Deceleration of the Trend in Inequality of Educational Opportunity in the Netherlands

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Outline

- Introduction
- Main results
- Inequality of Educational Opportunity
- method:
  - Multiple indicators for socioeconomic status
  - Using lowess smooth to estimate trend and change in trend
  - Using bootstrap to estimate confidence envelopes
- results
- conclusions

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- This has been confirmed with:
  - linear regression
  - ordered logits
  - loglinear models (uniform association, scaled association: RC-2)
  - sequential logits (Mare model)

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- However, there is reason to believe that the trend cannot continue.
- **When do we begin to observe a deceleration of the trend?**

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- It is a good approximation of a weighted sum of Mare coefficients that give more weight to transitions that:
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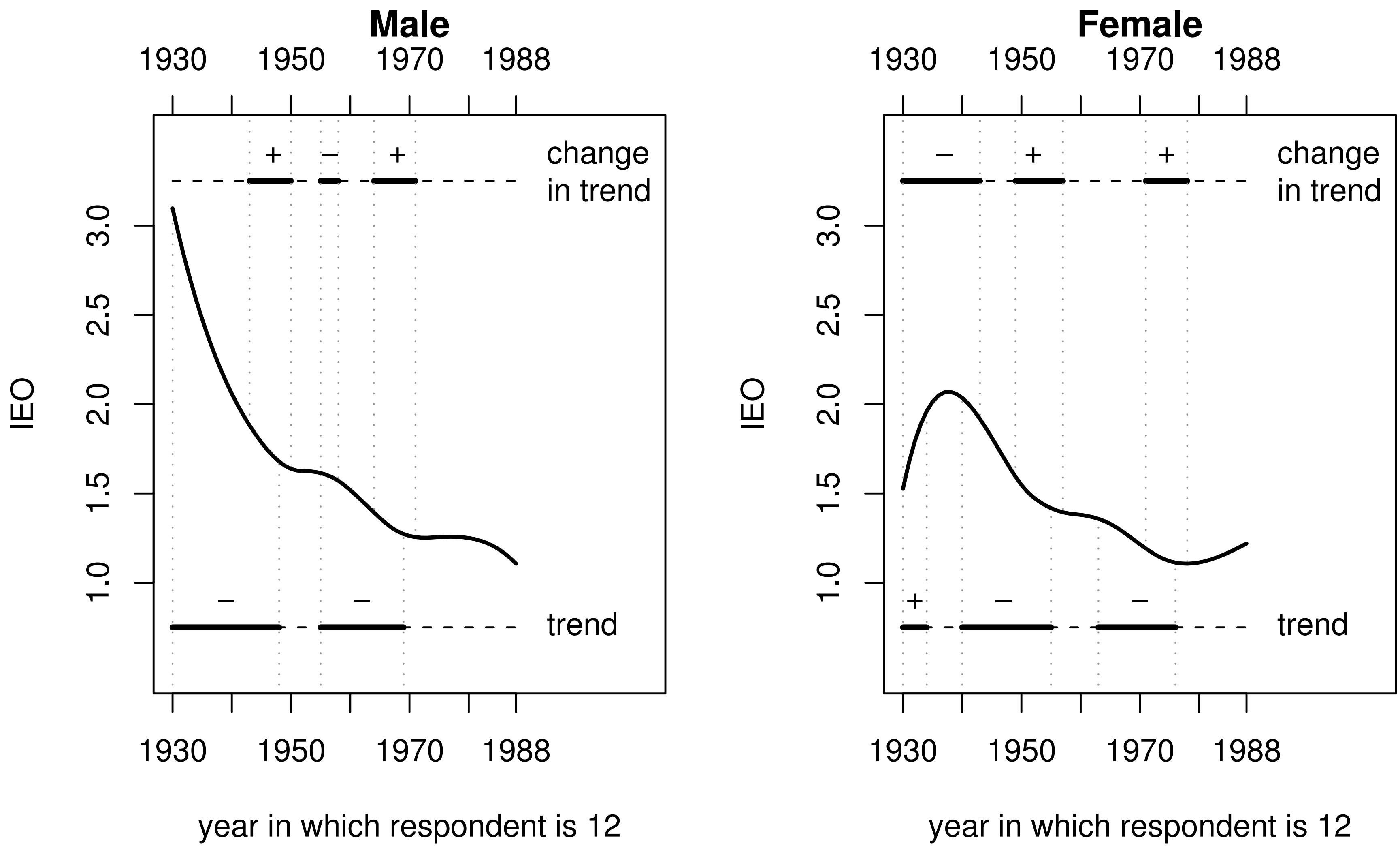
- Ordered logistic regression and log linear models don't have this relationship with the Mare model.

Main results: non-linear trend



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  - transition gives more access to higher subsequent levels of education.
- Effect of a unit change in SES on the highest achieved level of education is consistent with these criteria.

