The Past of Social Mobility in Argentina: Trends in Intergenerational Class Reproduction and Status Attainment at Labour Market Entry, Birth Cohorts 1915-1993

-- abridged version --

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  - European Consortium for Sociological Research, Barcelona ES, September 13, 2024
  - SILC Seminar, VU University Amsterdam, October 8, 2024
  - Gino Germani Institute, Buenos Aires, December 10, 2024

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Research Design

- Data: 8 ‘general’ population sample surveys, held between 1961 and 2023.
- Total sample: N-men: 9496; N-women: 8634 with valid first & parental occupation [no age restriction].
- 8 birth cohorts, equally sized, differently spaced, entering the labour market between 1915 and 1993 (cohort midpoints).
- Occupation in entry into the labour market.
- Occupational class measured by EGP11
- Hauser-Goodman scaled association model (bivariate)
- HG models embedded in Conditional Multinomial Logistic Regression [CMLR] model

OCCUPATIONS IN FIRST JOBS

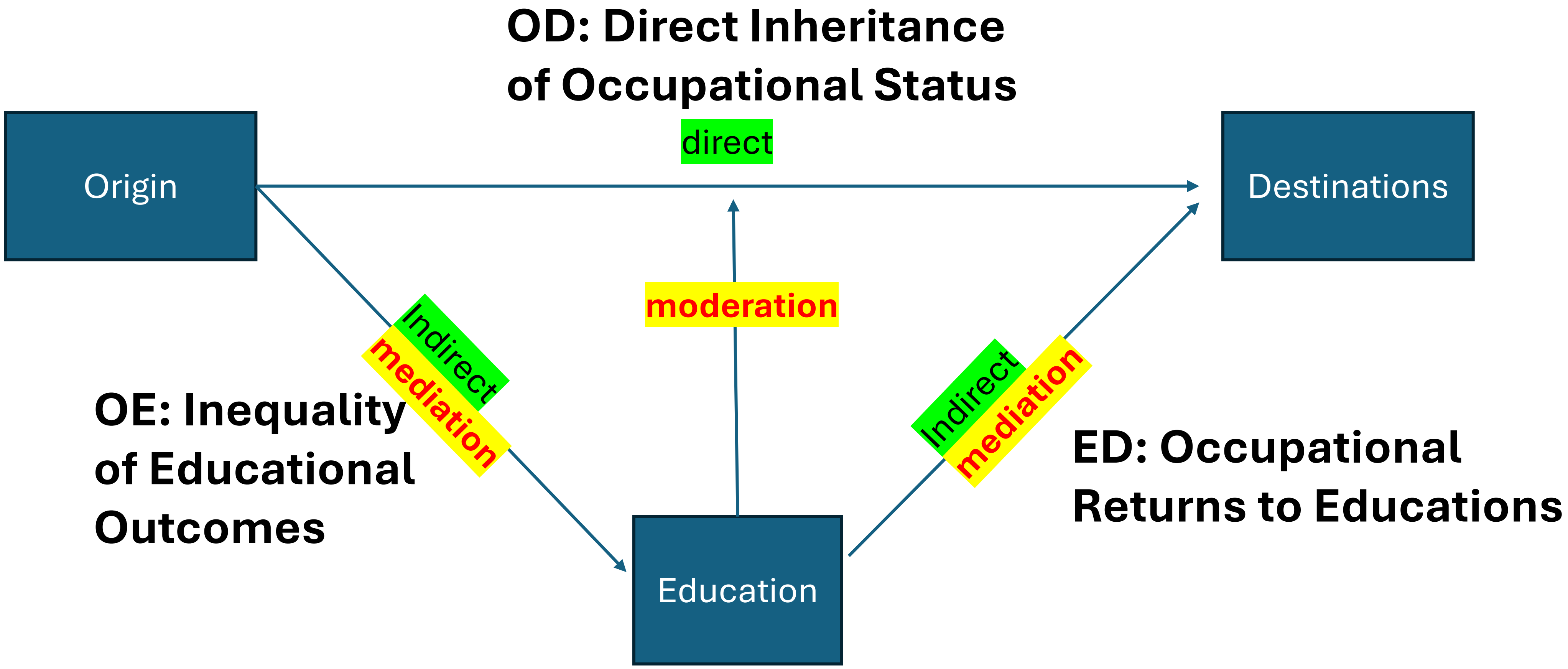
First jobs – the eight advantages

- Making first jobs (="occupation at entry into the labour market after completing education") was NOT invented by Blau & Duncan (1967), but they did inspire it much.
- There are eight benefits of using first jobs to study intergenerational mobility.
  1. First job is a major 'determinant' ('pivot') of occupational careers.
  2. Parental occupation matters for the occupational career mostly / exclusively at the beginning of the occupational career.
  3. Education has its strongest effect on occupation career at the beginning. However, education also matters a lot after career beginnings.
  4. Everybody who has ever been employed, has had a first job, including non-participating women (mothers), unemployed, disabled, retired, etc.
  5. Policy makers are most interested in the education to employment nexus.
  6. **First jobs allow for the study of historical trends by cohort comparison.**
  7. **Cohort comparisons provide a wider time window than period comparison**
  8. **In pooled cross-sections, first jobs allow for correction of survey effects.**

First jobs – some disadvantages

- Retrospective data with recall error and selective attrition.
- “First” is a complicated attribute.
- First jobs strongly determine the further occupational career, but there is also a lot of difference between first and subsequent jobs.
- **There is much more data on current / last jobs than on first jobs.**

OED model (multivariate)



Research questions

(In this analysis: only association (= relative mobility = fluidity).

- RQ1: How is the **pattern** of association OD structured?
