15 to 19 years old. The estimate for Canada is 0.26. The Swedish data are from Statistic Sweden's multigenerational register. To measure fathers' and sons' earnings, they use pre-tax labor market income from 1974 to 2007 which contains all of the labor market taxable insurance benefits. The sons' earnings are measured from when they were 30 to 40 years old while fathers' earnings are measured from 30 to 60 years old. The estimate for Sweden is 0.25. For the US, Corak et al. (2014) use Income and Program Participation (SIPP) matched to Social Security Administration (SSA)'s administrative earnings records: Summary Earnings Records (SER) and Detailed Earnings Records (DER). The sons' earnings are averaged over years the 2003 to 2007 when they were between the age of 28 and 43. The

fathers' earnings are averaged over the years 1978 to 1986 when they were 30 to 60 years old. The estimate for the US is 0.40.

Yuan (2017) uses panel data from the China Health and Nutrition Survey (CHNS) over the years 1989 to 2009 for estimating China's intergenerational income mobility. The author only uses the households that participate in the survey for over 16 years. He defines income as the sum of job earnings, annual bonuses and other cash, and non-cash incomes. To measure fathers' lifetime income, he averages the available data across all of the years. For the sons, the incomes when they are between 25 and 40 years old are averaged. Taking into consideration that OLS tends to cause underestimation while IV regression tends to cause overestimation of IGE, the author concludes that the income elasticity of China might lie between 0.5 and 0.6.

Landersø and Heckman (2017) examine Danish intergenerational income mobility by using full population register data of the entire 1973-1975 cohort. The parents' income is averaged over nine years when children were 7-15 years old. The children's income is measured at ages 37-39 for the 1973 cohort, ages 36-38 for the 1974 cohort and ages 35-37 for the 1975 cohort. They estimate IGE based on different income measures. Based on gross income, IGE is 0.352. When public transfers are included to gross income, the estimation decreases to 0.271 which shows the significance of redistribution in Denmark. This number further decreases to 0.221, when adding taxation into consideration.

Schnitzlein (2016) uses the German Socio-Economic Panel (SOEP) data to investigate German intergenerational elasticity. His preferred measure is the earnings of fathers and sons from 1984 to 1993. To measure fathers' lifetime earnings, Schnitzlein (2015) averages earnings over 10 years when the fathers were 30 to 55 years old. The earnings of sons are averaged over all years available to reduce measurement error as in the case of fathers and restricted to when the sons were between 35 and 42 years old, in order to avoid lifecycle bias. The IGE estimate for Germany is found to be 0.391. In addition, the author analyses the effect of a lower earnings limit on estimation results. When the lower earnings limit increases from 1200 Euros per year to 4800 Euros per year, the IGE estimate increases to 0.395. A further increase to 9600 Euros per year, results in a raise of the elasticity estimate to 0.436.

Lefranc (2011) analyses intergenerational earnings mobility for males who were born between the years 1931 to 1975 in France. The data are from Formation, Qualification, Profession

(FQP) surveys conducted by INSEE in four different waves: 1970, 1977, 1985, 1993, and 2003. This data set cannot be categorized as panel data set because new samples are drawn for different waves. Fathers' and sons' earnings are predicted at age 40 in order to eliminate lifecycle bias. The author finds that, over the full sample, the estimated intergenerational earnings elasticity in France is 0.53. Moreover, it is found that IGE in France follows a V-shaped pattern. For cohorts born in 1930s intergenerational elasticity is 0.6, then it decreases to 0.45 for the late 1940s and 1950s cohorts and continues with an increase to 0.55 for the early 1970s cohorts.

Piraino (2007) examines the intergenerational income mobility in Italy, using the data from the Bank of Italy's Survey on Household Income and Wealth (SHIW). Fathers' samples are from the years 1977, 1978, and 1979 when they were 30 to 50 years old. The sons' samples are from the years 2000, 2002, and 2004 when they were 30 to 45 years old. The preferred income measure in this study is annual net disposable income which includes self-employment income, wages, salaries, and other incomes from properties owned but excluding incomes from financial assets. Therefore, it is broader than earnings while narrower than the total market income. The estimated intergenerational income elasticity in Italy is found to be 0.554.

Cervini-Plá (2015) uses Survey of Living Conditions (ECV) data which is a part of the European Union Statistics on Income and Living Conditions (EU-SILC). To calculate the permanent income of sons and fathers, the author uses the incomes of sons when they were between 30 to 50 years old; while to estimate father's income, he uses the incomes of fathers when they were between 35 and 55 years old. As a result, intergenerational income elasticity of Spain is estimated as 0.46 whereas intergenerational earnings elasticity is 0.42.

Eberharter (2013) uses data from the British Household Survey (BHPS) in his empirical analysis on the intergenerational income mobility in the United Kingdom. One issue with this database is that it is not possible to identify the exact parent-offspring relations. Therefore, people in the household who have the marital status of "married" or "living with partner" are defined as parents. The parental income is measured when their offspring were 14 to 20 years old and averaged across the years 1991 to 1995. The offspring income is measured across the years 2004 to 2008 when they were older than 24 years old. The preferred income measure in this study is post-government household income which is the sum of pre-government household income, household public transfers, and household social security pensions; minus

household total family taxes. The intergenerational income elasticity for the United Kingdom is estimated as 0.504. Including a set of individual and family characteristics decreases this estimate to 0.426.