Example:

- Four level educational system, so three transitions
- One explanatory variable: SES
- Probability that individual i passes transition k given that it has passed all previous transitions:

$$p_{ki} = \frac{\exp(\alpha_k + \gamma_k SES_i)}{1 + \exp(\alpha_k + \gamma_k SES_i)}$$

- γ_k is the transition specific inequality for transition k
- The four levels of education are given values l_0 to l_3.

Example (continued)

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

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$$\partial E(ed)/\partial SES =$$

$$\{1 \times p_{1i}(1 - p_{1i}) \times [(l_1 - l_0) + p_{2i}(l_2 - l_1) + p_{2i}p_{3i}(l_3 - l_2)]\}\gamma_1 +$$

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$$\{p_{1i}p_{2i} \times p_{3i}(1 - p_{3i}) \times [(l_3 - l_2)]\}\gamma_3$$

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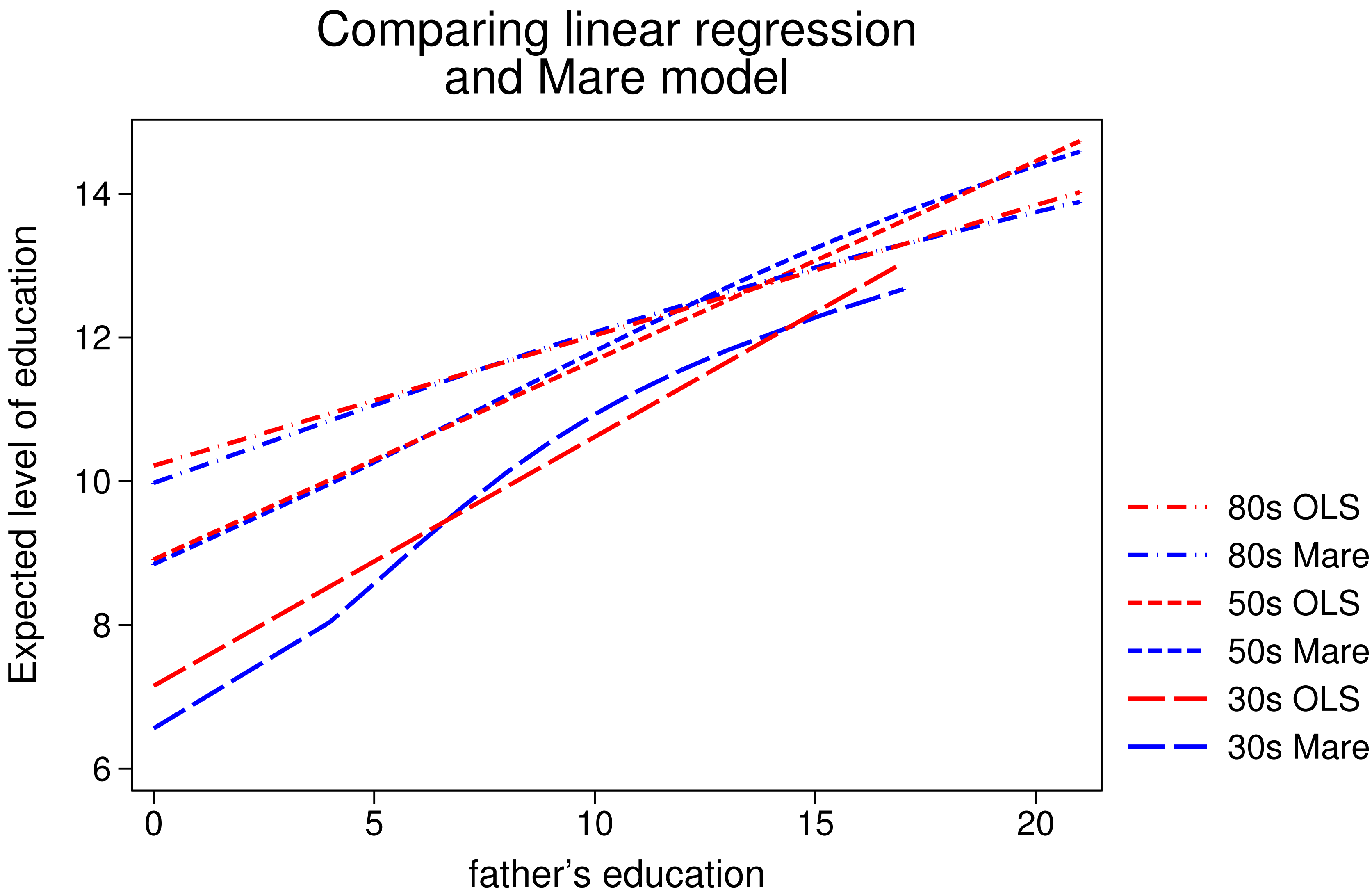
- Conceptually this is exactly the right summary measure of IEO.
- However, this is based on a linear approximation of the relationship between highest education and SES.
- In order to check whether this approximation is acceptable both a Mare model and a linear regression were estimated on Dutch data.

