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The Role of Repeated Moves and Heterogeneous Geographic Mobility Trajectories on Occupational Outcomes

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Understanding spatial mobility from early life into adulthood

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Geographical inequalities shape individuals' life chances and socio-economic achievement [1]

- Geographic mobility as a mechanism underlying social mobility and inequality

Geographic mobility experiences are often **repeated**

- How is the association between geographic mobility and social mobility affected by repeated moves over the life course?

Geographic mobility experiences are **not homogenous** across population groups and over the life course

- Differential experience underlie heterogeneous outcomes across movers [2]
- While moving in adulthood is often positively associated with occupational outcomes, moving in childhood is negatively associated with cognitive and educational outcomes [3]

1 Blau and Duncan (1967), Fielding (1992), Li and Heath (2016)
2 Van Ham (2003), Huinink et al (2014), Ballarino and Panichella (2021)
3 Tønnessen et al (2016), Vidal and Baxter (2017), Bernard (2023)

Objective 1: Assess the extent to which **repeat moves** affect estimates of occupational outcomes of geographic mobility

- Empirical issue: Effects of geographic mobility often considered permanent (e.g. mover *effect*) or attributed to the most recent move
- Methodological issue: Dealing with geographic mobility as a time-varying exposure / treatment

Objective 2: Assess heterogeneity in geographic mobility trajectories underlying occupational outcomes

Data come from the **Survey for Health, Ageing and Retirement in Europe** (SHARE)

- **Retrospective information** collected in waves 3 (2008/9) and 7 (2017)