- RQ2: How did the **strength** of the intergenerational association (OD) change between birth cohorts 1915 – 1993?
- RQ3: How are **changes in strength of association** related to changes in:
    - **OE**: Inequality in Educational Outcomes
    - **ED**: Occupational Returns to Education
    - **OD**: Durect Occupational Inheritance?

Conclusions / Answers to RQs

- The **pattern** of intergenerational association is very much as found in other countries:
  - Association among the **stayers** (immobility) is highest for Farmers (IV-c, VIIb) and Small Enterpreneurs (IV-a).
  - Among the **movers**, there is a clear mobility distance between the EGP11 classes, with Higher Controllers on top and Agricultural occupations at the bottom. Very similar to an ISEI hierarchy – although nor identical.
- **Weakening of both on-diagonal and off-diagonal association** is observed, but only when appropriate survey heterogeneity indicators are taken into account.
- Controlling education lowers the HG association parameters, but much more off-diagonal association than then the on-diagonal association: **mediation**
- Education has a complicated but interesting – and interpretable -- **moderation** effect on OD: controlling E **increases the off-diagonal part** of OD and **decreases the on-diagonal** part.

DATA

Argentina 1961-2021, 8 surveys with first occupation

Table 2: Eight AR mobility surveys with first job data

Mean

SURVEY	YEAR	FEMALE	AGE	AMBA	FISEI	ISEI1	AGE1st	EDUC
.0 Germani 1961	1961	10%	47.5	100%	38.7	33.6	14.3	6.8
2.0 CEDOP - UBA, 1995	1995	53%	47.5	100%	34.1	32.6	18.2	10.2
7.0 CEDOP-UBA, 2007, ISSP 2006, 2007	2007	52%	44.4	36%	33.6	31.2	18.9	11.0
9.0 CEDOP-UBA, 2010, ISSP 2009	2010	47%	47.1	35%	30.6	31.3		10.4
11.0 EDSA-UCA, 2010	2010	52%	43.5	59%	34.4	30.7	17.8	11.0
13.0 Chávez Molina, Ipar - IIGG-UBA, 2013	2013	51%	45.4	100%	42.0	33.6	17.7	10.3
15.0 IIGG-UBA, 2016	2015	51%	44.5	100%	38.3	32.5	17.0	13.0
18.0 Covid 2021	2021	53%	43.0	20%	35.1	32.0	18.6	11.4
Total	2006	48%	44.7	56%	35.1	31.8	17.8	10.6

Data heterogeneity

- 8 surveys with first jobs from Argentina, collected between 1961 and 2021 (60 years): Cohorts entered the labour market between 1925 and 1995 (70 years).
- N = 18,370 men and women, organized in 8 / 16 cohorts.
- The surveys vary in quality:
  - Sample coverage (metropolitan (AMBA), non-rural, national).
  - Sampling methods: probability multi-stage, quota-sampling
  - Measurement of occupations and education.
  - Definition of parental: father, father + mother, main provider
  - First jobs definitions
  - More ….
- Survey heterogeneity will likely affect any social mobility estimate and possibly confound them, as more recent surveys probably have higher quality than earlier ones.

