Linking process to outcome

Inequality of educational opportunities and inequality of educational outcomes

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  1. IEOpps (looking at the process) and IEOut (looking at the end result) are natural complements.
  2. Allows for a natural way to study the effect of educational expansion, and the disadvantaged position of other social groups on IEOut.

Outline

IEOpp and IEOut

Empricial applications
- The Netherlands
- USA

Conclusion

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- This model compares the odds of passing between lower status children and higher status children.
- In particular it looks at the ratio between the odds of students one unit status apart.
- This ratio is not influenced by how many people pass in general.

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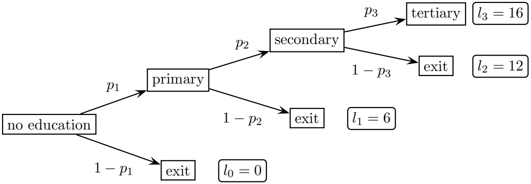
- The outcome is derived from this model.
- This is a way of extracting more information from a sequential logit/Mare model.

Example

Figure: Hypothetical educational system



Modeling transition probabilities and the expected level of education

$$p_{ki} = \frac{\exp(\alpha_k + \lambda_k SES_i)}{1 + \exp(\alpha_k + \lambda_k SES_i)} \quad \text{if} \quad pass_{k-1\,i} = 1$$

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$$E(ed) = (1 - p_{1i})l_0 + p_{1i}(1 - p_{2i})l_1 + p_{1i}p_{2i}(1 - p_{3i})l_2 + p_{1i}p_{2i}p_{3i}l_3$$

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$$\frac{\partial E(ed)}{\partial SES} =$$
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$$\{p_{1i} \times p_{2i}(1 - p_{2i}) \times [(1 - p_3)l_2 + p_3 l_3 - l_1]\}\lambda_2 +$$
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IEOpps and IEOut

proportion at risk

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IEOpps and IEOut

variance of the variable indicating whether one passes or not

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IEOpps and IEOut

expected increase in the level of education after passing

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IEOpps and IEOut

expected level of education for those that pass

$$\frac{\partial E(ed)}{\partial SES} =$$
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IEOpps and IEOut

minus the expected level of education for those that fail

$$\frac{\partial E(ed)}{\partial SES} =$$
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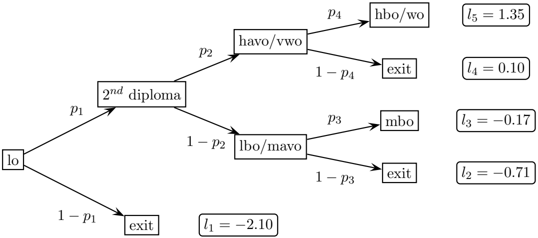
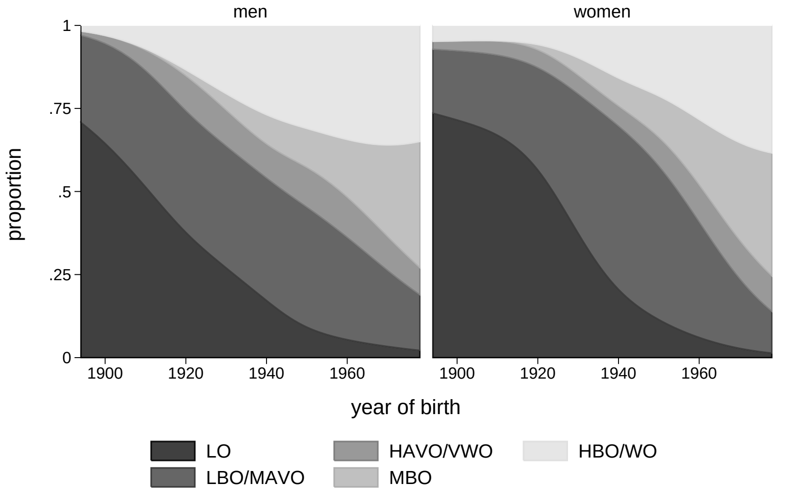
Outline

- IEOpp and IEOut
- Empricial applications
  - The Netherlands
  - USA
- Conclusion

Simplified model of Dutch educational system



Distribution of highest achieved level of education



Data

- International Stratification and Mobility File (ISMF) on the Netherlands.
- 51 surveys held between 1958 and 2005 with information on cohorts 1894-1978.
- 67,000 respondents aged between 27 and 65 with complete information.