Mazumder (2005) uses the 1984 Survey of Income and Program Participation (SIPP) matched to the Social Security Administration's Summary Earnings Records (SER) to estimate intergenerational elasticity for the USA. To deal with lifecycle bias, the offspring earnings are measured when the mean age was 32 and the fathers' earnings are measured when they were 47 years old. In this study, the author argues that even using a 5-year average of earnings is insufficient because the transitory variance in earnings is highly persistent. When the earnings are averaged over 2 years, IGE is 0.308; when averaged over 7 years, it is 0.470 and when averaged over 16 years, it is 0.6 for the pooled sample of sons and daughters.

Table I. Selected Literature on the Estimates of the IGE in Different Countries

Country	Study	Offspring's Age Range	Parent's Age Range	Data Source	Mobility Estimation
Australia	Murray et al. (2018)	28-31	44.47 (average age of parents)	HILDA	0.409
Canada	Corak et al. (2014)	33-36	30-60	Administrative Data, Statistics Canada	0.260
China	Yuan (2017)	25-40	53 (average age of fathers)	China Health and Nutrition Survey (CHNS)	between 0.5 and 0.6
Denmark	Landersø and Heckman (2017)	35–37, 36–38, and 37-39	when the children were 7–15 years old	Register Data, Statistics Denmark	0.352
Germany	Schnitzlein (2016)	35-42	30-55	German Socio-Economic Panel (SOEP)	0.391
France	Lefranc (2011)	28-50	28-50	FQP Surveys conducted by INSEE	0.530
Italy	Piraino (2007)	30-45	30-50	Bank of Italy Survey on Household Income and Wealth (SHIW)	0.554
Spain	Cervini-Plá (2015)	30-50	35-55	Survey of Living Conditions (ECV) and Family Expenditure Survey	0.420
Sweden	Corak et al. (2014)	30-40	30-60	Multigenerational Register, Statistics Sweden	0.250
United Kingdom	Eberharter (2013)	24+	when the children were 14-20 years old	British Household Panel Survey (BHPS)	0.504
USA	Mazumder (2005)	27-35	41 (average age of fathers)	SIPP matched to SER data	0.613
USA	Corak et al. (2014)	28-43	30-60	SIPP matched to SER and DER data	0.400

5.1.2 Log-Linear Correlation (Pearson Correlation) Estimates

The Pearson correlation measures the association between parents' and offspring's income variables whose dispersion is standardized. Therefore, it might represent more robust estimates than intergenerational elasticity especially when there are fluctuations observed in the marginal distributions of parents' or offspring's income over time. The differences between the estimation results of log-linear correlations and elasticities of a country in the same study are due to the variances of income in the parents and offspring's generations. For example; if a country has a higher elasticity than correlation, it shows that income inequality in that country has increased in recent years.

After analysing the intergenerational elasticities, Corak et al. (2014) continue with estimating the Pearson correlations of Canada, Sweden, and the US. Using the same dataset, the authors find the intergenerational correlation in earnings of 0.23 for Canada, 0.21 for Sweden, and 0.26 for the US. The earnings persistence is highest in the US and lowest in Sweden between these countries. However, it can be inferred that the observed differences in mobility are decreased when using log-linear correlation rather than elasticities.

Jäntti et al. (2006) estimate Pearson correlations of sons and daughters of Denmark, Finland, Norway, Sweden, the United Kingdom, and the US. The Danish data are from The Integrated Database for Labour Market Research (IDA). The Finnish data are from the Quinquennial Census Panel. For both countries, the offspring are born between 1958 and 1960 and the preferred income measure is earnings which include salaries, wages, and self-employment income. The Norwegian data are collected from tax returns and other government agencies. Earnings measure is annual and before tax deductions, it includes self-employment income, wages, sick-leave payments, and unemployment benefits. The Swedish data are from administrative registers of Statistics Sweden. The offspring are born in 1962 and the earnings include short-term sickness benefits and self-employment income. The United Kingdom data are from The National Child Development Survey (NCDS). The offspring are born in 1958. Lastly, for the United States, the National Longitudinal Survey of Youth (NLSY) data are used. Earnings include total wage and salary. For all countries, offspring income is measured between the age of 30 to 42, and incomes of the fathers are measured when they are between 35 and 64 years old. The Pearson correlation estimations of sons are 0.089 for Denmark, 0.157 for Finland, 0.138 for Norway, 0.141 for Sweden, 0.198 for the United Kingdom, and

0.357 for the US. Whereas for daughters, they are 0.045 for Denmark, 0.074 for Finland, 0.084 for Norway, 0.102 for Sweden, 0.141 for the United Kingdom, and 0.160 for the US. Correlation estimations for both sons and daughters suggest that intergenerational mobility is lowest in the US while highest in the Scandinavian countries and somewhere in between for the United Kingdom. Among Scandinavian countries, Denmark has the lowest persistence whereas Sweden has the highest. When comparing sons and daughters, it can be inferred that the differences between Pearson correlations of countries are smaller for the daughters. Moreover, there is a change in the ordering of Finland and Norway that, Finland seems to be more mobile than Norway in the case of daughters.

Eberharter (2013) does not report Pearson correlations of Germany, the United Kingdom, and the US. However, following Jäntti and Jenkins (2015), I calculated the approximate log-linear correlations of these three countries by using reported standard deviations of parents' and the offspring's incomes and the estimated income elasticities of both generations on Eberharter (2013)'s Tables 1 and 2. The preferred income measure in this study is disposable income which is post-tax and post-transfer income. The German data are from the German Socio-Economic Panel (SOEP) and the data for the US are from the US Panel Study of Income Dynamics (PSID). The data for the United Kingdom and the limitations of the database which is valid for all three countries are described in the previous subsection. The offspring incomes are averaged across years 2005-2009 for Germany, 2004-2008 for the UK, and 2003-2007 for the US; while parental incomes are averaged across the years 1988-1992 for Germany, 1991-1995 for the UK, and 1987-1991 for the US. The approximate log-linear correlations are 0.38, 0.483, and 0.48 for Germany, the UK, and the US respectively. According to these estimations, the US has higher mobility than the UK while it has lower mobility than Germany.⁷

⁷ Jäntti and Jenkins (2015) state that the orderings of the countries are statistically robust. There is no overlapping on the intervals for the correlations and according to the pairwise t-test, correlations are not the same.

