

Causal Analysis in the Social Sciences:

In Search for Exogenous Variation

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Contents

- This talk is about two revolutions in modern social research
 - A methodological revolution
 - The end of the age of (OLS) regression
 - A substantive revolution
 - Much seemingly well-established results obtained with traditional research methods have been overthrown
- Contents
 - Methods of causal inference: An overview
 - The substantive revolution: Some examples
- This talk follows the counterfactual framework
 - Morgan/Winship (2007) Counterfactuals and Causal Inference

Methods of Causal Inference: An Overview



Causal Inference

- We want to identify the causal effect of a treatment variable D on the outcome variable Y



I will use DAGs,
see Elwert (2013).

- Note: For establishing a causal effect it needs two things
 1. Establishing convincing empirical evidence for an association of D and Y
 2. Providing convincing theoretical arguments for the intervening causal mechanisms that produce this association

Fundamental Problem of Causal Inference

- The fundamental problem of causal inference
 - An individual causal effect is defined as: $\delta_i = y_i^1 - y_i^0$
 - However, in the “real world” a unit cannot be observed both in treatment ($D = 1$) and control ($D = 0$) at the same time
 - So we have to compare different units
 - Depending on how the units are assigned to treatment and control, one needs different assumptions for identifying the causal effect

Exogenous Variation

- Randomized assignment (experiment)
 - Assignment is exogenous
 - All variation observed in D is exogeneous and can therefore be used to identify the causal effect
 - The causal effect (average treatment effect, ATE) can simply be inferred from the mean difference in treatment and control group (NATE)

$$\text{NATE} = \text{ATE} = E[Y^1|D = 1] - E[Y^0|D = 0]$$

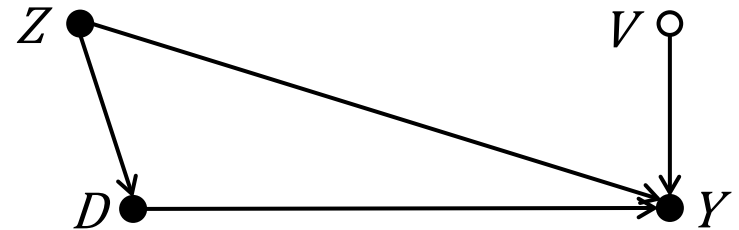
Fundamental Problem of Social Research

- In social research experiments are often not practicable
- Therefore, social research mostly relies on non-experimental (observational) data
- This creates a fundamental problem:
Due to **self-selection** treatment assignment is endogenous
 - Human beings decide according to their characteristics (or even the value of Y), whether they go into treatment or not
- Self-selection produces endogeneity
 - Therefore, the NATE is a biased estimate of the causal effect
 - Depending on the exact assignment mechanism, different approaches to causal analysis are needed

Selection on Observables

- Selection on observables

- Treatment assignment by observed confounder Z
 - The variation in D is endogenous, i.e., there is a spurious common variation between D and Y induced by the confounder Z
- Identifying assumption: conditional independence (CIA)
 - After conditioning for Z , variation in D is exogenous again
- Approaches available:
 - Stratification by Z (sub-group analysis)
 - Partialing Z out (regression)
 - Balancing Z (matching)



- In a regression framework:

$$y_i = \alpha + \beta d_i + u_i$$

- Exogeneity assumption $E(u_i|d_i) = 0$ is violated, because z_i is part of u_i
- The problem disappears, if one conditions (controls) for Z

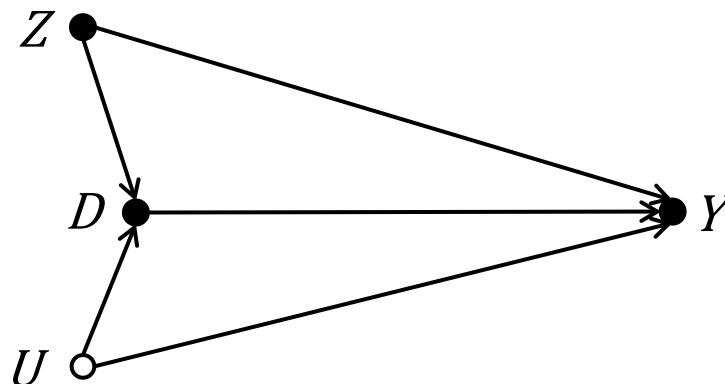
$$y_i = \alpha + \beta d_i + \gamma z_i + v_i$$