Variables

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- Father's occupational status is measured in ISEI scores, and standardized using the mean and standard deviation from the cohort 1940.
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- the main effect of cohort is measured by a restricted cubic spline with boundary knots at 1920 and 1970 and an interior knot in 1950.

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- Father's occupational status is measured in ISEI scores, and standardized using the mean and standard deviation from the cohort 1940.
- Level of education is scaled such as to maximize the direct effect of education on income , and it is standardized using the mean and standard deviation from the cohort 1940.
- the main effect of cohort is measured by a restricted cubic spline with boundary knots at 1920 and 1970 and an interior knot in 1950.
- The IEOpps are allowed to change linearly over cohorts.

sequential response model for men

	LO v more	LBO/MAVO v HAVO/VWO	LBO/MAVO v MBO	HAVO/VWO v HBO/WO
father's status	0.973	0.595	0.223	0.320
	(15.87)	(12.16)	(2.37)	(4.35)
father's status X cohort	-0.074	0.006	0.011	-0.016
	(-5.17)	(0.59)	(0.61)	(-1.13)
cohort	0.557	0.244	0.563	0.357
	(23.36)	(11.20)	(13.59)	(9.89)
cohort_1	0.001	0.020	-0.001	0.019
	(0.32)	(8.84)	(-0.32)	(4.90)
constant	-0.208	-0.968	-3.750	-0.357
	(-2.68)	(-12.32)	(-23.71)	(-2.75)
N	43539			
log likelihood	-48889.247			