BIVARIATE AND MULTIVARIATE ANALYSIS OF RELATIVE MOBILITY

	FEP by EGP1 - OUTFLOW											
	1 I :Higher Controllers	2 II :Lower Controllers	3 IIIa:Routine Nonmanual	4 IIIb:Lower Sales-Service	5 IVa:Selfempl with empl	6 IVb:Selfempl no empl	7 V :Manual Supervisors	8 VI :Skilled Worker	9 VIIa:Unskilled Worker	10 VIIb:Farm Labor	11 IVc:Selfempl Farmer	Total
1 I :Higher Controllers	35.9%	15.5%	14.5%	6.4%	7.6%	5.4%	15.2%	3.4%	3.7%	.8%	3.9%	7.6%
2 II :Lower Controllers	15.6%	21.2%	17.6%	12.2%	9.4%	8.0%	7.6%	7.0%	7.0%	2.4%	4.7%	10.8%
3 IIIa:Routine Nonmanual	5.6%	7.0%	12.0%	8.7%	2.9%	3.8%	3.3%	5.7%	5.2%	2.6%	1.3%	6.8%
4 IIIb:Lower Sales-Service	3.4%	4.5%	6.2%	8.8%	1.4%	4.5%	2.2%	4.8%	4.9%	2.2%	2.1%	5.6%
5 IVa:Selfempl with empl	7.8%	9.4%	7.0%	6.0%	50.0%	5.1%	6.5%	6.6%	3.8%	1.6%	7.3%	6.4%
6 IVb:Selfempl no empl	8.5%	11.3%	13.5%	14.3%	9.8%	39.2%	6.5%	17.2%	14.7%	6.7%	10.7%	15.6%
7 V :Manual Supervisors	3.8%	3.5%	2.1%	1.5%	1.1%	1.2%	17.4%	2.7%	2.5%	.5%	3.0%	2.3%
8 VI :Skilled Worker	4.5%	9.5%	10.3%	14.4%	4.3%	8.3%	5.4%	23.4%	17.2%	6.2%	4.7%	14.1%
9 VIIa:Unskilled Worker	7.2%	11.2%	10.7%	19.4%	6.2%	12.7%	22.8%	17.6%	25.9%	15.2%	6.9%	17.7%
10 VIIb:Farm Labor	2.0%	2.3%	1.5%	4.3%	.4%	3.7%	1.1%	4.8%	8.5%	33.7%	4.7%	6.0%
11 IVc:Selfempl Farmer	5.6%	4.7%	4.5%	3.9%	6.9%	8.0%	12.0%	6.9%	6.8%	28.1%	50.6%	7.2%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

	FEP by EGP1 - OUTFLOW											
	1 I :Higher Controllers	2 II :Lower Controllers	3 IIIa:Routine Nonmanual	4 IIIb:Lower Sales-Service	5 IVa:Selfempl with empl	6 IVb:Selfempl no empl	7 V :Manual Supervisors	8 VI :Skilled Worker	9 VIIa:Unskilled Worker	10 VIIb:Farm Labor	11 IVc:Selfempl Farmer	Total
1 I :Higher Controllers	14.3%	16.7%	22.8%	19.3%	1.5%	5.1%	1.0%	6.1%	12.3%	.4%	.6%	100.0%
2 II :Lower Controllers	4.4%	16.2%	19.7%	26.0%	1.3%	5.3%	.4%	8.8%	16.6%	.9%	.6%	100.0%
3 IIIa:Routine Nonmanual	2.5%	8.6%	21.5%	29.6%	.7%	4.0%	.2%	11.5%	19.7%	1.6%	.2%	100.0%
4 IIIb:Lower Sales-Service	1.9%	6.6%	13.3%	36.0%	.4%	5.7%	.2%	11.6%	22.4%	1.6%	.5%	100.0%
5 IVa:Selfempl with empl	3.7%	12.0%	13.3%	21.3%	11.9%	5.6%	.5%	14.0%	15.1%	1.0%	1.5%	100.0%
6 IVb:Selfempl no empl	1.7%	6.0%	10.5%	21.0%	1.0%	17.9%	.2%	15.1%	24.1%	1.8%	.9%	100.0%
7 V :Manual Supervisors	5.1%	13.0%	11.2%	15.2%	.7%	3.9%	3.9%	16.1%	28.1%	1.0%	1.7%	100.0%
8 VI :Skilled Worker	1.0%	5.6%	8.9%	23.5%	.5%	4.2%	.2%	22.7%	31.3%	1.8%	.4%	100.0%
9 VIIa:Unskilled Worker	1.2%	5.2%	7.2%	25.1%	.5%	5.1%	.7%	13.6%	37.3%	3.5%	.5%	100.0%
10 VIIb:Farm Labor	1.0%	3.2%	3.0%	16.7%	.1%	4.4%	.1%	10.9%	36.4%	23.3%	1.0%	100.0%
11 IVc:Selfempl Farmer	2.4%	5.3%	7.5%	12.4%	1.5%	7.9%	.8%	13.1%	24.2%	16.0%	9.0%	100.0%
	3.0%	8.2%	12.1%	22.9%	1.5%	7.1%	.5%	13.6%	25.6%	4.1%	1.3%	100.0%