Data

- International Stratification and Mobility File (ISMF) on the Netherlands.
- 25 surveys held between 1958 and 2003 with information on cohorts 1930-1988.
- 40,000 respondents aged between 24 and 65 have complete information on child's, father's and mother's education and father's occupation.
- Number of cases are unequally distributed over cohorts.

Expected levels of education



Ordered logistic regression

Proportional odds assumption

$$\frac{\partial}{\partial SES}\ln\left(\frac{\mathsf{Pr}(ed \leq 0)}{\mathsf{Pr}(ed > 0)}\right) = \frac{\partial}{\partial SES}\ln\left(\frac{\mathsf{Pr}(ed \leq 1)}{\mathsf{Pr}(ed > 1)}\right) = \frac{\partial}{\partial SES}\ln\left(\frac{\mathsf{Pr}(ed \leq 2)}{\mathsf{Pr}(ed > 2)}\right)$$

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Proportional odds assumption with Mare model

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$$-\gamma_1 = -\frac{\gamma_2}{p_{1i}} = -\frac{\gamma_3}{p_{1i}p_{2i}}$$

Stereotyped Ordered regression

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$$\frac{\partial}{\partial SES}\ln\left(\frac{\Pr(y=3)}{\Pr(y=0)}\right) = \frac{\partial}{\partial SES}\ln\left(\frac{p_1 p_2 p_3}{1-p_1}\right)$$

