Intergenerational Mobility in Switzerland
A Comparison of Methodological Approaches

Ben Jann and Simon Seiler

Institute of Sociology, University of Bern, jann@soz.unibe.ch

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Overview

- Introduction
- Data
- Methods and analysis
  - Mobility tables
  - Log-linear models
  - PRE approach
- Summary
Introduction

- Equal opportunity principle in meritocratic societies
  - The social position an individual can achieve should only depend on own effort/merit, but not on ascriptive characteristics such as, e.g., social origin or gender.

- Societies in which equal opportunity is granted are called “open”. They are characterized by high social mobility.
  - Mobility is usually understood as “equality of opportunity” – the outcomes may be unequal, but everyone, regardless of starting point, can have the same opportunity to get a good result. (Hout 2004: 970)

- To evaluate the openness of a society we can therefore analyze the degree to which the social position of an individual depends on the status of the individual’s parents.
Introduction

- International research shows that in most countries sizable effects of social origin do exist and persist over time. This indicates that in these societies the principle of equal opportunity is violated.
- Yet, only little research on the topic exists for Switzerland. In particular, from the existing literature it is unclear whether social mobility increased - as asserted by modernization theories (e.g. Lipset/Bendix 1959, Kerr et al. 1960, Blau/Duncan 1967) - or not.
- We therefore started a project to analyze the changes in social mobility in Switzerland over time.
- In particular, we analyze how *educational attainment* and *social class* of respondents depend on the education and class of their parents.
Data

- Required are data that contain the relevant status variables for the respondents as well as information about education and occupation of parents.
- Most large-scale surveys, such as the official surveys by the Federal Statistical Office, do not contain information on parents.
- Nonetheless, we were able to identify a number of surveys that can be used for these types of analyses. The results below are based on a selection of these surveys. More surveys are available (especially some older ones) and will be incorporated in future.
- We harmonized the variables in the different surveys to build a common database that can be analyzed in terms of birth cohorts. The age range of respondents we restricted to 30 through 69.
Data: Surveys

<table>
<thead>
<tr>
<th>Survey</th>
<th>Year/Wave</th>
<th>N</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Les Suisses et leur société</td>
<td>1991</td>
<td>1331</td>
<td>CH91</td>
</tr>
<tr>
<td>Schweizer Umweltsurvey</td>
<td>1994</td>
<td>2233</td>
<td>UWS94</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>1973</td>
<td>UWS07</td>
</tr>
<tr>
<td>ISSP “Social inequality”</td>
<td>1999</td>
<td>972</td>
<td>ISSP99</td>
</tr>
<tr>
<td>Swiss Household Panel</td>
<td>1999</td>
<td>5365</td>
<td>SHP99</td>
</tr>
<tr>
<td></td>
<td>2004</td>
<td>2420</td>
<td>SHP04</td>
</tr>
<tr>
<td>European Social Survey</td>
<td>2002</td>
<td>1450</td>
<td>ESS02</td>
</tr>
<tr>
<td></td>
<td>2004</td>
<td>1457</td>
<td>ESS04</td>
</tr>
<tr>
<td></td>
<td>2006</td>
<td>1267</td>
<td>ESS06</td>
</tr>
<tr>
<td></td>
<td>2008</td>
<td>1187</td>
<td>ESS08</td>
</tr>
<tr>
<td></td>
<td>2010</td>
<td>985</td>
<td>ESS10</td>
</tr>
<tr>
<td></td>
<td>2012</td>
<td>945</td>
<td>ESS12</td>
</tr>
<tr>
<td>MOSAiCH</td>
<td>2005</td>
<td>741</td>
<td>MOS05</td>
</tr>
<tr>
<td></td>
<td>2011</td>
<td>819</td>
<td>MOS11</td>
</tr>
<tr>
<td>European Values Study 2008</td>
<td>2008</td>
<td>830</td>
<td>EVS08</td>
</tr>
<tr>
<td>Statistics on Income and Living Conditions 2011</td>
<td>2011</td>
<td>6753</td>
<td>SILC11</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td>33068</td>
<td></td>
</tr>
</tbody>
</table>
Data: Number of Observations by Birthyear