- Now the exogeneity assumption $E(v_i|d_i, z_i) = 0$ is valid, if the CIA holds

➤ This fundamental insight spurred the “age of regression”

Selection on Unobservables

- Selection on Unobservables
 - Treatment assignment by observables Z and unobservables U
 - Even after conditioning for Z , treatment assignment is endogenous
 - There is common variation in D and Y induced by the unobservables



- **The modern consent:** selection on unobservables is ubiquitous in non-experimental social research
 - Most treatment variation available is endogenous
 - Many (most?) regression results are biased!
 - This fundamental insight will terminate the “age of regression”

Identifying Strategies under Selection on Unobservables

- Basically there are two possible strategies available
 - “Technification”
 - Structural equation modelling (SEM)
 - Better Research Design
 - Front-door conditioning (mechanisms based causal analysis)
 - Search for exogeneous variation in D
 - Instrumental variables approach (IV)
 - Regression discontinuity approach (RD)
 - Fixed-effects approach (FE)

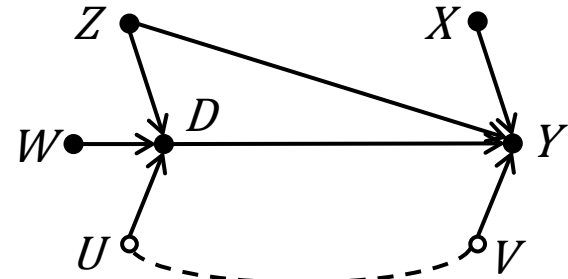
Structural Equation Modelling

- Structural equation modelling (SEM): the structural model

$$Y = f(D, Z, X) + V$$

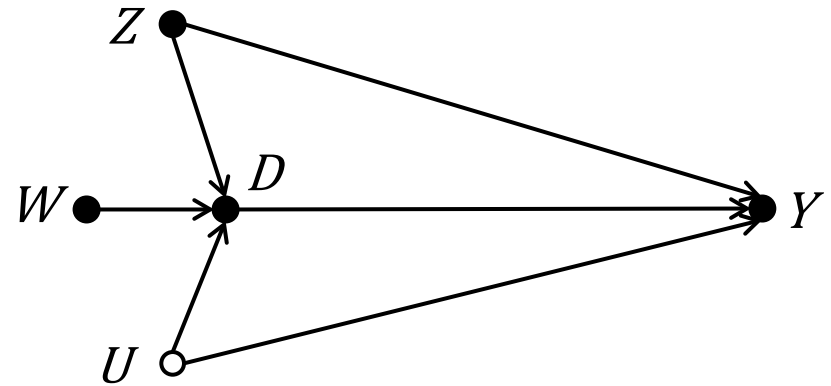
$$D = g(Z, W) + U$$

- One needs strong assumptions
 - Concerning the functional form of f and g
 - Concerning the common distribution of U and V
- The SEM assumptions are rarely justifiable and they are probably wrong in most social science research situations
 - Estimates will be biased in unknown direction
- Practical experience shows: Research areas, where SEM has been used abundantly, are full of contradictory results. Further, one can not decide, which ones of these results are correct
 - SEM has produced a big mess in social research



In Search for Exogenous Variation: IV

- Instrumental variables (IV) approach
 - Search for an IV (W) that is correlated with D , but not with Y
 - The variation in D that is produced by W (compliers) is exogenous
 - By comparing the treatment and control compliers, one can identify the causal effect



- IV works, if two assumptions hold:

$$\text{Cov}(D, W) \neq 0 \quad (\text{strong instrument})$$

$$\text{Cov}(U, W) = 0 \quad (\text{valid (exogenous) instrument})$$

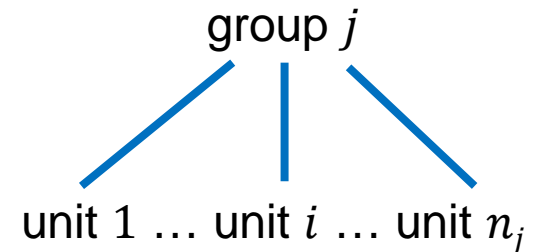
- Strength of an IV one can test, exogeneity not
 - An invalid IV will bias the causal effect estimate
 - Weak instruments ($r_{W,D} \sim 0,1$) produce under mild endogeneity of the instrument ($r_{W,U} \sim 0,1$) stronger bias than OLS