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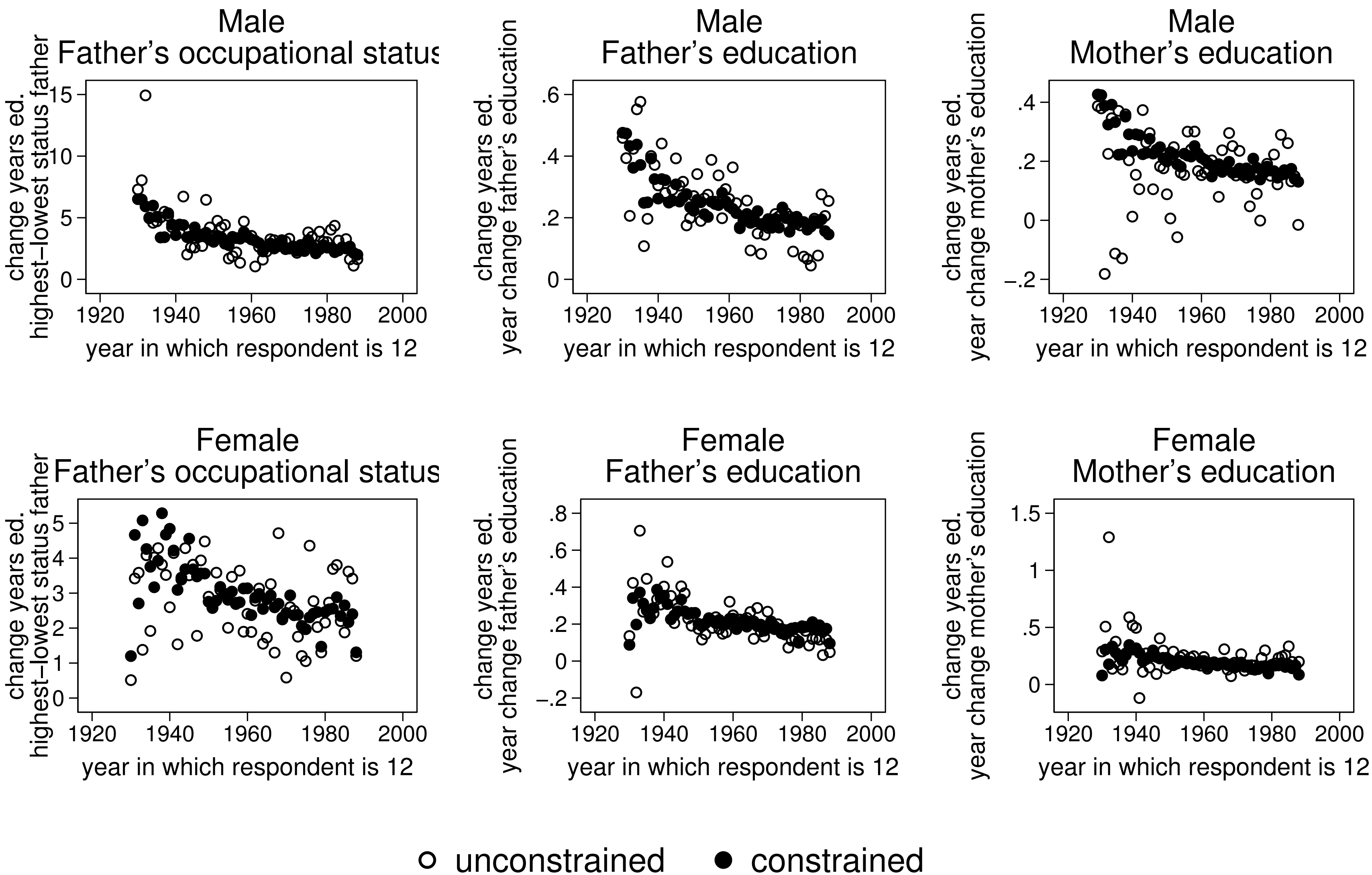
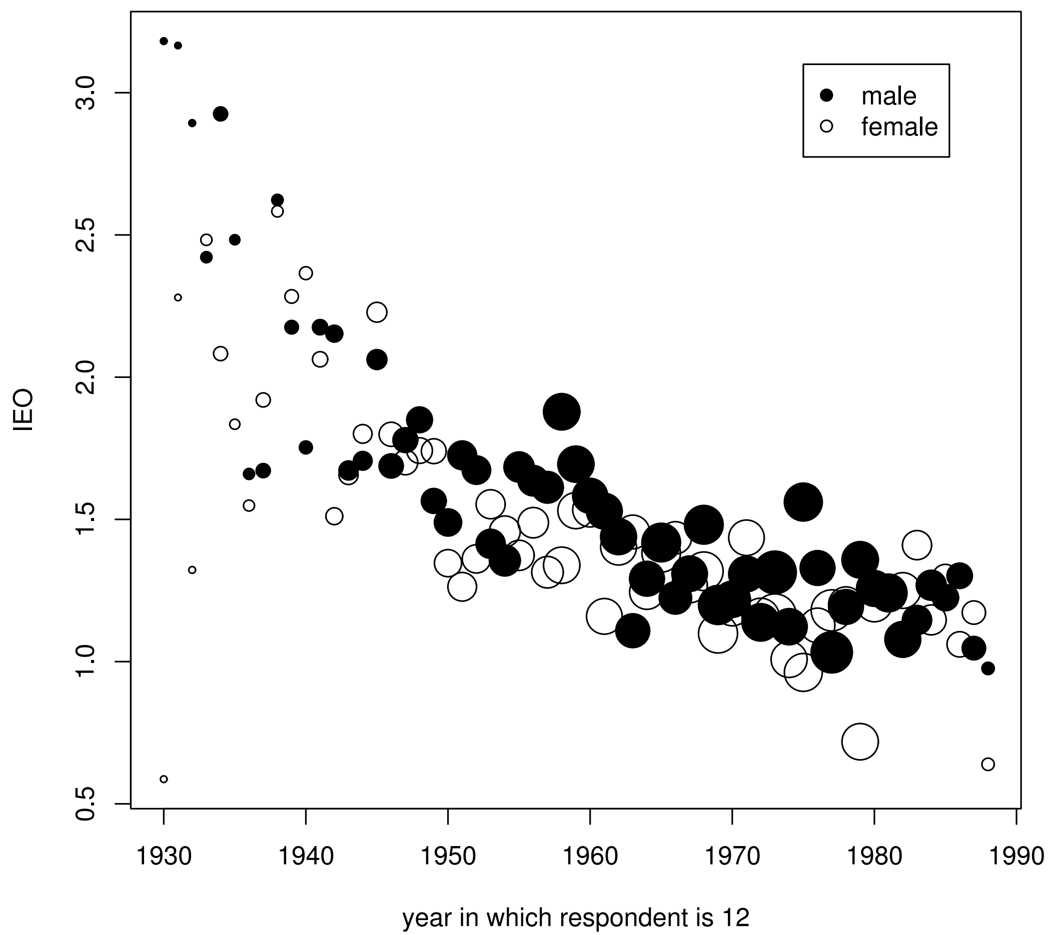
- Standard deviation of latent variable is constrained to 1 in 1970.
- β is the effect of a standard deviation change in family SES on the child's highest achieved level of education.