Hauser-Goodman scaled uniform association model - technically

- Goodman (1979) RC-II model
    - Association model = constraints on the pattern of odds-ratios within tables
    - Uniform association: all contiguous odds-ratio’s are the same: ln(odds) = ln[(Fij/Fij’)/(Fi’j/Ffi’j’)] = U. [This assumes ordering oi categories.]
    - Scaled uniform association: ln(odds) = U*(Ui-Ui’)* (Uj-Uj’)
    - Ui and Uj are distances between categories estimated from the data. The model does NOT assume ordering.
    - Compare tables with Ut
- Hauser (1984) added levels-parameters to Goodman RC-II:
    - Category-specific immobility parameters: IMMk
    - Compare tables with general immobility parameter: IMMt,

Hauser-Goodman model - sociologically

- Scaling parameters Ui and Uj reveal **mobility distances = social hierarchy**, in particular when constraining Ui = Uj within and between tables (equality and homogeneity)
- When Ui and Uj are **Z-standardized**, U becomes very much like a **pearson correlation** (same metric).
- HG model separates (trends in) association between **movers** (off-diagonal association) and **stayers** (on-diagonal association).
- HG model can be made **multivariate** by embedding it in the Conditional Multinomial Logistic Regression **[CMLR]** model.

Hauser-Goodman parameters

Parameters of the Hauser-Goodman model, FEGP * EGP1 pooled table

	I	II	III-a	III-b	IV-a	IV-b	V	VI	VII-a	VII-b	IV-c
Ui=Uj	1.720	1.117	0.947	0.178	0.768	-0.094	0.373	-0.292	-0.521	-2.463	-1.246
U	0.384										
IMMk	.787	.235	.241	.480	2.465	1.234	2.059	.528	.316	-.360	1.972

When Ui = Uj are Z-standardized, the U parameter looks very much like a pearson correlation!

CMLR: Conditional Multinomial Logistic Regression

- CMLR transfers the HG model of **aggregate cell counts** into **individual level multinomial** data
- Conditional: CMLR allows for covariates to scale the multinomial outcomes.
- Original: McFadden (1974) – Nobel Prize 2000.
- Advantages:
  - No ‘empty cell problem’
  - Multivariate
    - Controlling confounders (cohort, gender, region, survey controls
    - Controlling mediators (education) and calculate total and direct effects.

Table 1: Stepwise estimated CMLR models, entry into first job, 8 cohorts, 1915-1993. Eight surveys 1961-2021, N=18.131

Model specification		
D1	Cohort + IMMk + U + U_COHx	SCALED ASSOCIATION
D2	D1 + COHORT	MARGINALS
D3	D2 + IMM_COH	IMMOBILITY TREND
D4	D3 + FEMALE + FEMALE interactions on U and IMM	
D5	D4 + AMBA + AMBA interactions on U and IMM	AMBA CONTROLS
D6	D5 + survey main effects	SURVEY CONTROLS
D7	**D6 + survey interactions on U**	**SURVEY CONTROLS**
D8	**D7 + survey interactions IMM**	**SURVEY CONTROLS**
D9	D8 + education main effect	MEDIATION
D10	D9 + education interaction on U and IMM	MODERATION

Table 2: Stepwise estimated CMLR models, entry into first job, 8 cohorts, 1915-19923. Eight surveys 1961-2021, N=18.131.