Table II. Selected Literature on the Estimates of the Log-Linear Correlation in Different Countries

Country	Study	Offspring's Age Range	Parent's Age Range	Data Source	Mobility Estimation
Canada	Corak et al. (2014)	33-36	30-60	Administrative Data, Statistics Canada	0.230
Denmark	Jäntti et al. (2006)	30-42	35-64	The Integrated Database for Labour Market Research (IDA)	0.089
Finland	Jäntti et al. (2006)	30-42	35-64	Quinquennial Census Panel	0.157
Germany	Eberharter (2013)	24+	when the children were 14-20 years old	German Socio-Economic Panel (SOEP)	0.380
Norway	Jäntti et al. (2006)	30-42	35-64	Tax Returns and Other Government Agencies	0.138
Sweden	Jäntti et al. (2006)	30-42	35-64	Register Data, Statistics Sweden	0.141
Sweden	Corak et al. (2014)	30-40	30-60	Multigenerational Register, Statistics Sweden	0.210
United Kingdom	Jäntti et al. (2006)	30-42	35-64	The National Child Development Survey (NCDS)	0.198
United Kingdom	Eberharter (2013)	24+	when the children were 14-20 years old	British Household Panel Survey (BHPS)	0.483
USA	Corak et al. (2014)	28-43	30-60	SIPP matched to SER and DER data	0.260
USA	Eberharter (2013)	24+	when the children were 14-20 years old	PSID	0.480
USA	Jäntti et al. (2006)	30-42	35-64	NLSY and PSID	0.357

5.1.3 The Rank Correlation (Spearman Correlation) Estimates

The rank correlation provides information about positional mobility. The impact of income change on positional mobility can only be observed if there is a change that occurs across relative positions of people. In other words, equal absolute changes in income for each person in the population change incomes, yet positional mobility stays constant. Moreover, Spearman correlation does not require linearity and information related to marginal distributions is not significant for this mobility measure (Corak et al, 2014). Therefore, it differs from the Pearson correlation in these aspects. Another difference of the Spearman correlation is that it allows for zero or negative average incomes of parents and offspring.

After estimating the income elasticities, Murray et al. (2018) continue with investigating the rank correlation of Australia. Using the same panel dataset, the authors estimate the household rank correlation as 0.273. There is no conclusive result related to the impact of lifecycle bias. However, it is found that rank correlation is fairly robust to attenuation bias. There is approximately 9% increase observed in the rank correlation estimation as the parents' income is averaged over 5 years rather than 1 year. Whereas, the same procedure leads to more than 40% increase in income elasticity estimates.

Corak et al. (2014) lastly estimate the intergenerational percentile ranking correlation in earnings of Canada, Sweden, and the US in their study. The authors find the father-son Spearman correlations as 0.24 for Canada, 0.30 for Sweden, and 0.30 for the US. According to the estimation results, Sweden and the US are identical regarding the intergenerational earnings mobility and they are less mobile than Canada.

Bratsberg et al. (2017) examine the income rank mobility in Germany and Norway. The German data are from the German Socio-Economic Panel. The preferred income measure in the study is the average annual pre-tax household income. The offspring income is measured throughout the years 2001 to 2012 when they were aged between 25 and 55. The parents' income is measured between 1984 and 1986. The Norwegian data are from full population administrative data of Statistics Norway. The offspring income is averaged over the years from 1996 to 2006 when they were between 32 and 49 years old. The parental income is from the years 1987, 1979, and 1980. For both countries, parental income is measured when they were 28 to 60 years old. The rank correlations estimates are 0.245 for Germany and 0.223 for Norway.

Heidrich (2017) uses the data from the Swedish Initiative for Research on Microdata in the Social and Medical Sciences (SIMSAM) to investigate the intergenerational income rank correlations in Sweden. The parental income is measured when they were aged between 34 and 50; whereas, the offspring income is measured when they were aged between 32 and 34. The Spearman correlation estimation for Sweden is found to be 0.197.

Gregg et al. (2017) use the National Child Development Study (NCDS) data to investigate rank mobility in the United Kingdom. The family income is reported when the sons are aged 16, while the lifetime earnings of sons are measured when they were aged between 23 and 50. The authors estimate the rank-rank coefficient without including sons' period of worklessness. The estimate is 0.180. Then they include the period of worklessness into the analysis, the estimate increases to 0.194.

Chetty et al. (2014) estimate income rank mobility in the United States by using the data from Internal Revenue Service Databank. The offspring are born in the years 1980 to 1982. Their income is measured in 2011 and 2012 when they were 29 to 32 years old. The parental income is averaged between the years 1996 and 2000. The preferred income measure in the study includes labor earnings, capital income, unemployment insurance, disability benefits, and social security. Moreover, it is measured before the employee-level payroll taxes and individual income taxes are deducted. The estimation for the US is 0.287.

Mazumder (2015) uses the PSID data to analyse income rank mobility in the United States. The parental income is measured between the age of 25 and 55 whereas the offspring income is measured between the ages 35 and 45. In order to minimize the lifecycle bias, incomes of the both generation centred at the age of 40. The author reports the estimation as around 0.4 or higher, altering with the length of the time average of incomes.