Constrained and unconstrained model



Annual estimates of IEO



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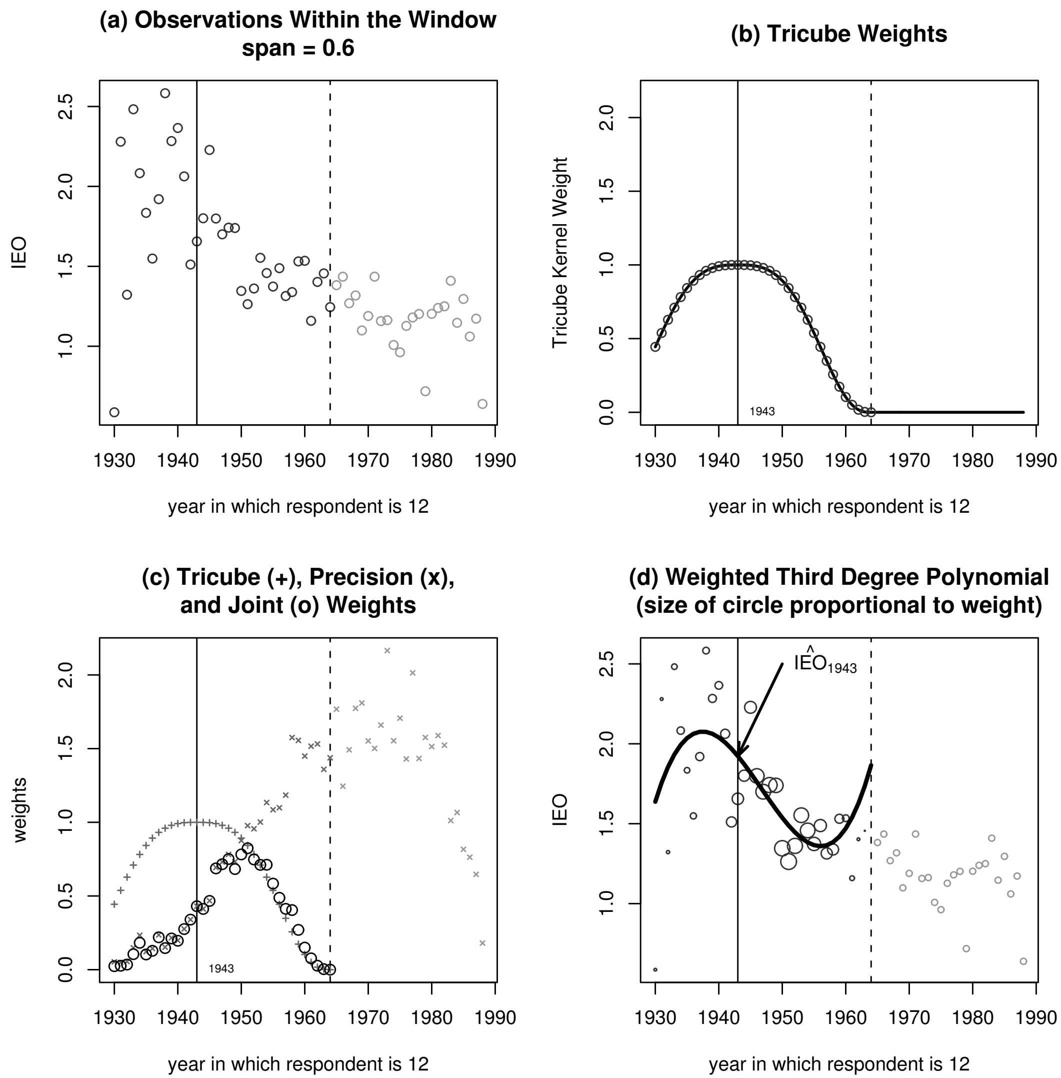
- If we think that IEO develops like a smooth curve over time, than nearby estimates also contain relevant information.
- The lowess curve creates an improved estimate of the IEO for each cohort using information from nearby cohorts.

Lowess curve in 1943

- Point on lowess curve in 1943
- Select closest 60% of the points.
- Give larger weights to nearby points.
- Adjust weights for precision of estimated IEO.
- WLS regression of IEO on time, time squared and time cubed on weighted points.
- Predicted value in 1943, is smoothed value of 1943.
- First derivative in 1943 is trend in 1943.
- Second derivative in 1943 is change in trend in 1943.

Lowess curve in 1943



bootstrap confidence intervals

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- The area containing 90% of the curves is the 90% confidence interval.

