A New Methodological Approach for Studying Intergenerational Mobility with an Application to Swiss Data

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Spring Meeting of the Research Committee on Social Stratification and Mobility (RC28) of the International Sociological Association (ISA) on “Social Inequality, Cohesion and Solidarity”
Tilburg, May 28–30, 2015
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- Data
- Results
  - Comparison of LMLEM and PRE
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  - PRE with multiple origin (and control) variables
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Introduction

- As a methodology to analyze the development of social mobility based on categorical variables such as class or educational attainment, Erikson and Goldthorpe (1992) and Xie (1992) independently proposed a variant of the log-linear model known as the *uniform difference model* (Unidiff) or the *log-multiplicative layer effect model* (LMLEM).

- The model has been the standard tool in social mobility research since. The model, however, also has some limitations. We therefore propose an alternative approach.

- Our approach is based on the concept of proportional reduction of error (PRE). It quantifies the degree to which information about parents helps predicting the status of the children.

- The approach, we believe, is more flexible than the LMLEM and provides results that are easier to interpret.
Starting point of the LMLEM is a simple two-way table of origin and destination, called a “mobility table,” such as the following:

<table>
<thead>
<tr>
<th>Parent’s education</th>
<th>compulsory or less</th>
<th>secondary vocational</th>
<th>secondary general</th>
<th>tertiary vocational</th>
<th>tertiary academic</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>compulsory or less</td>
<td>170</td>
<td>299</td>
<td>12</td>
<td>58</td>
<td>63</td>
<td>602</td>
</tr>
<tr>
<td>secondary vocational</td>
<td>37</td>
<td>708</td>
<td>27</td>
<td>134</td>
<td>260</td>
<td>1167</td>
</tr>
<tr>
<td>secondary general</td>
<td>5</td>
<td>19</td>
<td>3</td>
<td>20</td>
<td>16</td>
<td>62</td>
</tr>
<tr>
<td>tertiary vocational</td>
<td>7</td>
<td>51</td>
<td>15</td>
<td>104</td>
<td>52</td>
<td>229</td>
</tr>
<tr>
<td>tertiary academic</td>
<td>14</td>
<td>75</td>
<td>12</td>
<td>33</td>
<td>293</td>
<td>426</td>
</tr>
<tr>
<td>Total</td>
<td>232</td>
<td>1152</td>
<td>70</td>
<td>348</td>
<td>683</td>
<td>2485</td>
</tr>
</tbody>
</table>

Source: see data section. Selection: males, birth cohorts 1969-82
Log-Multiplicative Layer Effect Model

- Such a two-dimensional mobility table can be formalized as follows, where $F_{ij}$ are observed cell counts and $F_i.$ and $F. j$ are row and column totals.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>...</th>
<th>$j$</th>
<th>...</th>
<th>$J$</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$F_{11}$</td>
<td>...</td>
<td>$F_{1j}$</td>
<td>...</td>
<td>$F_{1J}$</td>
<td>$F_{1.}$</td>
</tr>
<tr>
<td>$i$</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>$i$</td>
<td>$F_{i1}$</td>
<td>...</td>
<td>$F_{ij}$</td>
<td>...</td>
<td>$F_{iJ}$</td>
<td>$F_{i.}$</td>
</tr>
<tr>
<td>$l$</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Total</td>
<td>$F_{.1}$</td>
<td>...</td>
<td>$F_{.j}$</td>
<td>...</td>
<td>$F_{.J}$</td>
<td>$F_{..}$</td>
</tr>
</tbody>
</table>

- In a log-linear model, the cell counts are expressed as a multiplicative function:

$$F_{ij} = \tau_{..} \cdot \tau_{i.} \cdot \tau_{.j} \cdot \tau_{ij}, \quad i = 1, \ldots, l, \ j = 1, \ldots, J$$
Now think of a table with an additional dimension (e.g. time points or birth cohorts).