In Search for Exogenous Variation: IV

- “Classical” IV applications follow bad practice
 - Instruments used are mostly weak, and nobody cares
 - Exogeneity of the instruments is made plausible only very sloppy
 - The consequence is that classical IV causal effect estimates are probably strongly biased and very inefficient (S.E.s are blown up)
- **Classical IV has produced a big mess in social research**
- “Modern” IV applications
 - Emphasize the strength of IVs (LATE)
 - Try to give more credibility to the exogeneity assumption
 - Instruments from natural experiments

In Search for Exogenous Variation: FE

- Fixed-effects (FE) approach
 - For more details see Brüderl/Ludwig (2014)
- FE Models can be used with all kinds of multi-level data
 - Higher level (level 2): group j
 - Lower level (level 1): units i
 - Units are nested within groups
 - Examples
 - Persons – repeated observations (panel data)
 - Families – siblings, schools – pupils, firms – workers, countries – citizens
- Basic idea
 - A multi-level regression model: $y_{ij} = \beta d_{ij} + \alpha_j + \varepsilon_{ij}$
 - Assumptions: no group-specific and no unit-specific confounders



In Search for Exogenous Variation: FE

- If treatment assignment is produced by unobservables α_j

- There is common variation in D and Y that is induced by the unobservables

- D is endogenous (spurious correlation)

- Identifying strategy: look for exogenous variation in D that is not affected by group-specific confounders

- By applying the within transformation one wipes out α_j

$$y_{ij} - \bar{y}_j = \beta(d_{ij} - \bar{d}_j) + (\varepsilon_{ij} - \bar{\varepsilon}_j)$$

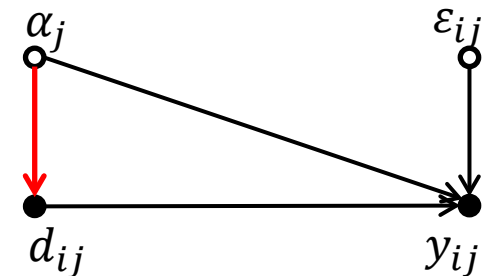
- Only (hopefully) exogenous within variation is left

- By using the within variation only, we can then identify the causal effect

- Main identifying assumption: strict exogeneity

$$E(\tilde{\varepsilon}_{ij} | \tilde{d}_{ij}) = 0$$

- In many situations this assumption will be reasonable



demeaned data: $\tilde{d}_{ij} = d_{ij} - \bar{d}_j$, etc.

The “New Wave” of Causal Analysis

- Ingredients of the new wave causal analysis
 - Do not invest in complex statistical modelling (SEM), but invest in better research design
 - Instead of “technification”, invest in “shoe leather”
 - “Those who worship at the altar of complex methods are prone to the error of thinking that technical sophistication can substitute for knowledge of the subject matter, careful theorizing, and appropriate research design” (Firebaugh 2008: 207f)
 - Clever designs that produce exogenous treatment variation
 - IVs from natural experiments
 - Panel data (or other clustered data that allow for within analysis)
 - Explicate in detail the exogeneity assumptions
 - How does treatment assignment work exactly?
 - Is it plausible that part of the assignment is exogenous?

 **Researchers should concentrate on a detailed investigation of the assignment mechanism and make it plausible that the variation used for causal analysis is truly exogenous**

The Substantive Revolution:

Kern, H. L. and J. Hainmueller (2009). Opium for the Masses:
How Foreign Media Can Stabilize Authoritarian Regimes.
Political Analysis 17:377–399