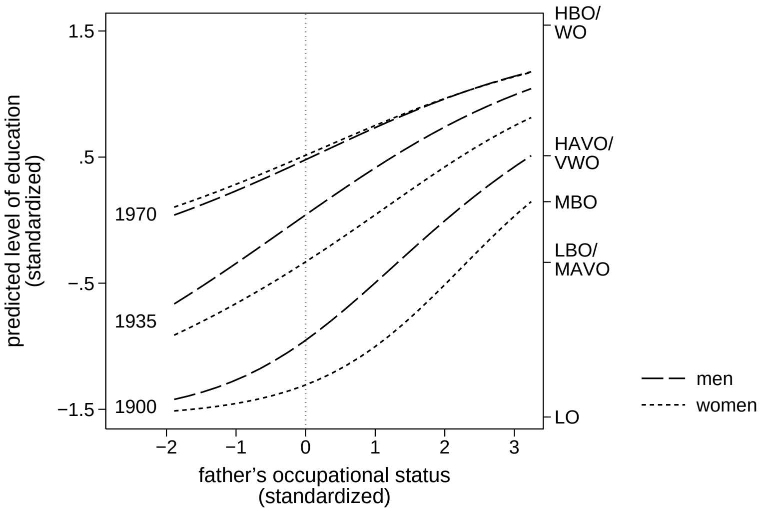
z statistics in parentheses

sequential response model for women

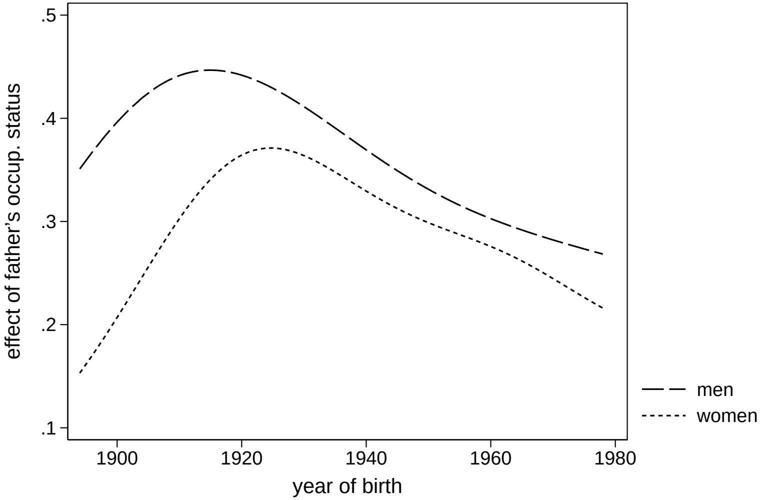
	LO v more	LBO/MAVO v HAVO/VWO	LBO/MAVO v MBO	HAVO/VWO v HBO/WO
father's status	0.971	0.947	0.317	-0.114
	(16.91)	(16.14)	(3.32)	(-1.27)
father's status X cohort	-0.083	-0.051	-0.003	0.056
	(-6.14)	(-4.62)	(-0.16)	(3.34)
cohort	0.729	0.215	0.367	0.288
	(30.59)	(7.43)	(8.24)	(6.14)
cohort_1	0.001	-0.004	-0.033	0.013
	(0.27)	(-1.60)	(-8.31)	(3.09)
constant	-1.283	-1.708	-3.482	-0.297
	(-16.53)	(-15.58)	(-20.17)	(-1.66)
N	43139			
log likelihood	-44457.068			

z statistics in parentheses

Predicted level of education



Change in IEOut over cohorts



Decomposition of IEOut

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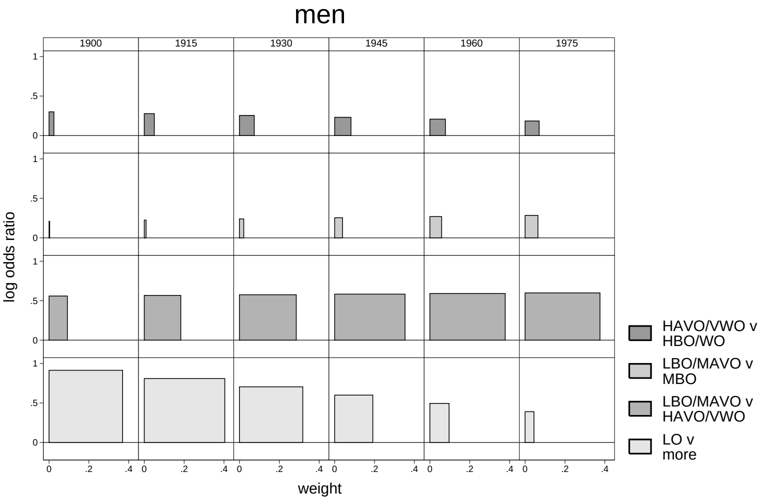
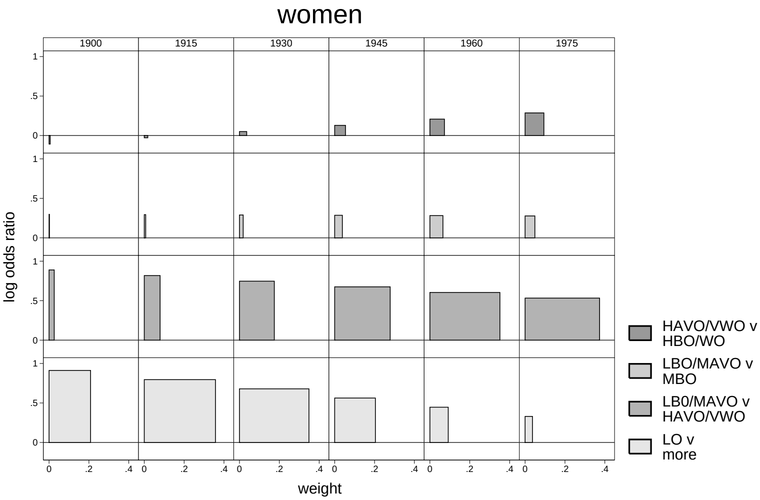
  IEOut = w_1 IEOpp_1 + w_2 IEOpp_2 + w_3 IEOpp_3 + w_4 IEOpp_4
- The contribution of the first transition is: w_1 IEOpp_1
- This can be visualized as the area of a rectangle with width w_1 and height IEOpp_1.
- IEOut is the sum of the areas of these rectangles