![Number of Observations by Birthyear](image-url)
## Data: Education

<table>
<thead>
<tr>
<th>Education categorie</th>
<th>Included levels of education</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  compulsory or less</td>
<td>No formal education; compulsory education; one year vocational training</td>
</tr>
<tr>
<td>2  secondary vocational</td>
<td>Vocational training and education; general education without baccalaureate</td>
</tr>
<tr>
<td>3  secondary general</td>
<td>General education with baccalaureate; vocational baccalaureate; college of education (without university of education)</td>
</tr>
<tr>
<td>4  tertiary vocational</td>
<td>Professional education and training; advanced federal professional and training diploma; professional education college; university of applied sciences; university of education</td>
</tr>
<tr>
<td>5  tertiary academic</td>
<td>University; federal institute of technology</td>
</tr>
</tbody>
</table>
Data: Education by birth cohorts

The bar charts illustrate the percentage distribution of male and female individuals across different birth cohorts from 1922-45 to 1969-82, categorized by education level:

- **Tertiary academic**
- **Tertiary vocational**
- **Secondary general**
- **Secondary vocational**
- **Compulsory or less**

Each bar is divided into segments representing these education levels for each cohort. The vertical axis represents the percentage range from 0% to 100%.
Data: Parent’s education by respondents birth cohort

01020304050607080901001922-451946-541955-611962-681969-82tertiary academictertiary vocationalsecondary generalsecondary vocationalcompulsory or less
## Data: Class (EGP)

<table>
<thead>
<tr>
<th>EGP Class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Upper service Higher-grade professionals, administrators and officials; managers in large industrial establishments; large proprietors</td>
</tr>
<tr>
<td>II</td>
<td>Lower service Lower-grade professionals, administrators and officials; higher-grade technicians; managers in small business and industrial establishments; supervisors of nonmanual employees</td>
</tr>
<tr>
<td>IIIII</td>
<td>Non-manual employee Routine non-manual employees in administration and commerce; sales personnel; other rank-and-file service workers</td>
</tr>
<tr>
<td>IVa,b</td>
<td>Self-employed Small proprietors, artisans, etc., with employees (IVa); without employees (IVb)</td>
</tr>
<tr>
<td>IVc, VIIb</td>
<td>Farmers Farmers and smallholders, self-employed fishermen (IVc); Agricultural workers (VIIb)</td>
</tr>
<tr>
<td>V, VI</td>
<td>Technicians and skilled workers Lower-grade technicians; supervisors of manual workers; skilled manual workers</td>
</tr>
<tr>
<td>VIIa,b</td>
<td>Semi-/unskilled workers Semi- and unskilled manual workers</td>
</tr>
</tbody>
</table>

EGP classification following Erikson, Goldthorpe and Portocarero (1983: 307)
Data: Class by birth cohorts

Jann/Seiler (University of Bern) Intergenerational Mobility in Switzerland Lausanne, 11.12.2013
Mobility tables

To study the relation between parent’s characteristics and child’s achievements, so called mobility tables can be used.

A mobility table is a two-way table of, for example, parent’s education against child’s education. The pattern of cell counts in such a table provides evidence about the degree to which child’s education depends on parent’s education.
Relation between respondent’s education and parent’s education (males, birth cohorts 1969-82, N = 2485, column percent)

<table>
<thead>
<tr>
<th>Parent’s education</th>
<th>Respondent’s education</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>compulsory</td>
<td>secondary</td>
<td>tertiary</td>
<td>Total</td>
<td></td>
</tr>
<tr>
<td>compulsory</td>
<td>73.1</td>
<td>25.5</td>
<td>11.7</td>
<td>24.2</td>
<td></td>
</tr>
<tr>
<td>secondary</td>
<td>18.1</td>
<td>62.0</td>
<td>41.7</td>
<td>49.5</td>
<td></td>
</tr>
<tr>
<td>tertiary</td>
<td>8.8</td>
<td>12.6</td>
<td>46.6</td>
<td>26.3</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td></td>
</tr>
<tr>
<td>Row percent</td>
<td>9.3</td>
<td>49.2</td>
<td>41.5</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>
Mobility tables: How much mobility is in this table?