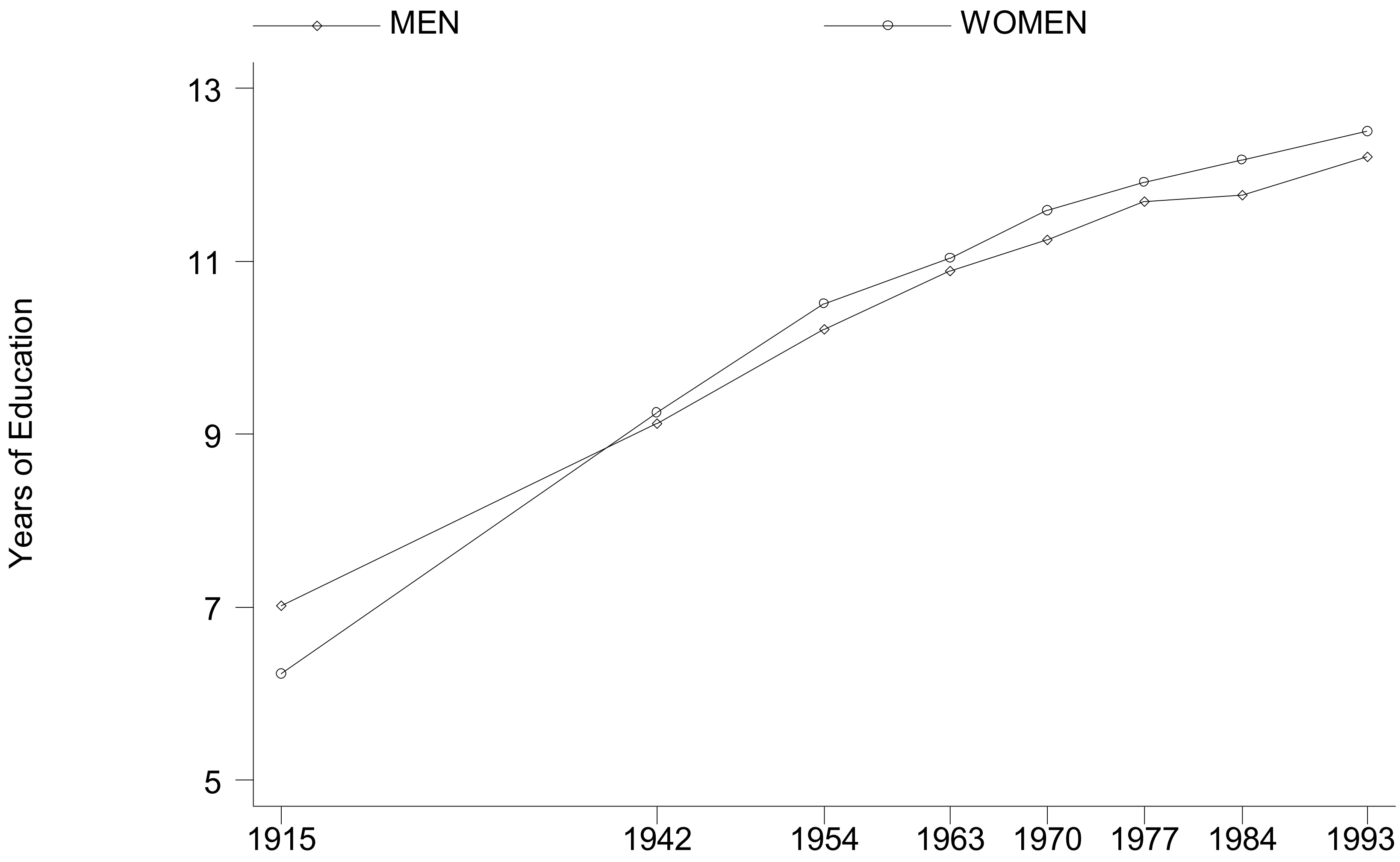
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
DF	23	173	174	177	180	187	194	201	202	204
U	0.472	0.339	0.356	0.357	0.385	0.381	0.405	0.399	0.294	0.315
U_COHx	-0.258	-0.051	-0.083	-0.098	-0.118	-0.104	-0.206	-0.151	-0.096	-0.135
IMM_COHx			0.215	0.294	0.191	0.201	0.202	-0.180	-0.164	-0.07
Female_ddd				-0.394	-0.394	-0.422	-0.426	-0.426	-0.487	-0.411
U_female				0.038	0.039	0.029	0.015	0.016	-0.019	-0.022
IMM_female				-0.387	-0.393	-0.389	-0.386	-0.399	-0.409	-0.411
AMBA_ddd					0.049	0.059	0.067	0.055	0.038	0.038
U_amba					-0.029	-0.022	0.015	-0.012	-0.038	-0.036
IMM_amba					-0.18	-0.184	-0.184	-0.003	-0.012	-0.015
ZEDUC_ddd									0.639	0.629
U_ZEDUC										0.035
IMM_ZEDUC										-0.108

U: scaled uniform association. IMM: immobility. ddd: destination scaling (Z). COHx: Cohorts scaled between 0 and 1; AMBA: Buenos Aires Metropolitan Area. ZEDUC: years of education (Z). Coefficients in red are not statistically significant.