Dahl and DeLeire (2008) use data from 1984 SIPP matched to SER and DER. Fathers' earnings are from the years 1951 to 2004 when they were between 20 and 55 years old. The sons' earnings are averaged from age 35 to 37. Their intergenerational income rank mobility estimate for the United States is 0.292.

Table III. Selected Literature on the Estimates of the Rank Correlation in Different Countries

Country	Study	Offspring's Age Range	Parent's Age Range	Data Source	Mobility Estimation
Australia	Murray et al. (2018)	28-31	44.47 (average age of parents)	HILDA	0.273
Canada	Corak et al. (2014)	33-36	30-60	Administrative Data, Statistics Canada	0.240
Germany	Bratsberg et al. (2017)	25-55	28-60	German Socio-Economic Panel (SOEP)	0.245
Norway	Bratsberg et al. (2017)	32-49	28-60	Full Population Administrative Data, Statistics Norway	0.223
Sweden	Corak et al. (2014)	30-40	30-60	Multigenerational Register, Statistics Sweden	0.300
Sweden	Heidrich (2017)	32-34	34-50	SIMSAM	0.197
United Kingdom	Gregg et al. (2017)	23-50	when the children were 16 years old	National Child Development Study (NCDS)	0.194
USA	Chetty et al. (2014)	29-32	when the children were 15-19 years old	IRS Databank	0.287
USA	Mazumder (2015)	35-45	25-55	PSID	around 0.4 or higher
USA	Corak et al. (2014)	28-43	30-60	SIPP matched to SSA	0.300
USA	Dahl and DeLeire (2008)	35-37	20-55	SIPP matched to DER	0.292

5.2 Intergenerational Wealth Mobility

Boserup et al. (2017) use data from Statistics Denmark's administrative registers. The preferred wealth mobility measure is the rank correlation. The children were aged between 45 and 50 in 2010. Their wealth is measured over the period 2009 to 2011. The parental wealth is measured over the period 1984 to 1986 when their mean age was 47.9. The authors' estimate is 0.272 for Denmark. In addition, the authors examine the wealth correlation over the lifecycle and find out a pattern that is U-shaped. The rank estimation starts from 0.35 at the beginning of the twenties and then decreases to a level close to 0.17 at mid-twenties and then increases to a point around 0.27 at the forties.

Fagereng et al. (2018) examine the intergenerational wealth mobility of Norway. The data are from Statistics Norway's administrative registers and tax records. The preferred wealth measure in the study is net wealth which is the sum of financial and non-financial assets; minus liabilities. The net wealth of parents is measured over the years 1994 to 1996 and the offspring wealth is measured between 2012 and 2014. In the analysis, the offspring were born between 1965 and 1986 and the average age of them in 2014 is 39.04; whereas, the average age of mothers is 45.66 and the average age of the fathers is 48.64 in 1994. The linear rank correlation is found to be 0.244.

Black et al. (2017) investigate intergenerational rank correlation of wealth in Sweden by using data from Statistics Sweden's Swedish Wealth Data. The preferred wealth measure is non-retirement total net wealth which includes housing and financial wealth. The offspring wealth is measured in 2006 when they were aged between 36 and 56 whereas the average age of parents was 68.6 when their wealth was measured in 1999. The wealth mobility estimate is 0.347 for Sweden.

Adermon et al. (2018) examine multigenerational wealth mobility in Sweden. The data are from Malmö county archives for the first two generations and Statistics Sweden's Wealth Register for the third generation. The first generation's observed taxable wealth is measured in 1945 and 1952 when they were around 48 and 55 years old. The second generation's taxable wealth is observed in 1985, 1988, and 1991 when they were between 57 and 63 years old. The third generation was around 42 and 49 years old when their wealth is measured in 1999 and 2006. The rank correlation between the first and second generations is 0.296 while

it is 0.391 between the second and third generations. Lastly, the estimation is 0.166 between the first and third generations; in other words, between the children and their grandparents.

Charles and Hurst (2003) use the PSID data for investigating intergenerational wealth mobility in the US. The preferred wealth mobility measure is intergenerational elasticity; thus, the sample is limited to positive wealth. Parental wealth is the average of the wealth reported in the years 1984 and 1989 when they are alive and not retired. The average age of parents is 52. The children's wealth is measured in 1999 when they are between the age of 25 and 65. The study does not analyse the effect of bequests; therefore, at least one parent is alive in 1999. The estimated intergenerational wealth elasticity is 0.365. When the authors decompose the wealth elasticity; 52% of it explained by income and the rest is accounted for portfolio choice, education, previous gifts, and expected bequests.

Conley and Glauber (2008) examine the intergenerational wealth elasticity of the US by using data from the PSID. The parents' wealth is measured in 1984 when the children were 6 to 21 years old; whereas, the children's wealth is measured from 1999 to 2003 when they were between 24 and 40 years old. The wealth elasticity estimation is 0.28. The authors address that the most important predictor of wealth is the children's own family income, which is the sum of the incomes of grown-up children and their spouses.

Pfeffer and Killewald (2018) use PSID data for investigating the multigenerational wealth mobility in the US. The preferred wealth mobility measure is the rank correlation. The wealth is measured when the offspring were aged between 25 and 64 in 2013 whereas their parents were aged between 25 and 64 in 1984. The wealth of their grandparents' are measured in 1984 and 1989. The wealth is equal to family net worth which is the sum of all financial assets, home equity, and real assets; minus financial obligations. The authors estimate offspring-parent wealth correlation first and then re-estimate the same correlation in a multigenerational setting. The rank correlation of wealth is estimated as 0.39, adding grandparental wealth lowers this estimate to 0.32. The estimated rank correlation between offspring and their grandparents is 0.23.