- **Total mobility**
  - Percentage of respondents whose educational achievement is unequal the education of their parents
  - \( \frac{(N - \text{Sum of diagonal})}{N} \)
  - Could also be divided into upward mobility and downward mobility

- **Chance mobility**
  - Expected amount of mobility if respondents’ education is independent from parents’ education

- **Structural mobility**
  - Minimum amount of mobility required to move from parents’ educational distribution to respondents’ educational distribution
  - \( \frac{\text{(Absolute deviations between marginal distributions)}}{2N} \)

- **Circular mobility**: Total mobility – structural mobility

- **Relative mobility**
  - Circular mobility / (Chance mobility – Structural mobility)
Mobility tables: How much mobility is in this table?

- **Total mobility** $T$

$$T = \frac{2485 - (170 + 757 + 480)}{2485} = 43.4\%$$

- **Chance mobility** $I$

$$I = \frac{2485 - \left( \frac{232 \times 602}{2485} + \frac{1222 \times 1229}{2485} + \frac{1031 \times 654}{2485} \right)}{2485} = 62.5\%$$

<table>
<thead>
<tr>
<th>Parent’s education</th>
<th>Respondent’s education</th>
<th>compulsory</th>
<th>secondary</th>
<th>tertiary</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>compulsory</td>
<td>170</td>
<td>311</td>
<td>121</td>
<td>602</td>
<td></td>
</tr>
<tr>
<td>secondary</td>
<td>42</td>
<td>757</td>
<td>430</td>
<td>1229</td>
<td></td>
</tr>
<tr>
<td>tertiary</td>
<td>20</td>
<td>154</td>
<td>480</td>
<td>654</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>232</td>
<td>1222</td>
<td>1031</td>
<td>2485</td>
<td></td>
</tr>
</tbody>
</table>
Mobility tables: How much mobility is in this table?

- **Structural mobility** $S$
  
  \[ S = \frac{|232 - 602| + |1222 - 1229| + |1031 - 654|}{2 \times 2485} = 15.2\% \]

- **Circular mobility** $C$
  
  \[ C = T - S = 43.4\% - 15.2\% = 28.2\% \]

- **Relative mobility** $R$
  
  \[ R = \frac{C}{I - S} = \frac{28.2\%}{(62.5 - 15.2)} = 59.6\% \]

<table>
<thead>
<tr>
<th>Parent’s education</th>
<th>Respondent’s education</th>
<th>compulsory</th>
<th>secondary</th>
<th>tertiary</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>compulsory</td>
<td></td>
<td>170</td>
<td>311</td>
<td>121</td>
<td>602</td>
</tr>
<tr>
<td>secondary</td>
<td></td>
<td>42</td>
<td>757</td>
<td>430</td>
<td>1229</td>
</tr>
<tr>
<td>tertiary</td>
<td></td>
<td>20</td>
<td>154</td>
<td>480</td>
<td>654</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>232</td>
<td>1222</td>
<td>1031</td>
<td>2485</td>
</tr>
</tbody>
</table>
Mobility tables

- The above statistics can be computed based on mobility tables for different birth cohorts to observe how social mobility changes over time.
- In the following this is done for education and class, separately for males and females.
- To obtain a smooth curve over birth cohorts we compute the mobility tables for specific birth years including surrounding years by means of kernel weights (bandwidth 5 years).
Social mobility over time: Class

Male

Female

Birthyear

Mobility (%)

Total
Structural
Circular
Relative

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Log-linear Models

- Such simple mobility table analyses can provide some first insights. However, a more sophisticated approach to measure the degree of dependence in a mobility table net of structural change are so called log-linear models.