CONCLUSIONS

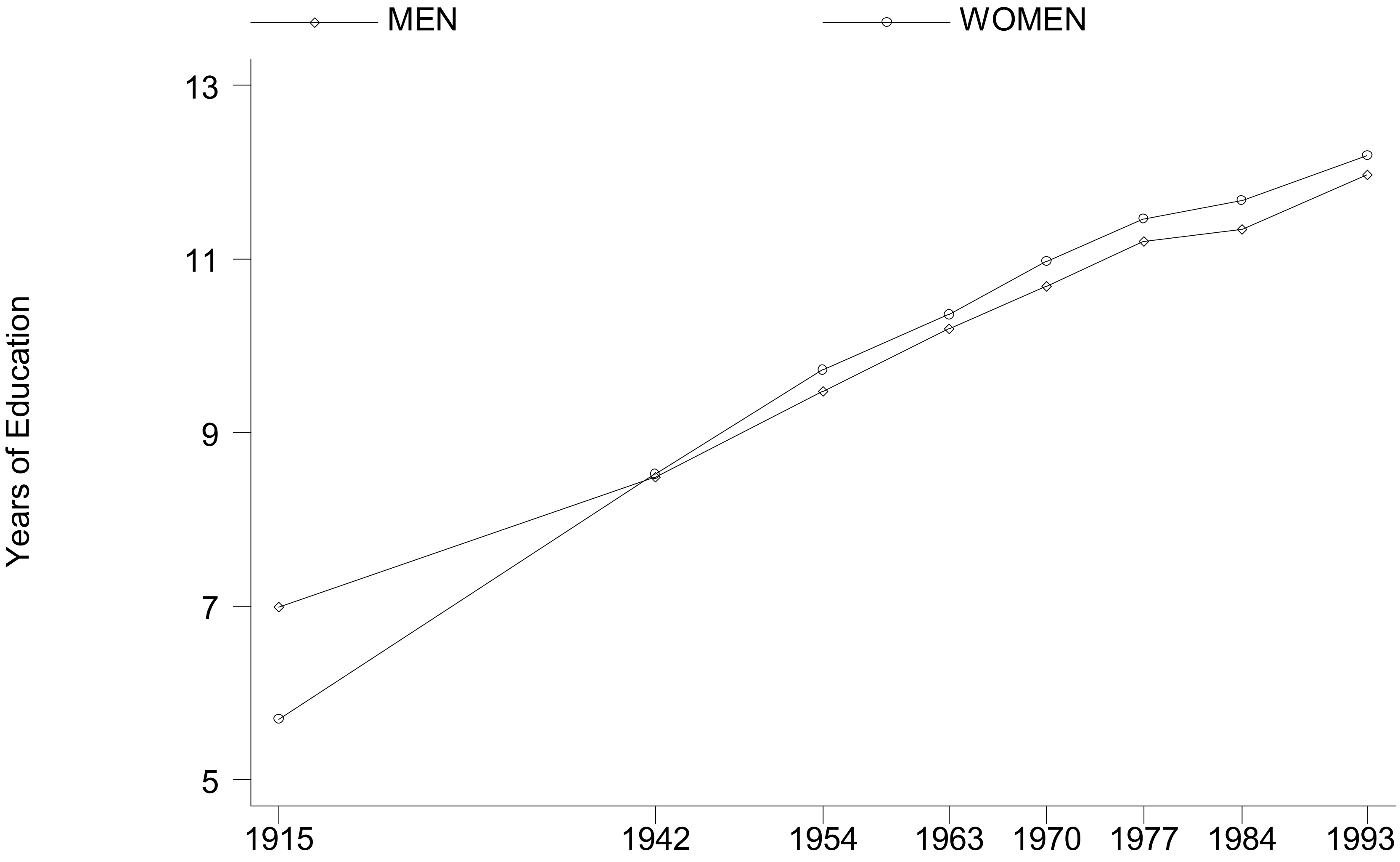
SURVEY HETEROGENEITY CONTROLS

Educational Expansion (before survey corrections)