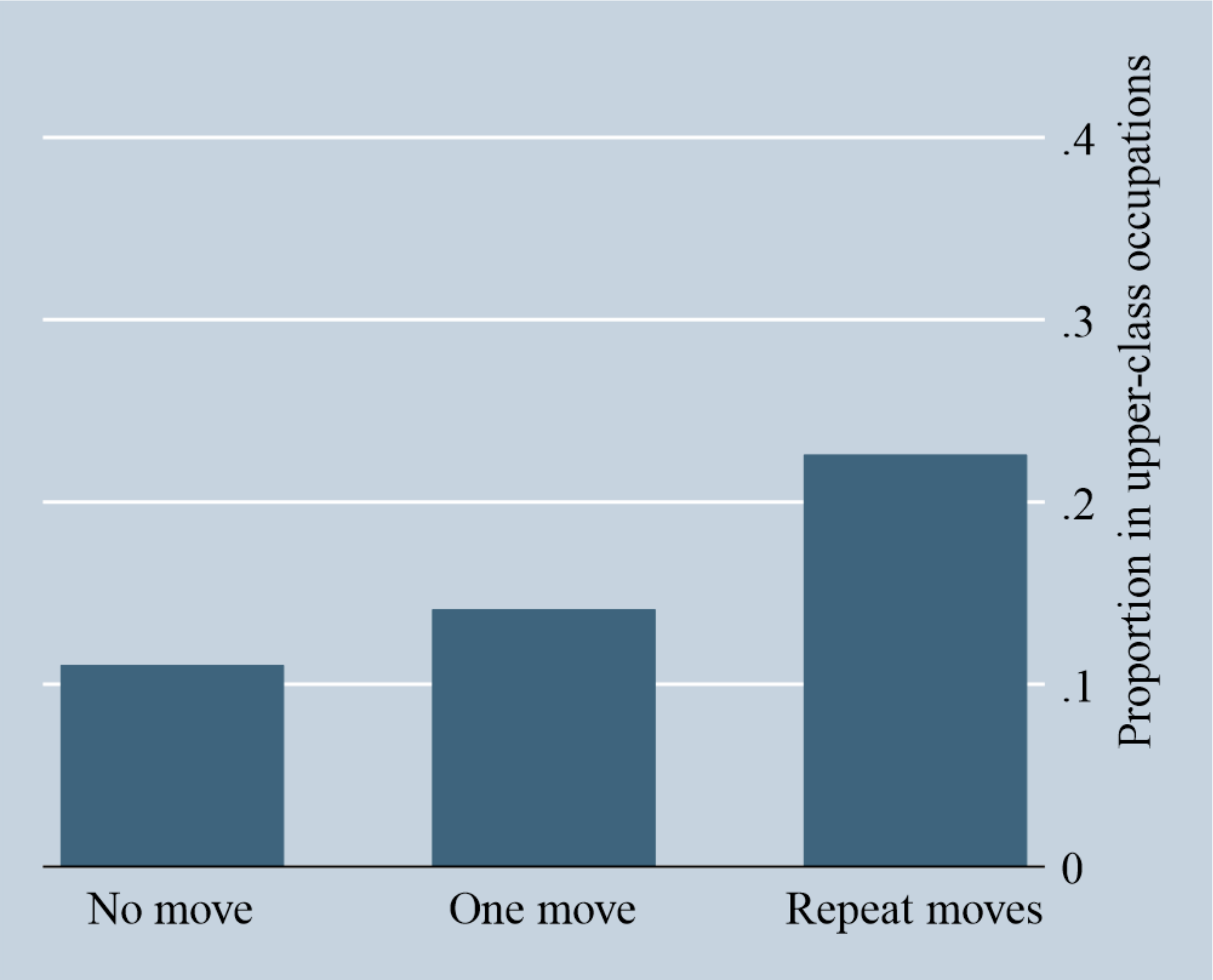
Analytical **sample**

- Individuals **born in 25 survey countries**, between **1950** and **1968**, with complete information on residential, occupational, education and family histories from birth to age 45 (N=31,901)

Measures

- Study outcome: **occupational status** at age 45
  (i) in an upper-class occupation; (ii) avoiding a working-class/agricultural occupation
- Independent variables: **move events** within age groups
  (i) of any distance; (ii) interregional (across NUTS 2); (iii) interregional to urban area
- Control variables: time-constant (gender, birth cohort, type of residential area in childhood) and time-varying (educational attainment, employment status and family status)

Upper-class occupation at age 45 by lifetime moves



Individuals who did **two or more interregional moves** since birth are **over-represented among upper-class occupations**

The bulk of research (and standard regression models) do not robustly assess outcomes of geographic mobility as these often ignore (or fail to properly address) previous moves

- *Time-varying treatment* – to dissociate the role of being a mover at a point in time (or the last observed move) from repeat moving (or moves at previous points in time)

- *Time-varying confounding* - the values of confounders can be affected by or are endogenous to past treatments (i.e. previous moves)

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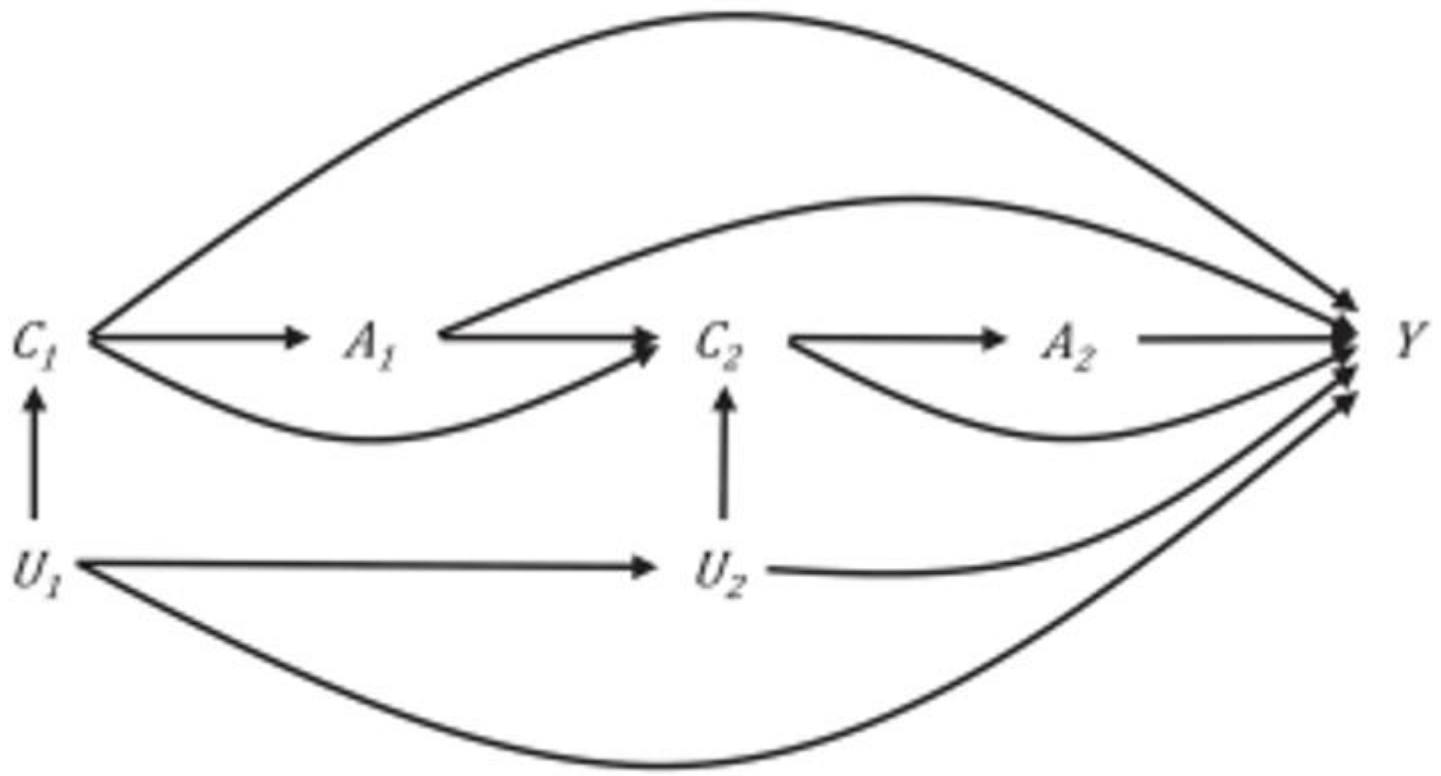
Time-varying treatment and confounding