- Given is a two-way frequency table (e.g. respondent’s educational achievement by education of parents):
Log-linear Models

- The observed cell frequencies in such a table can be expressed as:

\[ F_{ij} = \tau \cdot \tau_i \cdot \tau_j \cdot \tau_{ij} \]

where \( i \) stands for the row and \( j \) for the column.

- This is called a “log-linear model” because taking the logarithm leads to a linear expression:

\[
\log(F_{ij}) = \log(\tau) + \log(\tau_i) + \log(\tau_j) + \log(\tau_{ij})
\]

\[ = \mu + \mu_i + \mu_j + \mu_{ij} \]
Log-Linear Models

Now think of a table with an additional dimension (e.g. birth cohorts):

```
<table>
<thead>
<tr>
<th></th>
<th>k=1</th>
<th>k=2</th>
<th>k=3</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>F_{1,1}</td>
<td>F_{2,1}</td>
<td>F_{3,1}</td>
</tr>
<tr>
<td>R</td>
<td>F_{1,1,1}</td>
<td>F_{2,1,1}</td>
<td>F_{3,1,1}</td>
</tr>
<tr>
<td></td>
<td>F_{1,1,1}</td>
<td>F_{2,1,1}</td>
<td>F_{3,1,1}</td>
</tr>
<tr>
<td></td>
<td>F_{2,1,1}</td>
<td>F_{2,2,1}</td>
<td>F_{2,3,1}</td>
</tr>
<tr>
<td></td>
<td>F_{3,1,1}</td>
<td>F_{3,2,1}</td>
<td>F_{3,3,1}</td>
</tr>
<tr>
<td></td>
<td>F_{+,1,1}</td>
<td>F_{+,2,1}</td>
<td>F_{+,3,1}</td>
</tr>
</tbody>
</table>
```
Log-Linear Models

- Such a three-dimensional table can be expressed as follows (saturated model):

\[ F_{ijk} = \tau \cdot \tau_k \cdot \tau_i \cdot \tau_j \cdot \tau_{ik} \cdot \tau_{jk} \cdot \tau_{ij} \cdot \tau_{ijk} \]

where \( k \) stands for the additional dimension.

- Goal: Find a more parsimonious model to describe the variation in the association between rows and columns over \( k \).
Log-Linear Models

- Log-Multiplicative Layer Effect Model (LMLEM) (Xie 1992): Restrict the saturated model

\[ F_{ijk} = \tau \cdot \tau_k \cdot \tau_i \cdot \tau_j \cdot \tau_{ik} \cdot \tau_{jk} \cdot \tau_{ij} \cdot \tau_{ijk} \]

- Parameter \( \psi_{ij} \) describes the baseline pattern of deviations from independence given the marginal distributions (common pattern over all \( k \)).

- Parameter \( \phi_k \) is a scaling factor specific to subtable \( k \). It indicates how pronounced the deviations pattern is in subtable \( k \).

- That is, \( \phi_k \) indicates how strong the association between rows (parents’ education) and columns (respondents’ education) is in subtable (birthcohort) \( k \).
**LMLEM Results: Education**

![Graph showing LM effect on education over time for males and females.](image)

**Male**

<table>
<thead>
<tr>
<th>Year</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1940</td>
<td>0.30</td>
</tr>
<tr>
<td>1950</td>
<td>0.25</td>
</tr>
<tr>
<td>1960</td>
<td>0.20</td>
</tr>
<tr>
<td>1970</td>
<td>0.15</td>
</tr>
</tbody>
</table>

**Female**

<table>
<thead>
<tr>
<th>Year</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1940</td>
<td>0.25</td>
</tr>
<tr>
<td>1950</td>
<td>0.20</td>
</tr>
<tr>
<td>1960</td>
<td>0.15</td>
</tr>
<tr>
<td>1970</td>
<td>0.10</td>
</tr>
</tbody>
</table>

**Jann/Seiler (University of Bern)**

**Intergenerational Mobility in Switzerland**

Lausanne, 11.12.2013
LMLEM Results: Class (EGP)