Decomposition of IEOut for men



Decomposition of IEOut for women



Decomposition of weights

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  at risk $\times$ variance $\times$ gain

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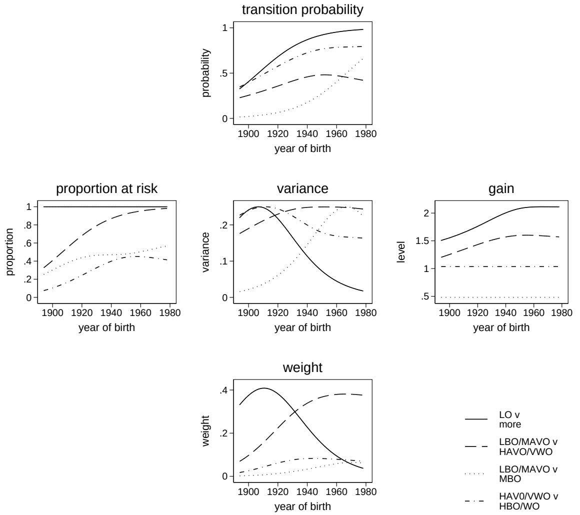
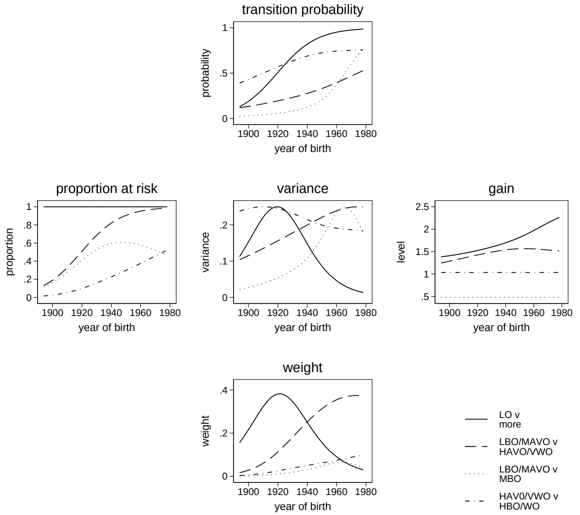
- These three elements are all a function of the proportions that pass the transitions

Decomposition of the weights for men



Decomposition of the weights for women



Outline

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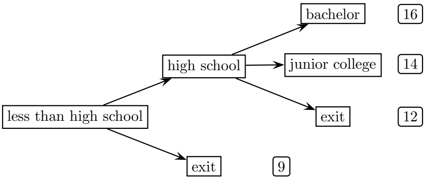
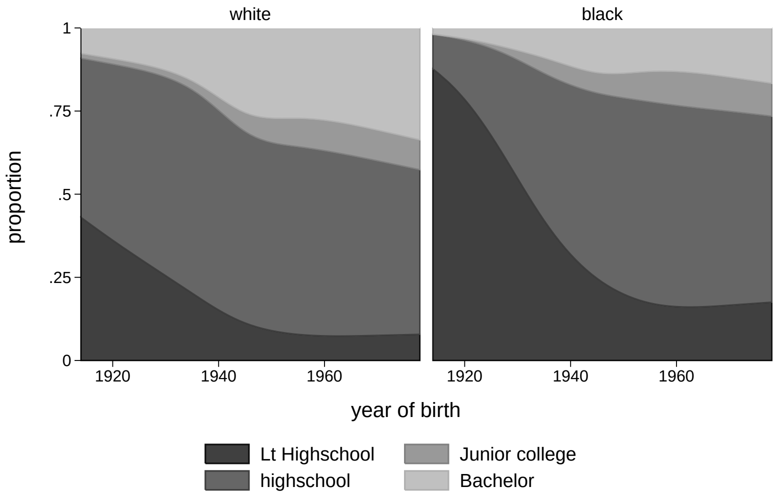
Conclusion

Simplified model of the US educational system



Distribution of highest achieved level of education



Data

- General Social Survey (GSS).
- 20 surveys held between 1977 and 2004 with information on cohorts 1913-1978.
- 13,400 men aged between 27 and 65 with complete information.