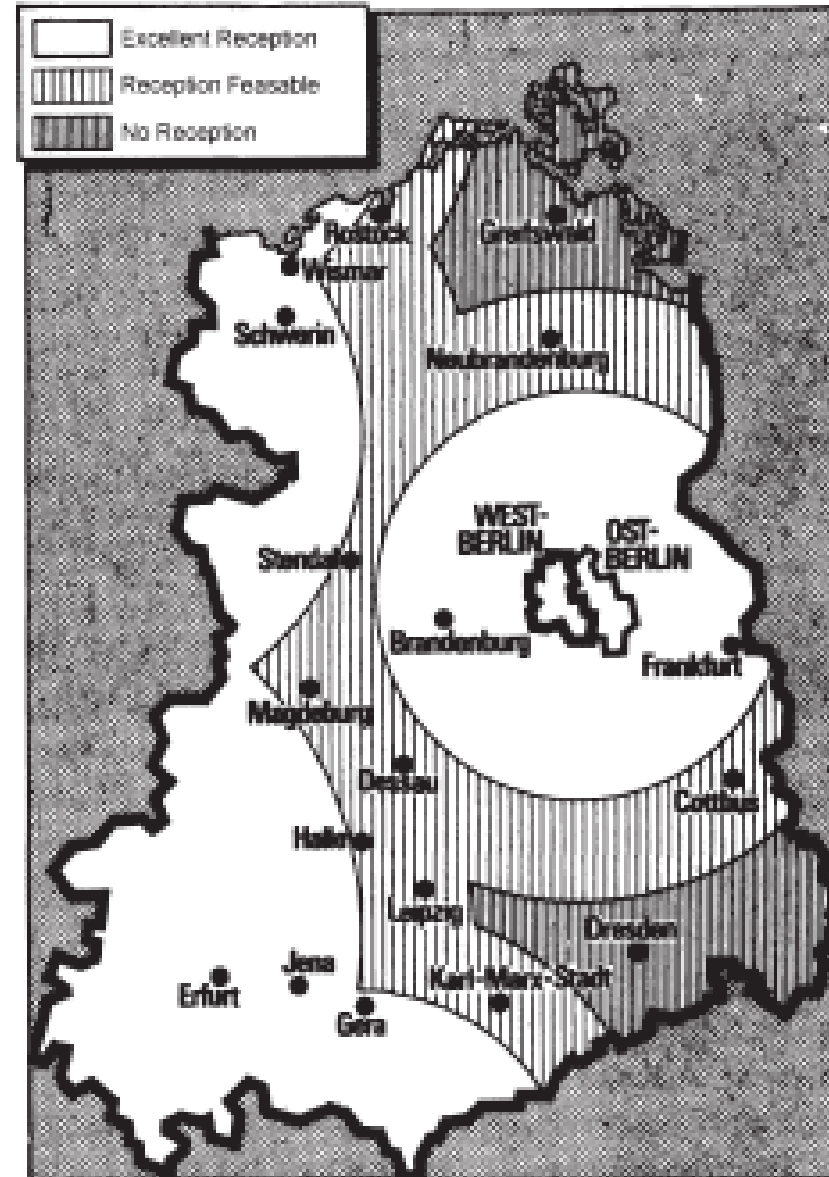


West-TV und Regimestabilität in der DDR

- Welchen Einfluss hatte das Anschauen von West-TV auf die Regimetreue von DDR Bürgern?
 - Informations-Hypothese: Information über die undemokratischen Zustände im Osten und das bessere Leben im Westen sollte die Regimetreue senken
 - Eskapismus-Hypothese: Das West-Unterhaltungsprogramm macht den „grauen“ DDR-Alltag erträglicher und erhöht die Regimetreue
 - „Brot und Spiele“, „Opium fürs Volk“
- Jugendsurvey 1988
 - 18-26 Jährige, PAPI, N=3564
 - *Y*: Überzeugt von der Marxistisch/Leninistischen Weltanschauung
 - *D*: Schauen von West-TV
- Bivariat findet man einen negativen Effekt
 - Aber: ziemlich sicher verzerrt durch Selbst-Selektion!

West-TV und Regimestabilität in der DDR

- Instrument aus einem natürlicher Experiment
 - Im Distrikt Dresden war es nicht möglich West-TV zu empfangen („Tal der Ahnungslosen“)
- LATE Annahmen
 - Monotonizität: Es ist sehr unwahrscheinlich, dass es Defier gibt
 - IV hat sehr starken Effekt auf D
 - Ignorability: Es gibt keine Indizien, dass Pro-Westler aus Dresden in andere Regionen migrierten, um West-TV sehen zu können
 - Exclusion: Dresdener unterscheiden sich in so gut wie nichts von den anderen Bürgern der DDR



Quelle: Kern/Hainmüller 2009

West-TV und Regimestabilität in der DDR

<i>Estimator</i>	<i>Diff.</i>	<i>LATE</i>
<i>Covariate set</i>	—	—
Convinced of Leninist/Marxist worldview		
West German TV	-0.079 (0.053)	0.147 (0.083)
Feel closely attached to East Germany		
West German TV	-0.013 (0.044)	0.217 (0.067)
Political power exercised in ways consistent with		
West German TV	-0.014 (0.047)	0.158 (0.078)

Note. $N = 3441$. The table shows treatment effect estimates

Quelle: Kern/Hainmüller 2009

The Substantive Revolution:

Ludwig, V., and J. Brüderl (2011) Is There a Male Marital Wage Premium?
Resolving an Enduring Puzzle with Panel Data from Germany and the U.S.
Unpublished manuscript.