Mean Education by Birth Cohort

Educational Expansion (after survey corrections)

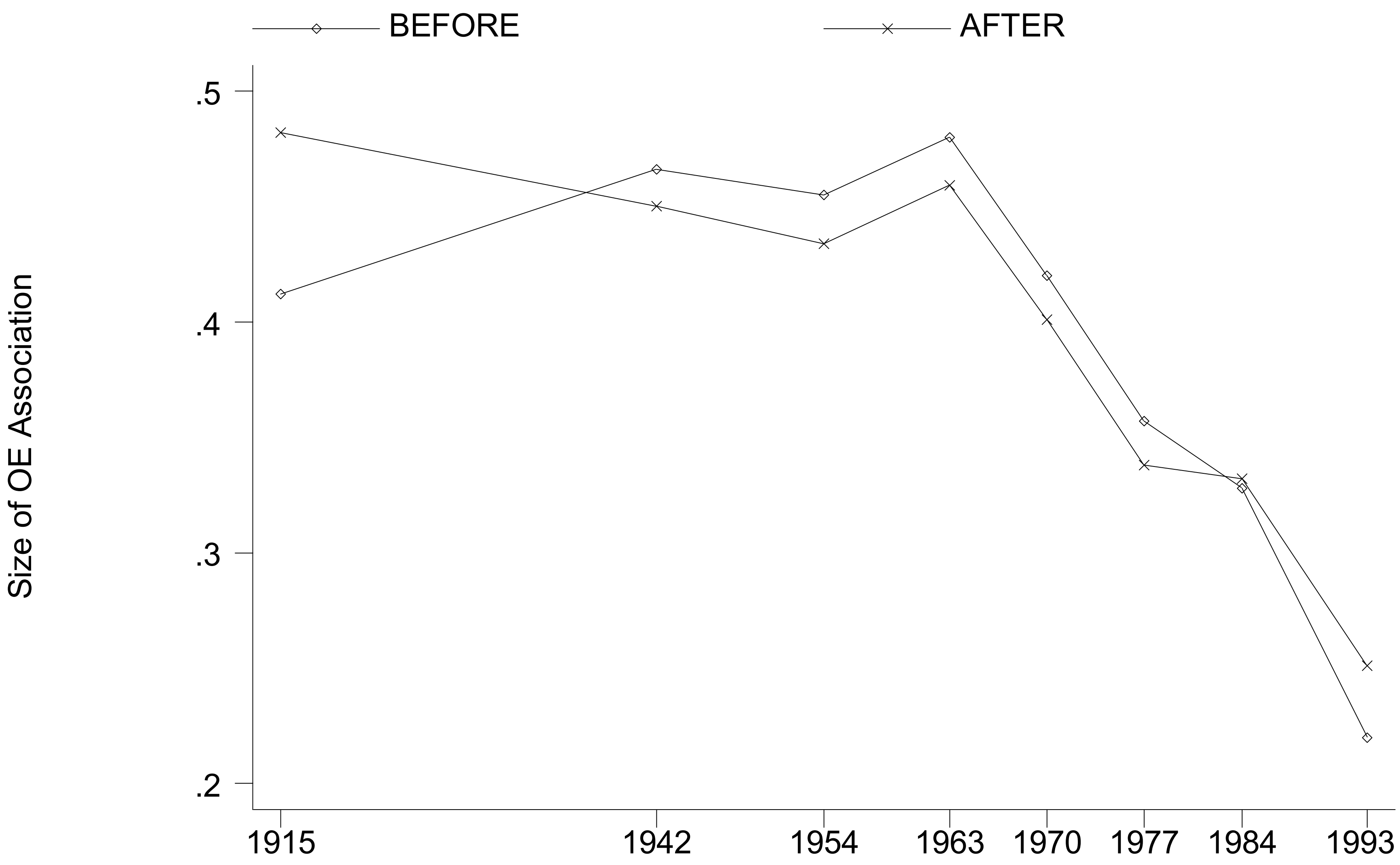


Mean Education by Birth Cohort

O → E Inequality of Educational Outcomes

- Before survey correction: OE = .500 - .167*COHx
- Correcting survey main effects: OE = .521 - .191*COHx
- Correcting survey interactions: OE = .598 - .272*COHx