Conditioning naively on a time-varying confounder affected by past treatment engenders **overcontrol bias** and **selection bias**

G-methods (Hernán and Robins 2024)

- Inverse probability weighting of marginal structural models (Robins et al 2000).
- The g-computation formula (Robins 1986).
- G-estimation of structural nested models (Robins et al 1992).

Regression-with-residuals (Wodtke 2018)

- Regression-based estimation of a constrained structural nested mean model

Objective: Estimate the average treatment effect of geographic mobility on occupational attainment at age 45

Standard linear probability model

(1) **without confounders –** confounded associations between geo mob and occup attainment

(2) **with confounders –** unconfounded associations assuming that previous moves do not alter values of confounders

Regression with residuals (Wodtke 2018)

with residualized time-varying confounders – unconfounded associations relaxing the assumption that previous moves do not alter values of confounders

Steps:

- Regress time-varying confounders at *time t* on treatment and confounfers *at time t-1*
- Use the residualized confounders in a linear probability model

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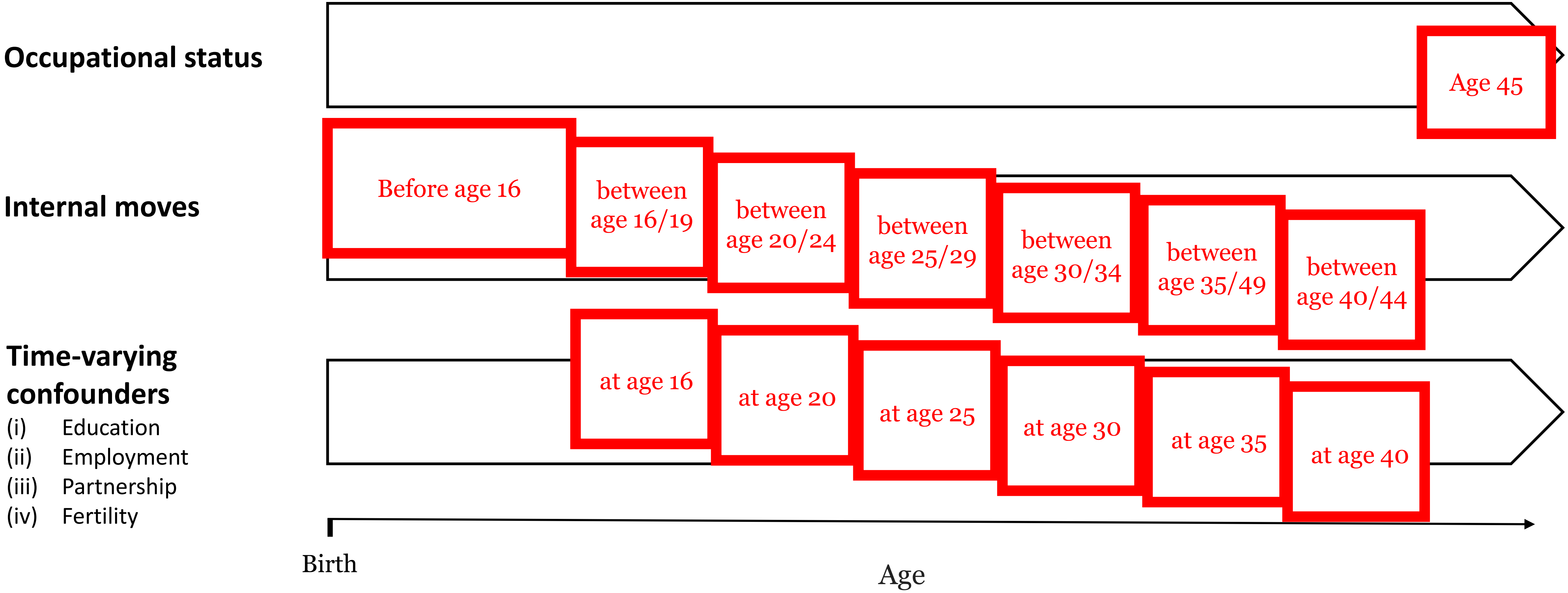
Regression adjustment (residualized time-varying confounders)