Jann/Seiler  (University of Bern)  Intergenerational Mobility in Switzerland  Lausanne, 11.12.2013  29
PRE Approach

- The Log-Multiplicative Layer Effect Model has often been used to analyze changes in intergenerational mobility over birth cohorts. The model, however, has some disadvantages.
  - First, it assumes a common baseline pattern of associations that remains constant over time. This assumption may be violated so that results are biased.
  - Second, it is difficult to extend the model to include control variables.
  - Third, there is no clear interpretation of the absolute values of $\phi_k$. In fact, the overall level of the $\phi_k$ parameters is meaningless, because the sum over $\phi_k^2$ is restricted to 1. This implies that $\phi_k$ cannot be compared across models.

- We therefore propose an alternative approach that is based on (categorical) regression models and the PRE principle (see Jann and Combet 2012)
PRE Approach

General ideas

- The stronger the effect of the status of the parents on the status of their children, the lower is intergenerational mobility.
- The „strength“ of an effect is easy to conceptualize for single regression coefficients. Things get more complicated, however, if we have to determine the strength of an effect that comprises multiple parameters.
- Instead of thinking in terms of model parameters, however, we can ask how “useful” the information on parents is to predict the status of their children.
- The better the position of children can be predicted based on parents characteristics, the stronger is the influence of social origin and the lower is social mobility.
- To quantify the predictive power of parents’ characteristics we can resort to the statistical concept of the Proportional Reduction of Error (PRE).
PRE Approach

Formally:

\[ PRE = \frac{E_0 - E_1}{E_0} = 1 - \frac{E_1}{E_0} \]

where \( E_0 \) is the sum of prediction errors under limited information and \( E_1 \) is the sum of prediction errors under full information.

Different error rules can be applied, yielding different PRE measures. Because our dependent variables are categorical, a sensible error rule – based on information theory (see Theil 1970) – is

\[ E_j = - \sum_{i=1}^{N} w_i \ln \left( \hat{P}_j(Y = y_i) \right), \quad j = 0, 1 \]

where \( w_i \) is the respondent’s survey weight.
PRE Approach

- \( \hat{P}_j(Y = y_i) \) is the predicted probability of the dependent variable taking on value \( y_i \), where \( y_i \) is the observed value for respondent \( i \).
- In our context, we use multinomial logistic regression to estimate these probabilities.
  - Restricted model \( (j = 0) \): Model without parents’ variables as predictors
  - Full model \( (j = 1) \): Model including parents’ variables as predictors
- For each birth cohort, we fit separate models. That is, the approach is fully flexible across cohorts and does not assume some sort of stable association pattern.
- The resulting PRE values then indicate how social mobility changed across cohorts.
PRE Results (compared to LMLEM): Education

![Graph showing the comparison between LML and PRE effects on education over time for both male and female populations. The graph displays the trends from 1940 to 1970, with separate lines for LML and PRE, showing the effect on education.](image-url)
PRE Results (compared to LMLEM): Class

Jann/Seiler (University of Bern)  Intergenerational Mobility in Switzerland  Lausanne, 11.12.2013
To obtain a more detailed picture, PRE can also be computed for single birth years. However, data limitations would lead to a wiggly curve with wide confidence intervals.

To stabilize model estimates and smooth the curve we again use kernel weights (bandwidth 5 years) to select observations to be included in a model for a specific time point.

Observations of the target birth year receive the largest weights, observations of surrounding birth years receive weights that decrease the larger the difference to the target birth year. Weights are zero if the difference is 5 or more years.
Smoothed PRE: Results for Education

![Graph showing the PRE effect on education for males and females from 1935 to 1975. The graph displays the categorical and smoothed PRE effects with error bars indicating the variability.]
Smoothed PRE: Results for Class

![Graph showing Smoothed PRE effect on class for Male and Female from 1935 to 1975. The graph includes categorical and smoothed categories.](image)

- Male
- Female

Jann/Seiler (University of Bern)
Intergenerational Mobility in Switzerland
Lausanne, 11.12.2013
PRE: Extensions