Variables

- Father's highest achieved level of education measured in (pseudo) years.

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Variables

- Father's highest achieved level of education measured in (pseudo) years.
- Respondent's highest achieved Level of education in (pseudo) years
- Time measured as a restricted cubic spline with one knot in 1946.

sequential response model for white men

	LT Highschool v. more	Junior College v. Highschool	Bachelor v. Highschool
south	-0.893	-0.138	0.014
	(-12.18)	(-1.38)	(0.24)
padeg	0.502	0.213	0.254
	(5.18)	(2.25)	(5.11)
padegXcoh	-0.012	-0.017	0.016
	(-0.62)	(-0.96)	(1.69)
coh	0.803	0.850	0.134
	(4.36)	(3.91)	(1.14)
coh_1	0.025	0.016	0.015
	(4.94)	(2.23)	(3.67)
_cons	-5.209	-7.321	-4.955
	(-5.77)	(-6.80)	(-8.77)
N	9051		
log likelihood	-8802.0056		

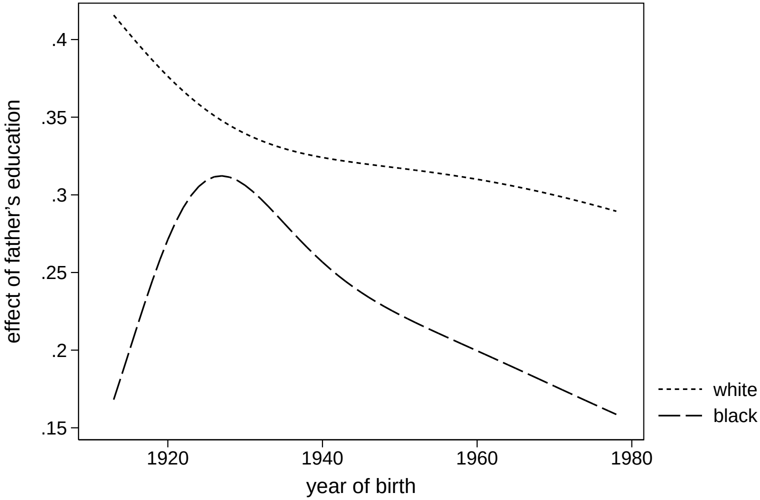
t statistics in parentheses

sequential response model for black men

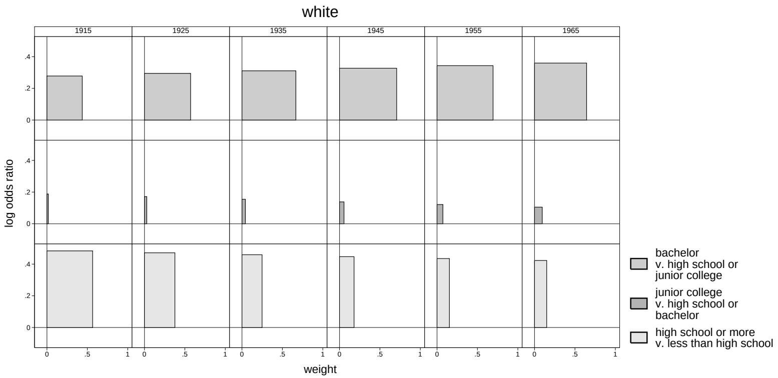
	LT Highschool v. more	Junior College v. Highschool	Bachelor v. Highschool
south	-0.615	0.125	0.273
	(-3.63)	(0.56)	(1.59)
padeg	0.262	0.320	0.161
	(1.25)	(1.09)	(0.85)
padegXcoh	-0.005	-0.043	0.020
	(-0.12)	(-0.81)	(0.58)
coh	1.415	1.125	0.012
	(3.67)	(1.77)	(0.03)
coh_1	0.048	0.022	0.018
	(4.23)	(1.01)	(1.21)
_cons	-6.083	-8.216	-3.807
	(-3.09)	(-2.55)	(-1.95)
N	1340		
log likelihood	-1369.9574		