Table IV. Selected Literature on the Estimates of the Intergenerational Wealth Mobility in Different Countries

Country	Study	Offspring's Age Range	Parent's Age Range	Data Source	Mobility Estimation
Denmark	Boserup et al. (2017)	45-50	47.9 (average age of parents)	Administrative Data, Statistics Denmark	0.272
Norway	Fagereng et al. (2018)	39.04 (average age of offspring)	45.66 (average age of mothers) and 48.64 (average age of fathers)	Statistics Norway	0.244
Sweden	Black et al. (2017)	36-56	68.6 (average age of parents)	Swedish Wealth Data, Statistics Sweden	0.347
Sweden	Adermon et al. (2018)	42-49	57-63	Wealth Register, Statistics Sweden	0.391
USA	Charles and Hurst (2003)	25-65	52 (average age of parents)	PSID	0.365
USA	Conley and Glauber (2008)	24-40	when the children were 6-21 years old	PSID	0.280
USA	Pfeffer and Killeward (2018)	25-64	25-64	PSID	0.320

5.3 Intergenerational Consumption Mobility

Walckirch et al. (2004) use data from the PSID to investigate intergenerational consumption mobility in the United States. The authors interested in the correlation between parents and child split-offs who are the children that have left their parents' house and set up their own. The consumption data are observed over the years 1968 to 1992. The average age of parents is 62.9 while it is 35 for split-offs in 1992. The authors only report correlation estimates of food consumed away from home. The correlation is the highest with an estimate of 0.198 when it is measured 1 to 5 years after the split; while, it is the lowest with an estimate of 0.146 when it is measured more than 21 years after the split.

Charles et al. (2014) use the PSID data which are collected in the years 2005, 2007, and 2009 to estimate intergenerational mobility in the United States. The median age of parents in the analysis is 38, whereas the median child is 38. They find intergenerational elasticity of consumption expenditures as 0.275; once it is controlled for income correlation, the estimation decreases to 0.085.

Attanasio and Pistaferri (2016) use the PSID data to observe the intergenerational rank correlation between fathers and their children in the United States. The consumption data are from the years 1999 to 2013. The authors define consumption as the sum of home and car insurance, health, education, child care, rent, clothing, spending on food, utilities, gasoline, parking and transportation, car repair, vacation, entertainment, and monetary value of food stamps. The authors do not report the numerical value of the rank correlation estimate of consumption; rather they state that consumption is more mobile than income.

Bruze (2018) examines the intergenerational consumption mobility of Denmark by using the Danish Expenditure Survey and Danish registries. The consumption data are observed over the years 1995 to 2009. The mean ages of parents are between 54-68 while the mean ages of children are 30 and 44 in the selected sample. The author uses total expenditures, housing conditions, dental expenditures, and car ownership as the proxies for household consumption. The intergenerational elasticity of consumption is 0.418 and the intergenerational rank correlation for consumption is 0.390.

6 Discussions

In this section, I would like to provide discussions related to intergenerational mobility studies that I've covered in section 5. I will discuss income, wealth and consumption mobility studies separately for different mobility measures as well as with each other; in order to find out the interaction among them. The section starts with comparing intergenerational income mobility studies that use elasticity as the preferred mobility measure. It is followed by comparisons of income mobility studies that use the Pearson correlation and rank correlation; and continues with intergenerational wealth and consumption mobility studies, respectively.

The comparability between studies is highly problematic since estimates are sensitive to various factors (Plá, 2015). Firstly, income measures. Some studies use earnings rather than income. According to Mazumder (2005), earnings mobility might be a better measure of mobility because earning capacity cannot be transferred to offspring as the way a house can. In all of the estimations in the study, Mazumder (2005) finds that IGE estimations made by using income have higher values than estimations using earnings. Moreover, even the studies use the same measure; they differ because some investigate the mobility according to father-son pairs, while others investigate for parents-son or parents-offspring pairs. Secondly, age ranges and longitude of years of income averaged. In order to deal with lifecycle bias, most of the studies choose offspring age around 30s and parental age around 40s. Furthermore, to decrease attenuation bias, studies mostly average income over 5 years. However, since these are different in each study, the degrees of biases present in the studies are also different. Thirdly, the adequacy and comparability of datasets. As discussed in data sources section, using survey or administrative data have an impact on mobility results. The data used in different countries and studies might not be equivalent due to the differences in sample selections, cohort years and variable definitions.

Bearing all these in mind, it can still be inferred from Table 1 that Scandinavian welfare states (Denmark, Sweden) have the highest income mobility with the lowest intergenerational elasticity estimates. They are followed by Canada which is also known as a welfare state. Compared to Scandinavian countries, Southern European countries (France, Italy and Spain) have lower intergenerational income mobility. In fact, Italy is the second most immobile country whose estimate is similar to China. For the United States, different elasticity estimates are reported from two studies. This difference is stemming from three factors.

Firstly, Mazumder (2005) uses SER data and do not have access to non-topcoded DER data as Corak et al. (2014). Secondly, Mazumder (2005) uses only the 1984 SIPP while Corak et al. (2014) prefer to use observations of the older cohorts less. Lastly, Corak et al. (2014) average income over 9 years. The authors state that when they use a period of 16 years as Mazumder (2005) does, they find similar results. Therefore, the most immobile country is the US which was once seen as the land of opportunity where family background has no significant effect on a child's chances of success.