- PRE has several advantages
  - It is easy to incorporate control variables (e.g. age, survey dummies, etc.)
  - Several origin variables can be used in the same model (education, class, father, mother)
  - Effects can be decomposed into direct and indirect effects.
PRE: Control Variables

- Education of Parents
- Education of Child
- Class of Parents
- Class of Child
PRE: Control Variables

Education of Parents → Education of Child

Age at Interview → Survey Dummies

Class of Parents → Class of Child

Age at Interview → Survey Dummies
PRE: Control Variables

![Graph showing the PRE effect on education for males and females from 1940 to 1970. The graph compares unadjusted and adjusted (Survey, Age) data. The x-axis represents the years 1940 to 1970, and the y-axis represents the PRE effect on education. The graph shows a general increase in the PRE effect over time, with some fluctuations. The unadjusted data is represented by blue dots, and the adjusted data by red dots.](image-url)
PRE: Control Variables

The graph illustrates the PRE effect on education for both male and female populations, showing the unadjusted and adjusted impacts (survey and age) over time from 1935 to 1975. The chart indicates a general trend of increasing PRE effect over the years, with adjustments showing slightly different patterns compared to unadjusted data.
PRE: Multiple Origin Variables

- Education of Parents
- Education of Child
- Age at Interview
- Class of Parents
- Class of Child
- Age at Interview
PRE: Multiple Origin Variables

- Education of Parents
- Class of Parents
- Education of Child
- Age at Interview

- Class of Parents
- Education of Parents
- Class of Child
- Age at Interview
PRE: Multiple Origin Variables

The diagram illustrates the intergenerational mobility in Switzerland, focusing on the PRE (Partial Rental Equivalence) effect on education. It compares males and females and shows the effect of parents' education only and parents' education and class across different years from 1935 to 1975.

- **Male**:
  - Parents' education only (blue line)
  - Parents' education and class (red line)

- **Female**:
  - Parents' education only (blue line)
  - Parents' education and class (red line)

The data is sourced from Jann/Seiler (University of Bern) and pertains to intergenerational mobility in Switzerland.
PRE: Multiple Origin Variables

![Graph showing PRE effect on class over time for males and females. The graph compares 'Parents’ education only' and 'Parents’ education and class' for both genders.](image)

- **Male**
  - Blue line: Parents’ education only
  - Red line: Parents’ education and class

- **Female**
  - Blue line: Parents’ education only
  - Red line: Parents’ education and class

Jann/Seiler (University of Bern)
Intergenerational Mobility in Switzerland
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PRE: Decomposition (direct and indirect effects)

Education and Class of Parents → Total Effect → Class of Child

Age at Interview
PRE: Decomposition (direct and indirect effects)

Education and Class of Parents → Education of Child

Indirect Effect

Direct Effect

Class of Child → Age at Interview
PRE: Decomposition (direct and indirect effects)

![Graph showing intergenerational mobility in Switzerland]

- Male:
  - Total effect
  - Direct effect (net of education)

- Female:
  - Total effect
  - Direct effect (net of education)

Source: Jann/Seiler (University of Bern)
The PRE approach seems to be viable and flexible model to analyze social mobility.

- It produces results that are comparable to the classic LMLEM.
- It can easily include multiple origin variables and control variables.
- It has a clear interpretation (proportional reduction of prediction errors): How much does the knowledge of parents’ characteristics improve the prediction of the child’s status?
Summary

- Substantive conclusion
  - Our results indicate that social mobility increased from birth cohorts 1935 to about 1960, but then started to decrease again.
  - In general, this pattern can be observed for both men and women and both education and class. The pattern, however, is least pronounced for men’s class.
  - For respondent’s education the PRE approach leads to more pronounced results than LMLEM. This indicates that the structure of association changed over time for education.
  - Net of parents education, parents’ class still has an effect on both respondent’s education and class. As expected, the effect on class is stronger.
  - Parents characteristics have a direct effect on respondent’s class, net of respondent’s education.
References