t statistics in parentheses

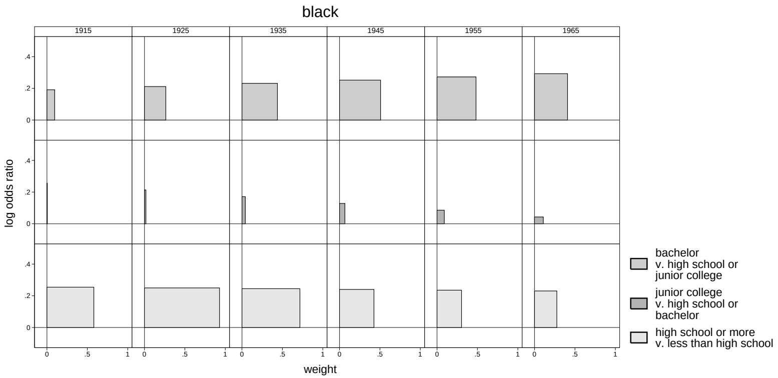
Change in IEOut over cohorts



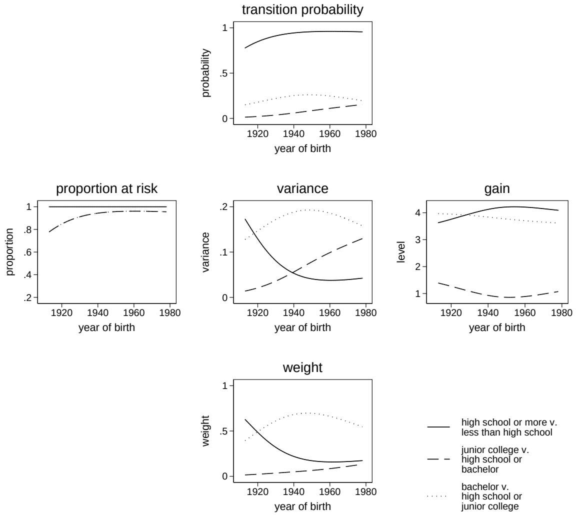
Decomposition of IEOut for white men



Decomposition of IEOut for black men



Decomposition of the weights for white men



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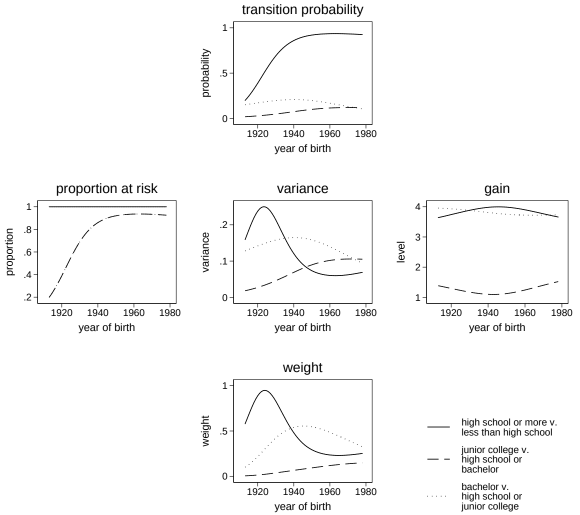

The `seqlogit` package

- These graphs where made with the `seqlogit` package in Stata.
- It can deal with any tree.
- To install type within Stata `ssc install seqlogit`.