When comparing the Pearson correlation estimates of income of Corak et al. (2014), Jäntti et al. (2006) and Eberharter (2013), it can be observed that Jäntti et al. (2006) have the lowest estimates; while, Eberharter (2013) has the highest estimates. These differences in the estimates might arise due to several reasons. Firstly, Eberharter (2013) uses data from surveys; whereas, the other studies mostly use administrative datasets. Secondly, the average ages used in the sample is the lowest in Eberharter (2013), which might cause lifecycle bias. These two factors possibly lead to higher estimation results. Thirdly, Jäntti et al. (2006) use earnings rather than income and the authors average earnings only over 2 years while the other studies use 5 year averages of income, which might cause lower estimates.

Despite the highly divergent ranges of Pearson correlation estimations, if the countries within the same study are compared; it can be inferred that income and earnings mobility in Scandinavian countries are higher than the UK and the US. However, there is no consensus between studies concerning mobility levels of the UK and the US. Jäntti et al. (2006) report significantly higher estimates for the US; while, Eberharter (2013) finds similar Pearson correlations for these two countries yet a little higher levels in the UK.

The last intergenerational income mobility measure used in the covered studies is the rank mobility. The authors of the studies in Table 3 suggest that the rank correlation estimates are robust across different samples and specifications. Therefore, the rank correlation might be more suitable for cross-country comparisons. It is seen from Table 3 that the income mobility estimates of different countries are closer to each other than estimates of studies using other two measures. As in Table 1 and Table 2, Canada and Scandinavian countries have the highest mobilities which are followed by Germany, Australia, and the US. However, in Table 3, Corak et al. (2014)'s estimate for Sweden and (2014) Gregg et al. (2017)'s estimate for the UK are not in line with the generalization made by using other income mobility measures. This time, the UK has the highest mobility among other countries whereas Sweden has the

lowest mobility rate with the United States. Nevertheless, this does not necessarily mean that the offspring of low-income families from the UK do better than children in other countries in absolute terms. Since the ranks are constructed within each country, it may be the case that an upward movement in income rank distribution in the US might result in improving living standards more than the same movement observed in the UK. Corak et al. (2014) argue that observed same rank correlation estimates of Sweden and the US are because of downward bias present in the US's estimation due to measurement error and small sample size. Therefore, it can be inferred that even with the more robust nature of rank correlation measure, biases still exist and cross-country comparisons suffer from the biases as well as different specifications and samples.

When it comes to intergenerational wealth mobility studies, these studies prefer to measure the wealth of offspring and their parents at a later point in their lives in order to be able to make more accurate mid-life wealth estimates. These studies are differentiated from each other regarding several aspects. Some of the studies use wealth elasticity measure and exclude zero or negative wealth observations from their samples; while, others use rank correlations. Some of them use administrative data while others use survey data. Indeed, using survey data might be a better choice in order to be able to capture inter vivos wealth transfers from parents which are not included in administrative data because they are non-taxable. Moreover, some of the studies analyse wealth mobility over two generations; whereas, in others, a multigenerational approach is used. Among these studies, the authors who analyse wealth mobility in a multigenerational setting have different reasons to do so. Pfeffer and Killewald (2018) argue that intergenerational wealth persistence is understated when only the relation between children and parents is considered. On the contrary, Adermon et al. (2018) argue that studies using only two generations overestimate wealth mobility since grandparental wealth has a weak but positive effect on grandparental wealth. These conflicting results might be due to the ages of generations used in the studies. It should be remembered that as the children and their parents are younger; the grandparental wealth becomes more important.

Bearing these differences in mind, it can be deduced from Table 4 that Denmark and Norway are the most mobile countries in wealth. The estimates of Sweden are rather surprising. Since Sweden is always associated with promoting equality of opportunity; one can expect lower estimation results as other Scandinavian welfare states. Nevertheless, Sweden has the lowest wealth mobility with estimates even higher than the United States.

Lastly, the studies about intergenerational consumption mobility investigate to what extent children inherit their parents' living standards. Despite its potential importance, there are not many consumption mobility studies in the literature due to data limitations. The studies about the United States draw different conclusions when comparing consumption and income mobility. Charles et al. (2014) state that consumption mobility in the US is not significantly greater than income mobility. On the contrary, Attanasio and Pistaferri (2016) find that consumption is more mobile. For Denmark, Bruze (2018) argues that consumption mobility is less than income mobility. The author makes significantly higher consumption mobility estimates than the United States with using both elasticity and rank correlation. Therefore, according to these studies, Denmark is less mobile than the United States in terms of consumption.

In the light of the discussion above, I would also argue the similarity between intergenerational wealth and consumption mobility. Decomposition of these mobilities shows that they are mostly explained by income. Moreover, both of them are most likely to be associated with children's mimicry of parental financial decision-making behaviour. For example, children can learn from their parents how much to save. Therefore, their consumption behaviour as well as investment behaviour, which eventually creates their wealth, are affected. Another possible mechanism might be inter vivos transfers that affect children's wealth accumulation and consumption levels. The children who get financial transfers from their parents might converge their consumption and wealth levels closer to their parents' levels. Furthermore, wealth mobility might also depend on parents' portfolio composition and preference for risk-taking. The children whose parents are risk-loving might mimic their parents, invest in risky assets and get higher returns. This behaviour results in lower intergenerational wealth mobility levels in countries.

7 Conclusion

This study provides a summary of the literature on intergenerational income, wealth and consumption mobility. In order to estimate the intergenerational mobility in a country, studies utilize different intergenerational mobility measures. The most commonly used mobility measures in the literature are the intergenerational elasticity, the log-linear correlation (Pearson correlation), the rank correlation (Spearman correlation), and transition matrices. These mobility measures provide complementary perspectives on intergenerational mobility.