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Upper-class occupational attainment by age 45 – Age at move (*ref.* never moved)

Interregional move	LPM	LPM w/tv confounders	
	B/(SE)	B/(SE)	
Age 0-15	0.04**	0.02**	
	(0.01)	(0.01)	
Age 16-19	0.03*	0.01	
	(0.01)	(0.01)	
Age 20-24	0.06***	0.01	
	(0.01)	(0.01)	
Age 25-29	0.10***	0.04**	
	(0.02)	(0.01)	
Age 30-34	0.09***	0.04**	
	(0.01)	(0.01)	
Age 35-39	0.03	0.01	
	(0.02)	(0.02)	
Age 40-44	0.04*	-0.00	
	(0.02)	(0.02)	

* p<.05, ** p<.01, *** p<.001

Notes: OLS regressions. All models include gender, type of birth area, and birth cohort. Time-varying confounders include education, employment and family status.

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Upper-class occupational attainment by age 45 – Age at move (*ref.* never moved)

Interregional move	LPM	LPM w/tv confounders	RWR
	B/(SE)	B/(SE)	B/(SE)
Age 0-15	0.04**	0.02**	0.08***
	(0.01)	(0.01)	(0.00)
Age 16-19	0.03*	0.01	-0.18***
	(0.01)	(0.01)	(0.01)
Age 20-24	0.06***	0.01	0.01
	(0.01)	(0.01)	(0.00)
Age 25-29	0.10***	0.04**	0.01
	(0.02)	(0.01)	(0.01)
Age 30-34	0.09***	0.04**	0.01*
	(0.01)	(0.01)	(0.01)
Age 35-39	0.03	0.01	0.00
	(0.02)	(0.02)	(0.01)
Age 40-44	0.04*	-0.00	-0.01
	(0.02)	(0.02)	(0.02)

After adressing time-varying confounding (RWR):

Moving before adulthood is more importantly associated with upper occupational attaiment than moving in adulthood.

* p<.05, ** p<.01, *** p<.001

Notes: OLS regressions. All models include gender, type of birth area, and birth cohort. Time-varying confounders include education, employment and family status.

Aknowledging that geographic mobility is repeated and self-reinforcing leads to more realistic estimates of their outcomes, however estimation is not straightforward.

- Past moves influence values of the determinants of subsequent moves (i.e. time-varying confounders)
- Particularly an issue for highly mobile populations or groups with higher moving propensities
- There are growing sets of statistical methods that enable addressing time-varying confounding, if this proves to be and issue (e.g. Marginal structural models, G-estimation, regression with residualized time-varying confounders)

Thank you!

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https://vidalsergi.wordpress.com

https://webs.uab.cat/lifelongmove/

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