Outline

IEOpp and IEOut

Empricial applications

The Netherlands

USA

Conclusion

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  - the proportion that passes is closer to .50,
  - the expected increase in level of education increases

Conclusion

- IEOut depends in an understandable way on the IEOpps and transition probabilities.
- IEOut is a weighted sum of IEOpps, and the weights increase if:
  - the proportion at risk increases,
  - the proportion that passes is closer to .50,
  - the expected increase in level of education increases
- This is not a new model, it is just another way of looking at the results from a sequential logit/mare model

Conclusion

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  - identify important and less important transitions,

Conclusion

- This relationship can be used to:
  - to relate IEOut to the IEOpps.
  - identify important and less important transitions,
  - to explain differences in IEOut with well documented phenomena like educational expansion or racial differences in educational attainment.

References

Robert D. Mare.
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levels of education

Dutch name	English name	years[†]	ISCED
LO	primary	6	1
LBO	junior vocational	10	2C
MAVO	junior general secondary	9 / 10	2B[‡]
MBO	senior secondary vocational	14	3C
HAVO	senior general secondary	11	3B[‡]
VWO	pre-university	12	3A
HBO	higher professional	15	5B
WO	university	16	5A

[†] Years refer to the situation after 1968

[‡] These levels were originally intended to be terminal levels of education for most students (so 2C or 3C) but evolved into levels that primarily grant access to subsequent levels of education.

Scaling of education

$$\ln(inc) = \beta_0 + \underbrace{\beta_1}_{0} lo + \beta_2 lbo\_mavo + \beta_3 havo\_vwo + \beta_4 mbo + \beta_5 hbo\_wo + \cdots$$

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Scaling of education

$$\ln(inc) = \beta_0 + \underbrace{\beta_1}_{0} lo + \beta_2 lbo\_mavo + \beta_3 havo\_vwo + \beta_4 mbo + \beta_5 hbo\_wo + \cdots$$

$$ed = \underbrace{\alpha_1}_{0} lo + \alpha_2 lbo\_mavo + \alpha_3 havo\_vwo + \alpha_4 mbo + \underbrace{\alpha_5}_{1} hbo\_wo$$

$$\begin{aligned}
\ln(inc) &= \beta_0 + \gamma_1 ed + \cdots \\
&= \beta_0 + \gamma_1 (\underbrace{\alpha_1}_{0} lo + \alpha_2 lbo_mavo + \alpha_3 havo_vwo + \\
&\quad \alpha_4 mbo + \underbrace{\alpha_5}_{1} hbo_wo) + \cdots
\end{aligned}$$

Scaling of education

$$\begin{aligned}
\gamma_1 &= \beta_5 \\
\alpha_1 &= 0 \\
\alpha_2 &= \frac{\beta_2}{\beta_5} \\
\alpha_3 &= \frac{\beta_3}{\beta_5} \\
\alpha_4 &= \frac{\beta_4}{\beta_5} \\
\alpha_5 &= 1
\end{aligned}$$

Scaling of education

		b	z
α			
	LO	0	.
	LBO/MAVO	0.395	(21.91)
	MBO	0.549	(19.21)
	HAVO/VWO	0.667	(24.65)
	HBO/WO	1	.
γ			
	year	-0.0868	(-2.41)
	year_1	0.0707	(1.67)
	year_2	-0.115	(-2.53)
	constant	0.643	(12.09)
β			
	age	0.115	(25.28)
	age^2	-0.0715	(-20.19)
	fisei	0.476	(5.47)
	fiseiXyear	-0.0827	(-1.36)
	fiseiXyear_1	0.0560	(0.78)
	fiseiXyear_2	-0.0812	(-1.08)
	year	0.833	(34.88)
	year_1	0.287	(9.07)
	year_2	-0.190	(-5.53)
	constant	5.058	(153.45)

Causality, bias, and unobserved heterogeneity

Partial IEO can be measured at two levels:

group level
: difference between the group high status children and the group low status children.

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- The model used in this presentation will provide unbiased estimates at the group level,

Causality, bias, and unobserved heterogeneity

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group level difference between the group high status children and the group low status children.

individual level the results of a counterfactual thought experiment.

- The model used in this presentation will provide unbiased estimates at the group level,
- but not at the individual level.