MWP Example from Ludwig/Brüderl (2011)

- Married men earn more than unmarried men
 - Marital wage premium (MWP)
 - “... one of the most well documented phenomena in social science” (Waite & Gallagher 2000: 99)
- Early studies used cross-sectional data
 - Self-selection: high wage men more attractive marriage partners
- However, also recent longitudinal studies find a MWP
 - Ahituv/Lerman (2007) Demography NLSY79, FE (fixed-effects) regression: 7.6 %
 - Pollmann-Schult (2011) European Soc. Rev. SOEP 1985-2008, FE regression: 4.2 %
- Thus, using the best available data and methodology, it seems marriage makes men more productive workers
 - Remark: Not the effect on labor hours is investigated here, but the effect on productivity (gross hourly wage rate)
- However, we are not convinced
 - Self-selection may operate on wage growth (not only on level)

MWP Example: Explanations for a Causal MWP

- Family economics (Becker 1981)
 - Precondition: there is a traditional division of labor
 - Married men specialize on market work
They accumulate more market specific skills specialization
 - Married women specialize on household work
Married men are released from strenuous housework work effort
They can put more effort in their market work
- Lifestyle explanation
 - After marriage men are domesticated by their wives domestication
- Demand side explanation
 - Paternalism of employers employer favoritism

MWP Example: Arguments for a Spurious MWP

- (Self)-selection of high wage males into marriage
 - They gain more from specialization and therefore are more willing to marry
 - They are more attractive marriage partners
 - Due to their higher wage
 - Due to other unobservables correlated with wage
e.g. cognitive skills, social skills, beauty
- It is not only level, but also „steepness“ of the career
 - Promising young men (steep wage-profile) are attractive partners
 - Some evidence on this: Dougherty 2006
 - Standard FE models yield upwardly biased estimates
- To get unbiased estimates one should use FEIS

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + \gamma m_{it} + \alpha_{1i} + \alpha_{2i} \exp_{it} + \alpha_{3i} \exp_{it}^2 + \xi_{it}$$

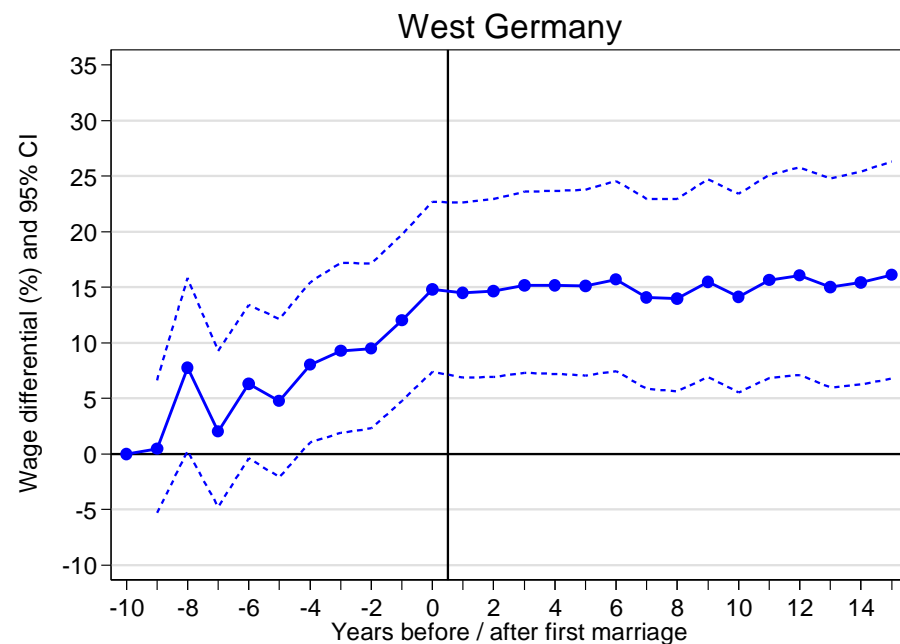
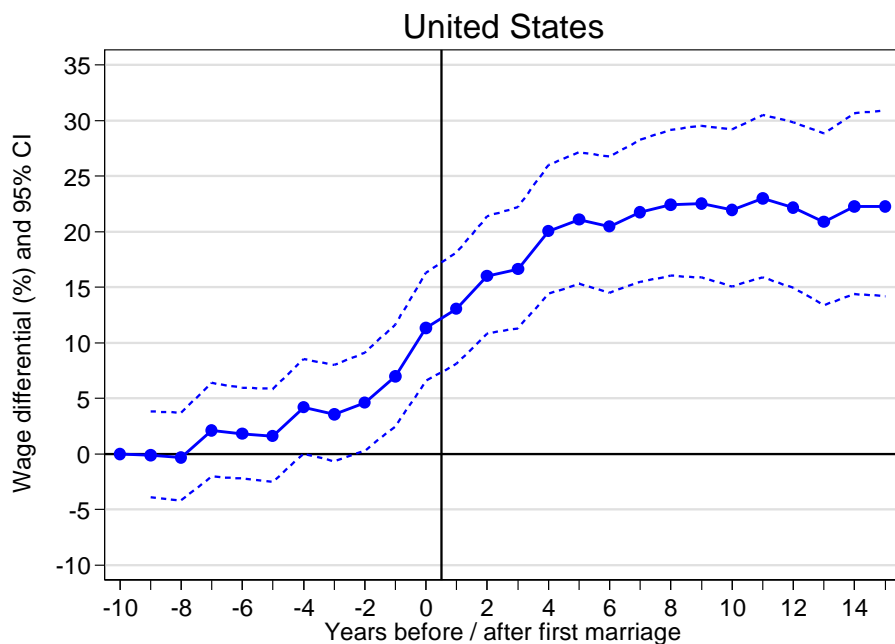
FEIS Estimation