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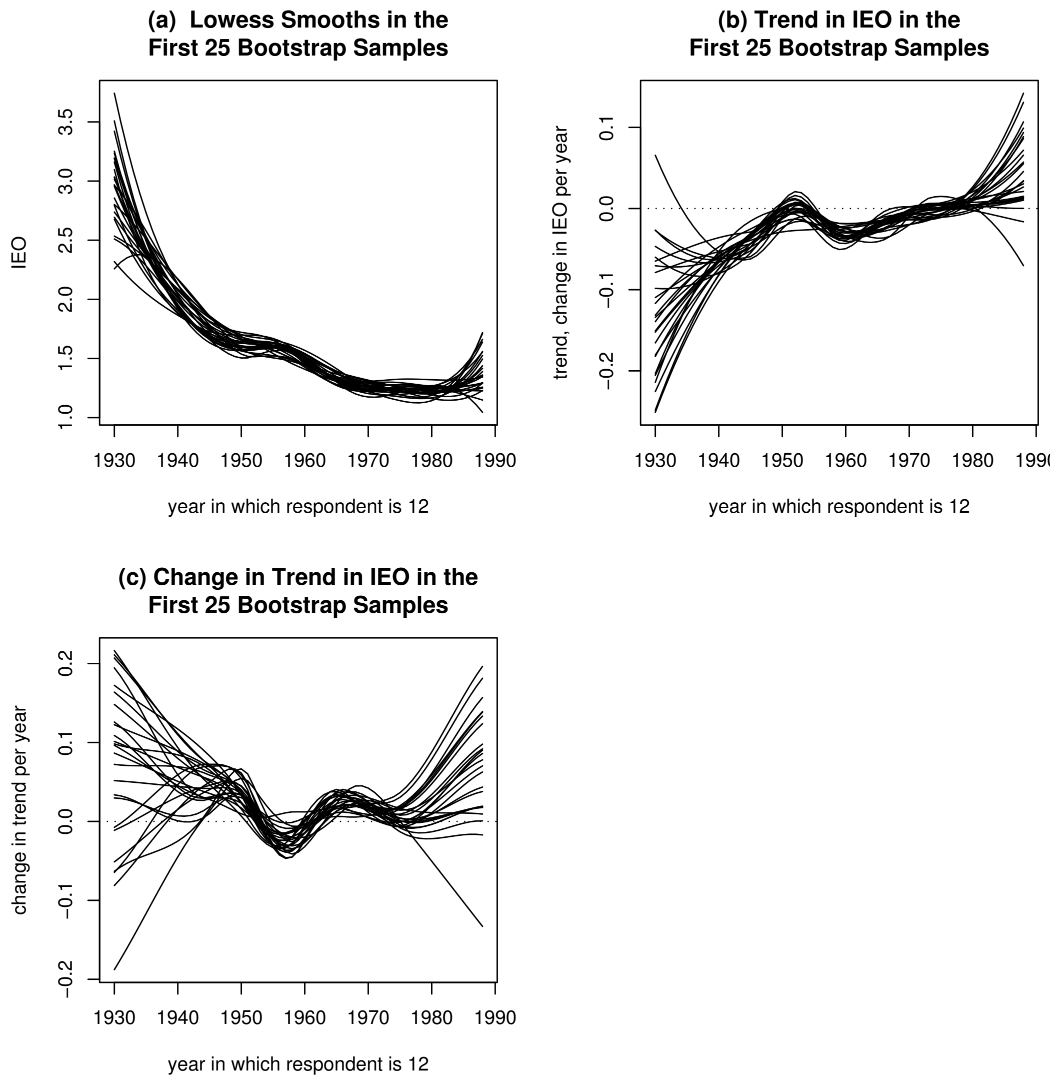
- The standard errors and covariances give information about what values of IEO could plausibly occur in a ‘new’ dataset.
- ‘New’ dataset is a random draw from a multivariate normal distribution with mean vector at the the estimated IEOs and the estimated variance covariance matrix.