The saturated log-linear model for such a three-dimensional table is

\[ F_{ijk} = \tau_{...} \cdot \tau_{i..} \cdot \tau_{.j.} \cdot \tau_{..k} \cdot \tau_{i.k} \cdot \tau_{.jk} \cdot \tau_{ij.} \cdot \tau_{ijk} \]

with \( i = 1, \ldots, I \), \( j = 1, \ldots, J \), and \( k = 1, \ldots, K \)
Log-Multiplicative Layer Effect Model

- To ease interpretation, Xie (1992) proposed a simplified model in which $\tau_{ij} \cdot \tau_{ijk}$ is replaced by $\exp(\psi_{ij} \cdot \phi_{..k})$. This is called the log-multiplicative layer effect model:

  $$F_{ijk} = \tau_{...} \cdot \tau_{i..} \cdot \tau_{.j} \cdot \tau_{..k} \cdot \tau_{i.k} \cdot \tau_{.jk} \cdot \exp(\psi_{ij} \cdot \phi_{..k})$$

  $$i = 1, \ldots, I, \quad j = 1, \ldots, J, \quad k = 1, \ldots, K$$

- The $\psi_{ij}$ parameters capture the overall pattern of dependencies between origin and destination.

- The $\phi_{..k}$ are cohort-specific scaling factors. That is, the higher $\phi_{..k}$, the more pronounced is the pattern of dependencies in cohort $k$ and, hence, the stronger is the association between origin and destination, assuming that there is a stable basic pattern of associations across cohorts.

- To identify the model, constraints have to be placed on $\phi_{..k}$. Following Xie (1992), we use constraint $\sum_k \phi_{..k}^2 = 1$. 
The PRE Approach

- The LMLEM provides a parsimonious and intuitive way to describe changes in social mobility across time and also allows testing against a null model with time-constant origin effects. However, the model has a number of limitations.
  - 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.
The 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).
The 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, an entropy-based definition (see Theil 1970) appears appropriate:

\[ E_m = - \sum_{i=1}^{N} w_i \ln \left( \hat{p}_m(Y = y_i) \right), \quad m = 0, 1 \]

where \( w_i \) is the respondent’s survey weight and \( \hat{p}_m(Y = y_i) \) is the predicted probability of the dependent variable taking on observed value \( y_i \) under model \( m \).
The PRE Approach

- To estimate $\hat{p}_m(Y = y_i)$ we use multinomial logit models.
- That is, the probabilities under restricted information are modeled as

$$p_0(Y = y_i) = \frac{\exp(\beta_{y_i}^iZ_i)}{\sum_{\ell=1}^J \exp(\beta_{\ell}^iZ_i)}$$

where $Z_i$ is a vector of control variables (possibly just a constant) and $\beta_{\ell}^i$ is an outcome-specific coefficient vector.

- Likewise, the probabilities under full information are modeled as

$$p_1(Y = y_i) = \frac{\exp(\beta_{y_i}^iZ_i + \gamma_{y_i}^iX_i)}{\sum_{\ell=1}^J \exp(\beta_{\ell}^iZ_i + \gamma_{\ell}^iX_i)}$$

where $X_i$ is a vector of parents’ characteristics.
The PRE Approach

- **Categorical variant:**
  - Estimate separate models for different birth cohorts and compute a separate PRE value for each cohort.
  - Gives only a crude picture because single birth years usually have to be collapsed into broader cohorts.

- **Smoothed variant:**
  - Compute a PRE value for each birth year, but include data from surrounding years using kernel weights to stabilize estimation.
  - We use weights
    \[ w_i(t^*) = w_i \cdot \frac{1}{h} K \left( \frac{t^* - t_i}{h} \right) \]
    
    where \( t^* \) is the target birth year, \( t_i \) is observations \( i \)'s birth year, and \( K() \) is the Epanechnikov kernel. We set bandwidth \( h \) to 5, so that the data window covers a maximum of ±4 years around target birth year.

- For both variants, confidence intervals are obtained by bootstrap methods.
Data

- Required are data that contain the relevant status variables for the respondents as well as information about education and occupation of parents.
- Most Swiss 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 Swiss 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: Included Surveys

<table>
<thead>
<tr>
<th>Survey</th>
<th>Year/Wave</th>
<th>N&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>Les Suisses et leur société</td>
<td>1991</td>
<td>1331</td>
<td>CH91</td>
</tr>
<tr>
<td>Swiss Environmental Survey</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>MOSAïCH (ISSP)</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</td>
<td>2011</td>
<td>6753</td>
<td>SILC11</td>
</tr>
</tbody>
</table>

Total: 33068

<sup>a</sup> Number of observations available for our analyses.
Data: Number of Observations by Birthyear

![Graph showing the number of observations by birth year across different datasets.](image-url)
# Data: Classification of Education