- Detrending transformation (FEIS estimation)
 - Analogous to FE, where data are demeaned, we “detrend” the data
 - 1) Estimate for each unit the individual growth curve $y_{it} = \alpha_{1i} + \alpha_{2i}t + \zeta_{it}$ and get predicted values $\hat{y}_{it} = \hat{\alpha}_{1i} + \hat{\alpha}_{2i}t$
 - 2) Subtract predicted values from actual outcomes to get detrended outcomes $\tilde{y}_{it} = y_{it} - \hat{y}_{it}$
 - 3) Repeat steps 1) and 2) to detrend also the regressors $\tilde{x}_{it} = x_{it} - \hat{x}_{it}$
 - 4) Pool the detrended data and run a POLS regression
 - The intuition is that after detrending only variation around the trend is left. Only this around-trend variation is used to estimate the causal effect. Thus, heterogeneous growth can no longer bias estimates
- An ado `xtfeis.ado` is obtainable from Volker Ludwig

MWP Example: Data and Research Strategy

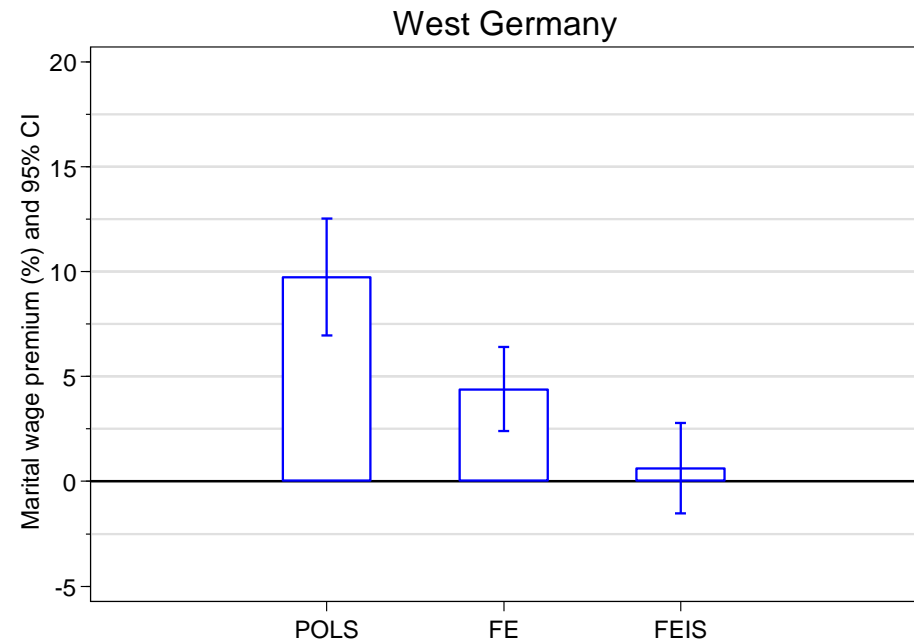
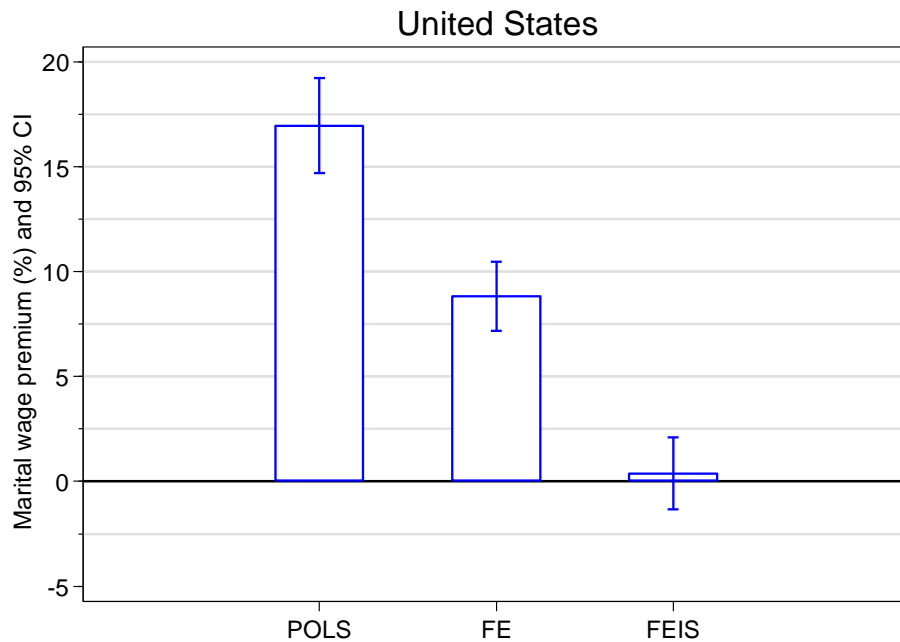
- German Socio-Economic Panel (SOEP), waves 1984-2010
 - West German resident males
 - Cohorts 1946 to 1975
 - No self-employees, private sector workers
 - Never-married when first observed, at least 4 obs. (N=1,520)
- National Longitudinal Study of Youth (NLSY79), 1979-2004
 - Males
 - No self-employees
 - Never-married when first observed, at least 4 obs. (N=4,452)

MWP Example: Results on Wage Growth



In both countries those men who marry eventually seem to be on a steeper wage-profile.

MWP Example: Results on the MWP



POLS grossly overestimates the MWP. Our FE results replicate the results found by Ahituv/Lerman (2007) and Pollman-Schult (2011). However, as the FEIS results show, these estimates are still too high.

In both countries there is no MWP!

The Substantive Revolution:

Kroh, M. (2013) Unequal Political Voice and Family Background.
Unpublished manuscript.