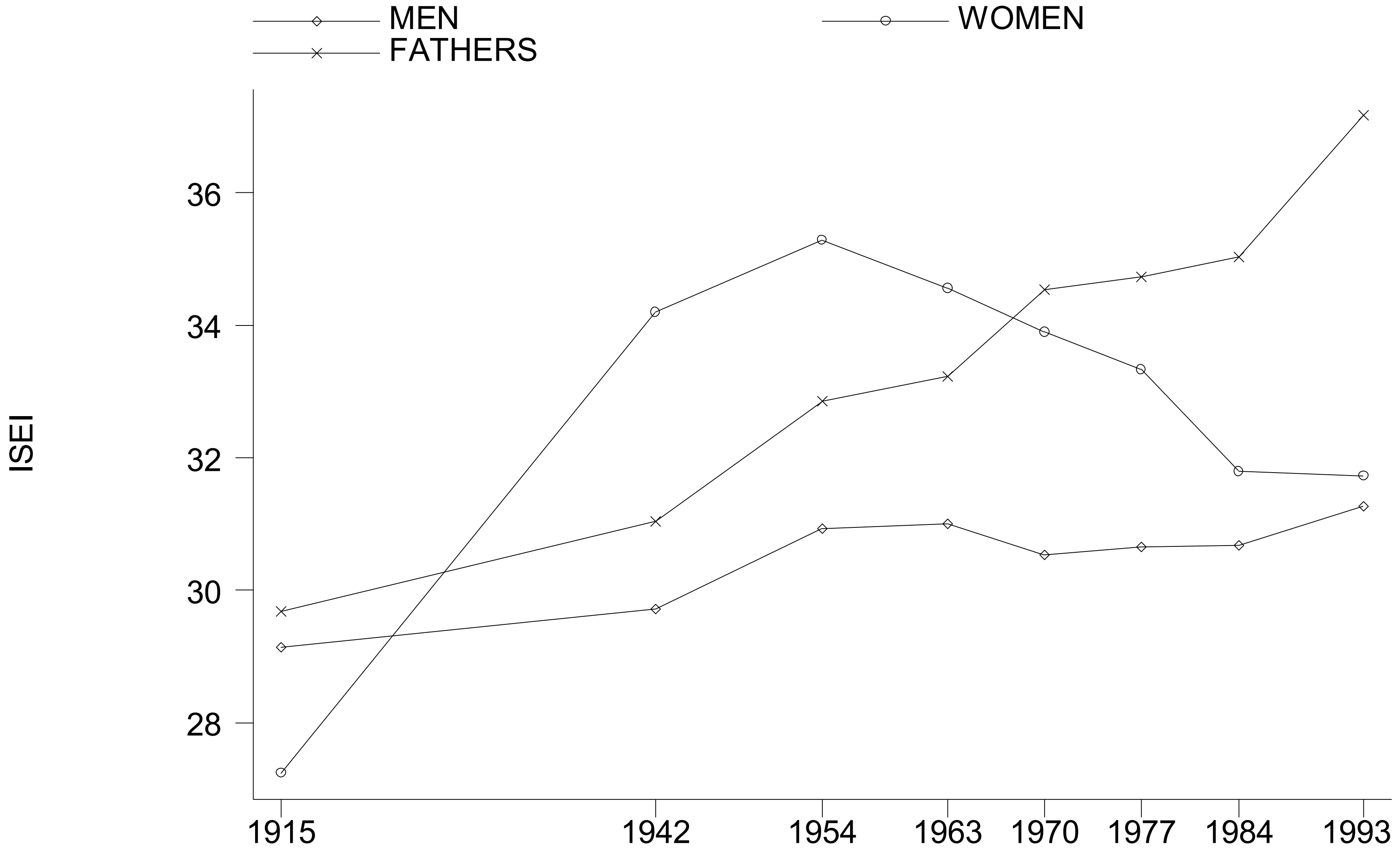
OE association BEFORE and AFTER survey heterogeneity



OE by Birth Cohort before and after correcting heterogeneity

STRUCTURAL MOBILITY

Structural Mobility: Destinations vs Origins



Mean Occupational Status by Birth Cohort

Structural Mobility (at entry into the labour market)

- The simplest, but most important conception of structural mobility is the mean difference between origins and destinations
- We show this in ISEI scaled occupational categories
- Conclusions
  - **Women hold higher ranked** occupations than men – at entry into the labour market
  - Both men and women are on average **downwardly mobile** relative to their father
  - **The gap is widening**: strong occupational upgrading among the fathers; little to no upgrading among men; occupational downgrading among women