<table>
<thead>
<tr>
<th>Educational level</th>
<th>Included educational degrees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compulsory or less</td>
<td>No formal education; compulsory education; one year vocational training</td>
</tr>
<tr>
<td>Secondary vocational</td>
<td>Vocational training and education; general education without baccalaureate</td>
</tr>
<tr>
<td>Secondary general</td>
<td>General education with baccalaureate; vocational baccalaureate; college of education (without university of education)</td>
</tr>
<tr>
<td>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>Tertiary academic</td>
<td>University; Federal Institute of Technology</td>
</tr>
</tbody>
</table>
Data: Education by Birth Cohort
## Data: Social Class Scheme

<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 non-manual employees</td>
</tr>
<tr>
<td>III</td>
<td>Non-manual employees 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>

Results

- Comparison of LMLEM and PRE
- Smoothed PRE
- PRE with multiple origin variables
- Direct and indirect origin effects
Results: Comparison of LMLEM and PRE

Education

<table>
<thead>
<tr>
<th>Year</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>1940</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>1950</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>1960</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>1970</td>
<td>0.08</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Jann/Seiler (University of Bern) Intergenerational Mobility in Switzerland

Tilburg, May 28, 2015
Results: Comparison of LMLEM and PRE

- As discussed above, the LMLEM assumes a common structure of associations between origin and destination categories that remains stable across cohorts.
- Differences between the LMLEM and PRE results may be due to a violation of this assumption.
- We thus included, as grey bars, a cohort-specific goodness-of-fit measure for the LMLEM:

\[
\bar{\chi}^2_k = \frac{1}{N_k} \sum_{i=1}^{I} \sum_{j=1}^{J} \left( F_{ijk} - \hat{F}_{ijk} \right) \frac{2}{\hat{F}_{ijk}}
\]

with \( F_{ijk} \) as the observed cell frequencies, \( \hat{F}_{ijk} \) as the cell frequencies predicted by the model and \( N_k \) as the number of observations in cohort \( k \). High values of \( \bar{\chi}^2_k \) indicate bad fit (the scale of \( \bar{\chi}^2_k \) is not relevant here and is omitted).
Results: Comparison of LMLEM and PRE

Class

<table>
<thead>
<tr>
<th>Year</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>1940</td>
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<td>0.20</td>
</tr>
</tbody>
</table>

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Results: Smoothed PRE

Education

<table>
<thead>
<tr>
<th>Year</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>1935</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1945</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1955</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1965</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Categorical
- Smoothed

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Intergenerational Mobility in Switzerland
Tilburg, May 28, 2015
Results: Smoothed PRE

Class

<table>
<thead>
<tr>
<th>Year</th>
<th>Male</th>
<th>Female</th>
</tr>
</thead>
<tbody>
<tr>
<td>1935</td>
<td></td>
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<tr>
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<tr>
<td>1955</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1965</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1975</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Categorical vs Smoothed PRE

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Results: PRE with multiple origin (and control) variables

- Education of Parents
- Class of Parents
- Education or Class of Child
- Age at Interview
Results: PRE with multiple origin (and control) variables

Education

### Male

- **Parents' education only**
- **Parents' education and class**

### Female

- **Parents' education only**
- **Parents' education and class**

**PRE**

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Intergenerational Mobility in Switzerland

Tilburg, May 28, 2015
Results: PRE with multiple origin (and control) variables

![Diagram showing intergenerational mobility trends in Switzerland]

- Male: Parents' education only vs. Parents' education and class
- Female: Parents' education only vs. Parents' education and class

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Results: Direct and indirect origin effects

- Education and Class of Parents
- Total Effect
- Class of Child
- Age at Interview
Results: Direct and indirect origin effects

- Education
- Class of Parents
- Education of Child
- Indirect Effect
- Direct Effect
- Class of Child
- Age at Interview
Results: Direct and indirect origin effects

- Male
- Female

PRE effect on class

Total effect
Direct effect (net of education)

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Intergenerational Mobility in Switzerland
Tilburg, May 28, 2015
Conclusions

- The PRE approach seems to be a viable and flexible model to analyze social mobility.
  - It produces results that are comparable to the classic LMLEM. Remaining deviations between PRE and LMLEM seem to be mainly driven by misfit of the 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?
Conclusions

- **Substantive conclusions**
  - Our results indicate that social mobility increased among birth cohorts in the mid 1930s 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.