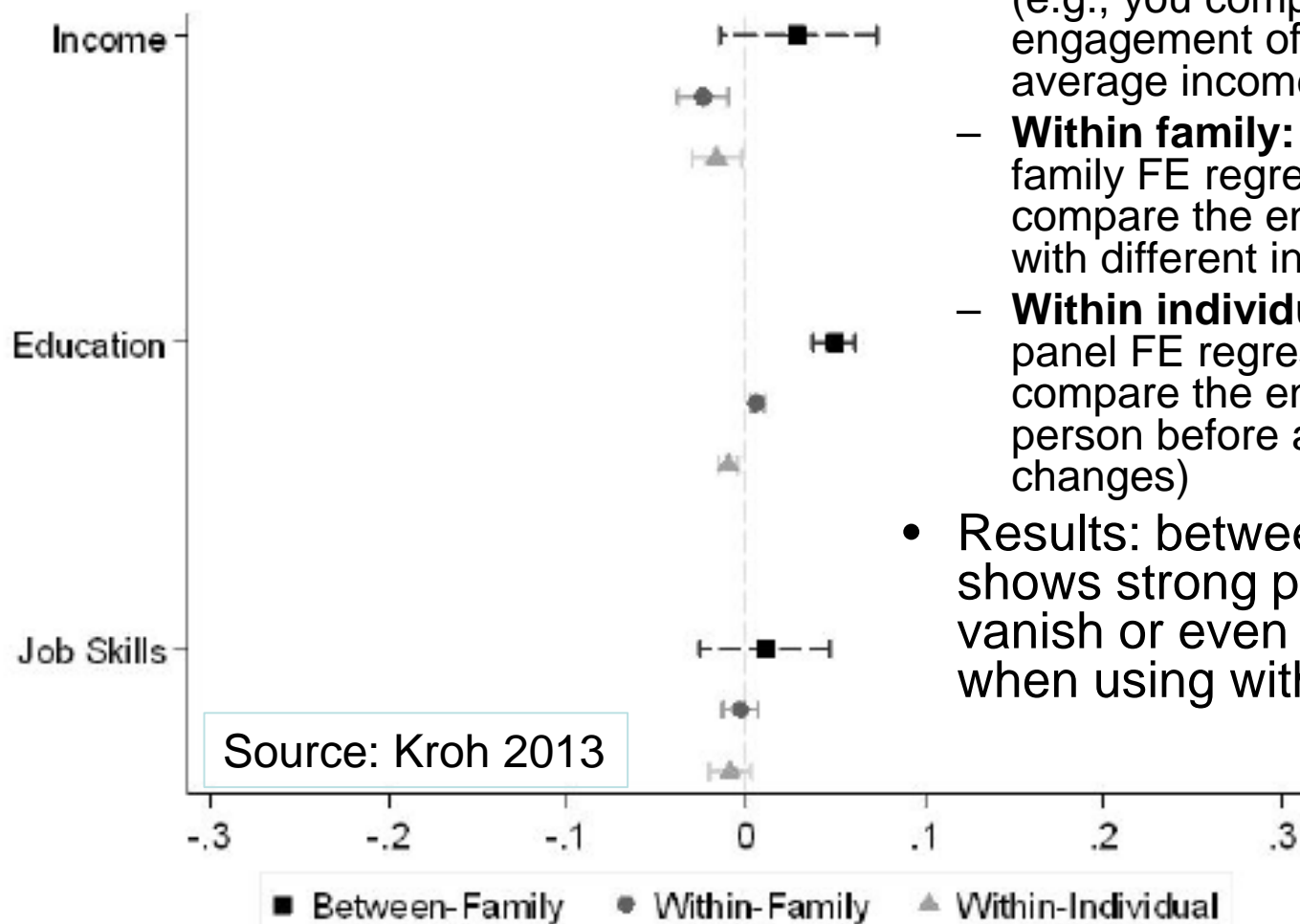


The FE Revolution in Social Research

- Kroh (2013) on political engagement
 - Hundreds of studies have shown that people with higher income show more political engagement
 - However, there is good reason to suspect that this result is biased due to time-constant unobserved heterogeneity
 - Particularly, there may be family unobservables that make kids more active citizens and provide the basis for better labor market positions (e.g., some kind of family “habitus”, genetic transmission of cognitive and non-cognitive skills)
 - Data: SOEP and BHPS
 - Outcome: four point-scale measuring the amount of involvement in a citizens' group, political party, local government and volunteer work in clubs or social services
 - Kroh replicates the conventional result when using POLS
 - However, by using FE panel and siblings models he shows that an increase in income has the opposite effect
 - With an income increase political engagement actually declines!

The FE Revolution in Social Research

- SOEP results on political engagement (Kroh 2013)



- **Between family:**
between regression on family means (e.g., you compare the average engagement of families with different average incomes)
- **Within family:**
family FE regression (e.g., you compare the engagement of siblings with different incomes)
- **Within individual:**
panel FE regression (e.g., you compare the engagement of a person before and after income changes)
- Results: between regression shows strong positive effects that vanish or even become negative when using within approaches

Literature

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Front-Door Conditioning

- Intervening mechanism through M and N
 - We can identify the causal effect by a two step procedure
 - $D \rightarrow M$ and $D \rightarrow N$ are identified, because Y is a collider
 - $M \rightarrow Y$ and $N \rightarrow Y$ are identified, by conditioning on D
 - Piecing the two steps together gives the total causal effect
 - Main Assumptions
 - The mechanism is exhaustive
 - There is not a third intervening variable
 - The mechanism is isolated
 - M and N are not affected by U
 - I know of no application of this approach
 - Formerly, this approach has been championed by Pearl