International elasticity and log-linear correlation examine to what extent the parents' incomes affect children's income; therefore, they can be described as more consequential measures. Whereas, rank-based measures capture the relative association between the children's and their parents' positions in the marginal distributions.

Besides their conceptual differences in intergenerational mobility, these four mobility measures have also differentiated in terms of their robustness to attenuation and lifecycle biases. The intergenerational elasticity is attenuated by only the measurement error in parental income (wealth or consumption); while, the log-linear correlation, the rank correlation, and transition matrices are attenuated by the mismeasurement of both children's and their parent's income (wealth or consumption). Lifecycle bias is observed in all four intergenerational mobility measures. It affects intergenerational elasticity estimates strongly; whereas, rank-based estimates are more robust to lifecycle and attenuation biases. In order to minimize these biases, multi-year averages of lifetime income (wealth or consumption) histories of parents and children might be used.

To study intergenerational mobility, different data sources such as surveys, tax records, and other administrative datasets are used. Each data source is preferred according to its distinctive qualities. Surveys are known for capturing rich socioeconomic status information; tax records are presumed to be very accurate and have high coverage; and administrative datasets of government benefit programs provide income and consumption information that cannot be fully captured by any other data sources. Since each data source has its weaknesses and strengths, researches can combine the administrative and survey data sources to construct more robust estimates.

According to the intergenerational income mobility literature which is using the elasticity and log-linear correlation, Scandinavian countries are the most mobile countries; whereas, the United Kingdom and the United States are the least mobile ones. On the contrary, intergenerational wealth mobility studies and intergenerational income mobility studies which are utilizing rank correlation report that Sweden is found to be even less mobile than the United States. Similarly, intergenerational consumption mobility studies estimate higher persistence of consumption across generations for Denmark than the United States. Nevertheless, drawing firm conclusions regarding intergenerational mobility levels of different countries should be avoided. Since each study has nuanced approaches to intergenerational mobility, comparability between studies is highly problematic.

References

- Abowd, J. M., & Stinson, M. H. (2013). Estimating measurement error in annual job earnings: A comparison of survey and administrative data. *Review of Economics and Statistics*, 95(5), 1451-1467.
- Adermon, A., Lindahl, M., & Waldenström, D. (2018). Intergenerational wealth mobility and the role of inheritance: Evidence from multiple generations. *The Economic Journal*, 128(612), F482-F513.
- Atkinson, A. (1981). On Intergenerational Income Mobility in Britain. *Journal of Post Keynesian Economics*, 3(2), 194-218.
- Attanasio, O. P., & Pistaferri, L. (2016). Consumption inequality. *Journal of Economic Perspectives*, 30(2), 3-28.
- Black, S. E., & Devereux, P. J. (2011). Recent Developments in Intergenerational Mobility. *Handbook of Labor Economics*, 4, 1487-1541.
- Black, S. E., Devereux, P. J., Lundborg, P., & Majlesi, K. (2017). Poor little rich kids? The determinants of the intergenerational transmission of wealth.
- Boserup, S. H., Kopczuk, W., & Kreiner, C. T. (2017). *Intergenerational wealth formation over the life cycle: Evidence from danish wealth records 1984-2013*. Working Paper, University of Copenhagen.
- Bratberg, E., Davis, J., Mazumder, B., Nybom, M., Schnitzlein, D. D., & Vaage, K. (2017). A comparison of intergenerational mobility curves in Germany, Norway, Sweden, and the US. *The Scandinavian Journal of Economics*, 119(1), 72-101.
- Bruze, G. (2018). Intergenerational mobility: New evidence from consumption data. *Journal of Applied Econometrics*, 33(4), 580-593.
- Caballé, J. (2016). Intergenerational mobility: measurement and the role of borrowing constraints and inherited tastes. *SERIEs*, 7(4), 393-420.
- Cervini-Plá, M. (2015). Intergenerational Earnings and Income Mobility in Spain. *Review of Income and Wealth*, 61(4), 812-828.

- Charles, K. K., Danziger, S., Li, G., & Schoeni, R. (2014). The intergenerational correlation of consumption expenditures. *American Economic Review*, *104*(5), 136-40.
- Charles, K. K., & Hurst, E. (2003). The correlation of wealth across generations. *Journal of political Economy*, *111*(6), 1155-1182.
- Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, *129*(4), 1553-1623.
- Conley, D., & Glauber, R. (2008). Wealth mobility and volatility in black and white. *Washington DC: Center for American Progress*.
- Corak, M., Lindquist, M. J., & Mazumder, B. (2014). A comparison of upward and downward intergenerational mobility in Canada, Sweden and the United States. *Labour Economics*, *30*, 185-200.
- d'Addio, A. C. (2007). Intergenerational transmission of disadvantage: mobility or immobility across generations?.
- Dahl, M. W., & DeLeire, T. (2008). *The association between children's earnings and fathers' lifetime earnings: estimates using administrative data*. University of Wisconsin-Madison, Institute for Research on Poverty.
- Dearden, L., Machin, S., & Reed, H. (1997). Intergenerational mobility in Britain. *The Economic Journal*, *107*(440), 47-66.
- Deaton, A., & Zaidi, S. (2002). *Guidelines for constructing consumption aggregates for welfare analysis* (Vol. 135). World Bank Publications.
- Eberharter, V. V. (2013). The Intergenerational Dynamics of Social Inequality—Empirical Evidence from Europe and the United States.
- Fagereng, A., Mogstad, M., & Ronning, M. (2018). Why do wealthy parents have wealthy children?. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2019-22).