First 25 bootstrapped curves



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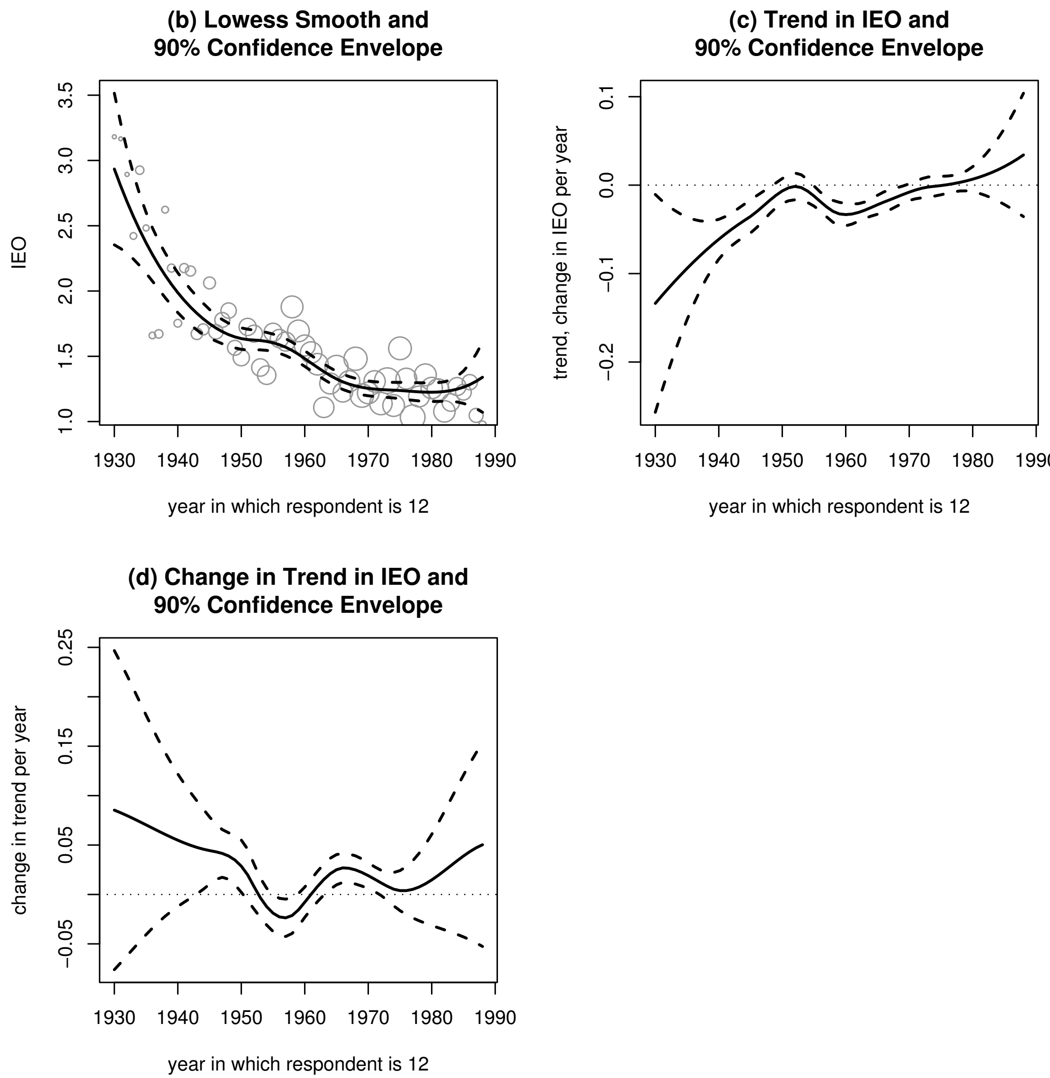
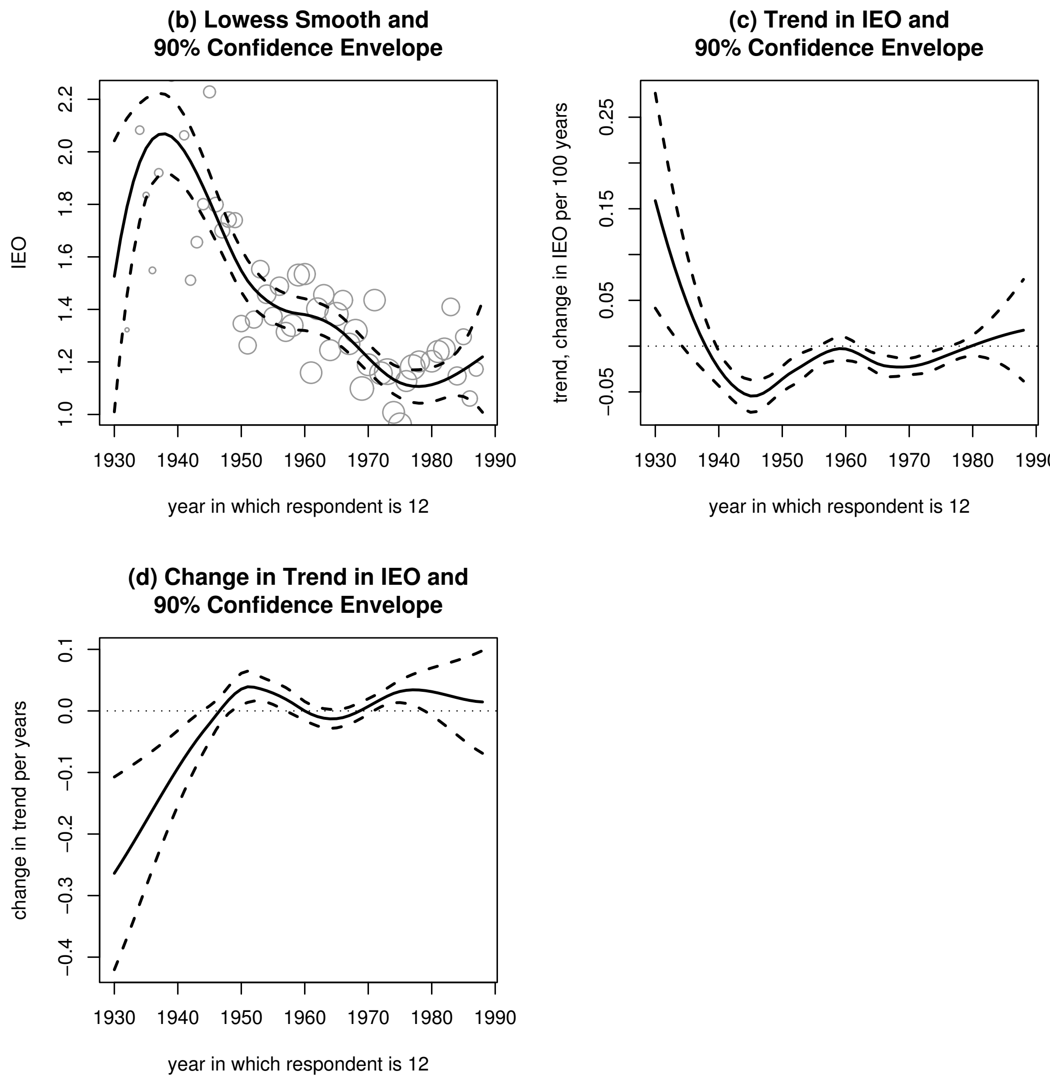
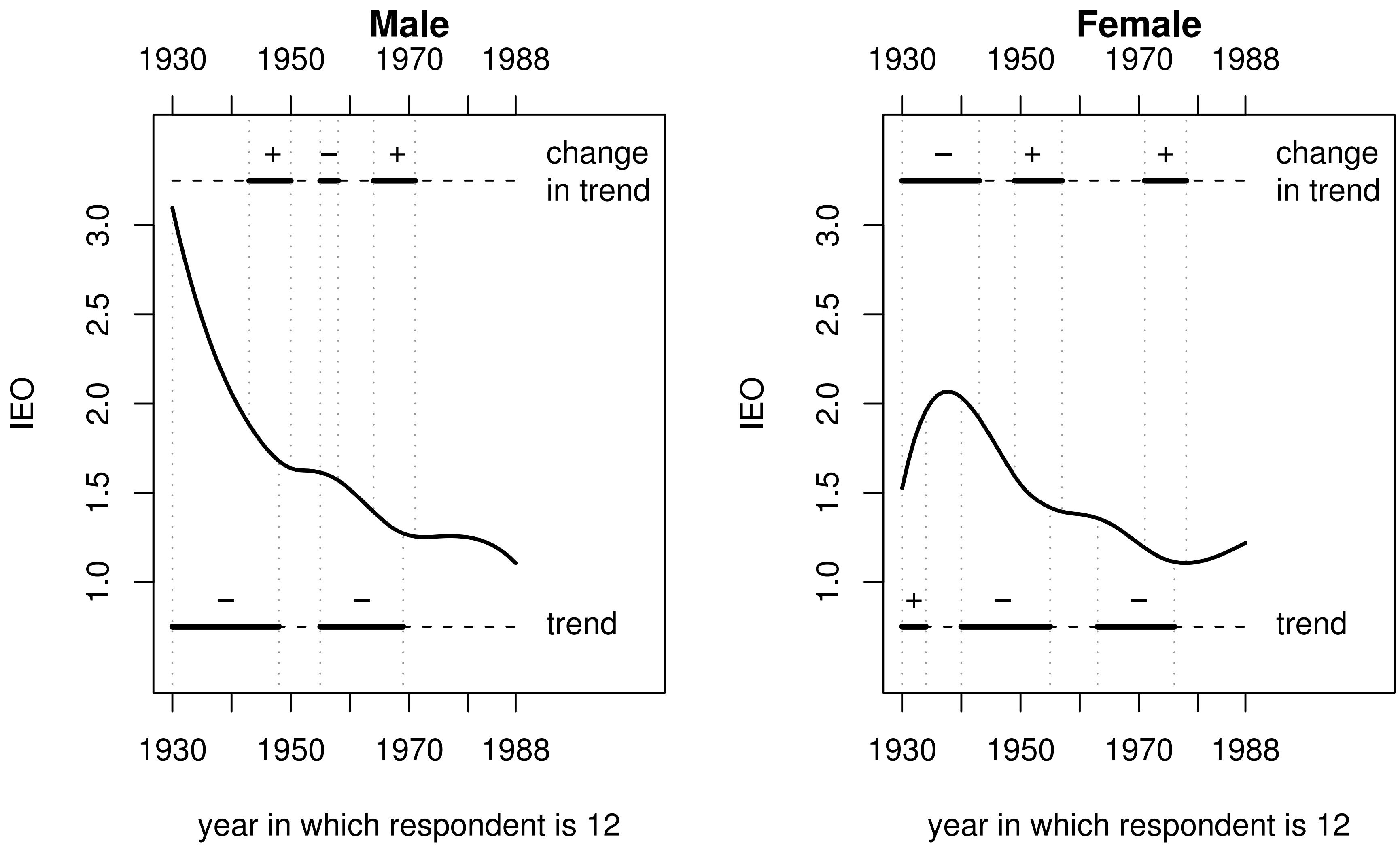
Male trend


(b) Lowess Smooth and
90% Confidence Envelope
IEO
1.0
1.5
2.0
2.5
3.0
3.5
1930
1940
1950
1960
1970
1980
1990
year in which respondent is 12
(c) Trend in IEO and
90% Confidence Envelope
trend, change in IEO per year
−0.2
−0.1
0.0
0.1
1930
1940
1950
1960
1970
1980
1990
year in which respondent is 12
(d) Change in Trend in IEO and
90% Confidence Envelope
change in trend per year
−0.05
0.05
0.15
0.25
1930
1940
1950
1960
1970
1980
1990
year in which respondent is 12

Female trend



Summary of results



Conclusions

- IEO is well measured by linear regression if one is interested in comparing the total IEO of an educational system across time and/or across space.
- IEO remained positive between 1930-1988.
- The trend in IEO was primarily negative.
- But, the trend in IEO in the Netherlands has slowed down since the 1970s and has become non-significant.