- Fitzgerald, J. M. (2011). Attrition in models of intergenerational links using the PSID with extensions to health and to sibling models. *The BE journal of economic analysis & policy*, 11(3).
- Frick, J. R., Jenkins, S. P., Lillard, D. R., Lipps, O., & Wooden, M. (2007). The Cross-National Equivalent File (CNEF) and its member country household panel studies. *Schmollers Jahrbuch: Zeitschrift für Wirtschafts-und Sozialwissenschaften*, 127(4), 627-654.
- Friedman, M. (1957). Introduction to "A Theory of the Consumption Function". *NBER Chapters*, 1-6.
- Grawe, N. D. (2006). Lifecycle bias in estimates of intergenerational earnings persistence. *Labour economics*, 13(5), 551-570.
- Gregg, P., Macmillan, L., & Vittori, C. (2017). Moving towards estimating sons' lifetime intergenerational economic mobility in the UK. *Oxford bulletin of economics and statistics*, 79(1), 79-100.
- Haider, S., & Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *American Economic Review*, 96(4), 1308-1320.
- Heidrich, S. (2017). Intergenerational mobility in Sweden: a regional perspective. *Journal of Population Economics*, 30(4), 1241-1280.
- Jäntti, M., Bratsberg, B., Roed, K., Raaum, O., Naylor, R., Osterbacka, E., ... & Eriksson, T. (2006). American exceptionalism in a new light: a comparison of intergenerational earnings mobility in the Nordic countries, the United Kingdom and the United States.
- Jäntti, M., & Jenkins, S. P. (2015). Income mobility. In *Handbook of income distribution* (Vol. 2, pp. 807-935). Elsevier.
- Jenkins, S. (1987). Snapshots versus movies: 'lifecycle biases' and the estimation of intergenerational earnings inheritance. *European Economic Review*, 31(5), 1149-1158.
- Landersø, R., & Heckman, J. J. (2017). The Scandinavian fantasy: The sources of intergenerational mobility in Denmark and the US. *The Scandinavian journal of economics*, 119(1), 178-230.

- Lefranc, A. (2011). Educational expansion, earnings compression and changes in intergenerational economic mobility: Evidence from French cohorts, 1931-1976. *Unpublished manuscript, University of Cergy.*
- Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data. *Review of Economics and Statistics*, 87(2), 235-255.
- Mazumder, B. (2015). Estimating the intergenerational elasticity and rank association in the US: Overcoming the current limitations of tax data.
- Mazumder, B. (2016). Estimating the Intergenerational Elasticity and Rank Association in the United States: Overcoming the Current Limitations of Tax Data. *Research in Labor Economics*, 43, 83-129.
- Mazumder, B. (2018). Intergenerational mobility in the United States: What we have learned from the PSID. *The Annals of the American Academy of Political and Social Science*, 680(1), 213-234.
- Medalia, C., Meyer, B. D., O'Hara, A. B., & Wu, D. (2019). Linking Survey and Administrative Data to Measure Income, Inequality, and Mobility. *International Journal of Population Data Science*, 4(1).
- Menchik, P. L. (1979). Inter-generational transmission of inequality: an empirical study of wealth mobility. *Economica*, 46(184), 349-362.
- Meyer, B. D., & Sullivan, J. X. (2003). *Measuring the well-being of the poor using income and consumption* (No. w9760). National Bureau of Economic Research.
- Mitnik, P., Bryant, V., Grusky, D. B., & Weber, M. (2014). New Estimates of Intergenerational Income Mobility Using Administrative Data. *Statistics of Income, Internal Revenue Service. mimeo (in preparation).*
- Murray, C., Clark, R. G., Mendolia, S., & Siminski, P. (2018). Direct measures of intergenerational income mobility for Australia. *Economic Record*, 94(307), 445-468.
- Nilsen, Ø. A., Vaage, K., Aakvik, A., & Jacobsen, K. (2008). Estimates of intergenerational elasticities based on lifetime earnings.

- Nybom, M., & Stuhler, J. (2017). Biases in standard measures of intergenerational income dependence. *Journal of Human Resources*, 52(3), 800-825.
- Pfeffer, F. T., & Killewald, A. (2018). Generations of advantage. Multigenerational correlations in family wealth. *Social Forces*, 96(4), 1411-1442.
- Piraino, P. (2007). Comparable estimates of intergenerational income mobility in Italy. *The BE Journal of Economic Analysis & Policy*, 7(2).
- O'Neill, D., Sweetman, O., & Van de gaer, D. (2007). The effects of measurement error and omitted variables when using transition matrices to measure intergenerational mobility. *Journal of Economic Inequality*, 5(2), 159-178.
- Schnitzlein, D. D. (2016). A New Look at Intergenerational Mobility in Germany Compared to the U. S. *Review of Income and Wealth*, 62(4), 650-667.
- Schoeni, R. F., & Wiemers, E. E. (2015). The implications of selective attrition for estimates of intergenerational elasticity of family income. *The Journal of Economic Inequality*, 13(3), 351-372.
- Solon, G. (1989). Biases in the estimation of intergenerational earnings correlations. *The Review of Economics and Statistics*, 172-174.
- Solon, G. (1992). Intergenerational income mobility in the United States. *The American Economic Review*, 393-408.
- Solon, G. (1999). Intergenerational mobility in the labor market. In *Handbook of labor economics* (Vol. 3, pp. 1761-1800). Elsevier.
- Waldkirch, A., Ng, S., & Cox, D. (2004). Intergenerational linkages in consumption behavior. *Journal of Human Resources*, 39(2), 355-381.
- Yuan, W. (2017). The Sins of the Fathers: Intergenerational Income Mobility in China. *Review of Income and Wealth*, 63(2), 219-233.
- Zimmerman, D. J. (1992). Regression toward mediocrity in economic stature. *The American Economic Review*, 409-429.