Replication of "Educational Expansion and Its Heterogeneous Returns for Wage Workers" by Michael Gebel and Friedhelm Pfeiffer

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Theoretical Part

Summary of Gebel & Pfeiffer (2010)

- basic idea: examine evolution of returns to education in West German labour market.
- Focus on change in returns to education over time as a consequence to education expansion in Germany.
- methodology:
  - Wooldrigdge's (2004) **conditional mean independence**
  - Garen's (1984) **control function** approach, that requires an *exclusion restriction*
  - as well as OLS
- data: SOEP 1984-2006

Data and Variables

- Log of hourly wage
- Years of education (constructed from categorical variable)
- Age and age squared
- Gender
- Father's education
- Mother's education
- Father's occupation
- Rural or urban household
- Number of Siblings (as instrument)

TODO: more detailed table? (Comment) not necessary (Comment) Leave data intro when talking about the model later on?

Background Information

- **increase in educational attainment** in the 1960s. From 1984 to 2006, average years of schooling increased:
  - woman: 11.3 -> 12.8
  - men: 11.9 -> 12.9
- **How can educational expansion affect the returns to education?**
  - Standard theory: an increase of labor supply of high-skilled workers should decrease the returns to education
  - High-educated workers with higher unobserved motivation / ability which positively affects wages
  - More "less talented" accepted to higher education & thereby decreasing the average productivity levels of higher educated workers –> overall effect not clear
- unobserved characteristics leading to **selection bias**:
  - higher ability and motivation to stay longer in education
  - select jobs with expected higher returns.

Econometric Approach

Empirical Framework (Derivation) I

The study is based on the **correlated random coefficient model** (Wooldridge, 2004) specified as:

$$\ln Y_i = a_i + b_i S_i$$

with $a_i = a' X_i + \varepsilon_{ai}$, and $b_i = b' X_i + \varepsilon_{bi}$

where $\ln Y_i$: log of wages and S_i years of schooling of individual i

- The model has, therefore, an **individual-specific intercept** a_i and **slope** b_i dependent on **observables** X_i and **unobservables** ε_{ai} and ε_{bi}.
- Do not assume that b_i and S_i are independent –> Individuals with higher expected benefits from education are more likely to remain longer in education –> b_i may be correlated with S_i indicating positive self-selection.

Empirical Framework (Derivation) II

- focus: estimate average partial effect (APE), which is the return per additional year of education for a randomly chosen individual (or averaged across the population)

$$E(\partial \ln Y/\partial S) = E(b_i) = \beta$$

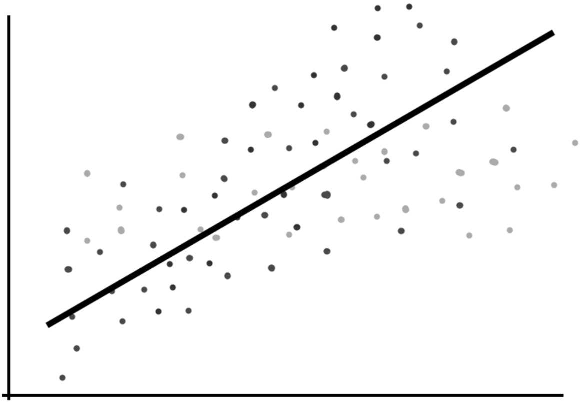
In case of homogeneous returns to education the wage equation reduces to:

$$\ln Y_i = a' X_i + \bar{b} S_i + \varepsilon_{ai}$$

- Unobserved heterogeneity may only affect the **intercept** of the wage equation.

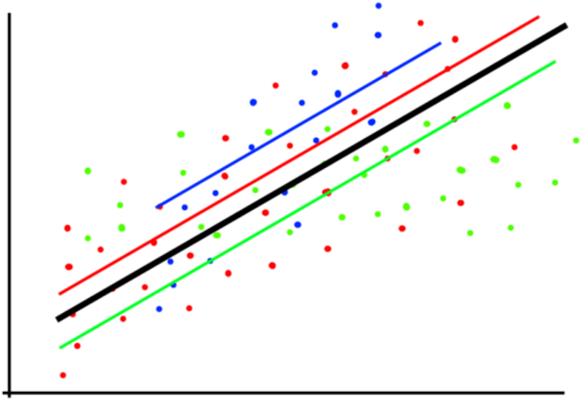
- still potential endogeneity if ε_{ai} correlates with S_i

Empirical Framework (Intuition) I



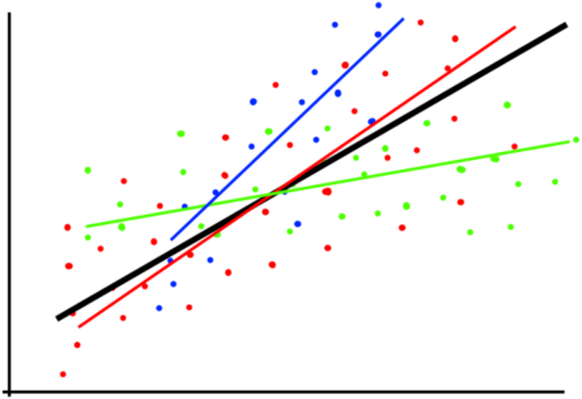
- Simple OLS

Empirical Framework (Intuition) II



- Multiple OLS with homogeneous return to Educ

Empirical Framework (Intuition) III



- Correlated Random Coefficient Model

Distinction to conventional methods

- OLS
  - ability and “background” bias
- IV Methods
  - if education is correlated with **unobserved individual heterogeneity**, IV methods may fail to identity APE.
    - alternative: **L**ocal **A**verage **T**reatment **E**ffect.

Conditional Mean Independence

According to Wooldridge (2004, pg. 7), **APE** is identified by:

$$E(\ln Y_i \mid a_i, b_i, S_i, X_i,) = E(\ln Y_i \mid a_i, b_i, S_i) = a_i + b_i S_i \qquad (A.1)$$

$$E(S_i \mid a_i, b_i, X_i) = E(S_i \mid X_i) \text{ and } \mathrm{Var}(S_i \mid a_i, b_i, X_i) = \mathrm{Var}(S_i \mid X_i) \qquad (A.2)$$

TODO: add interpretation of assumptions

- basically:
  - X_i should be good predictors of treatment S_i (Wooldridge 2004, pg 7).
  - (A.1): Redundancy of X_i given a_i and b_i.
  - (A.2): In the first two conditional moments of S_i, a_i and b_i are redundant. "Staying longer in Education is determined by X covariates"

Estimator for β and GLM

$$\hat{\beta} = \frac{1}{N} \sum_{i=1}^{N} \left(\left(S_i - \hat{E}(S_i \mid X_i) \ln Y_i \right) \Big/ \hat{Var}(S_i \mid X_i) \right)$$

$$E(S_i \mid X_i) = e^{\gamma X_i} \quad \text{and} \quad Var(S_i \mid) = \sigma^2 e^{\gamma X_i}$$

Where σ^2 can be consistently estimated by the mean of squared Pearson residuals and standard errors are bootstrapped.

Control Function Approach I

- Based on proposition by Garen (1984).
- Similar to Heckman two-step estimator.
- Models schooling choice explicitly in first step
- CF approach can identify APE in heterogeneous returns while standard IV approach may not.

First stage: modelling schooling choice

$$S_i = c' X_i + dZ_i + v_i \quad \text{with} \quad E(v_i \mid Z_i, X_i) = 0$$

where:

- X_i and Z_i influence the educational decision.
- v_i: Error term incorporating unobserved determinants of education choice.
- Z_i: Exclusion restriction (instrument).

Control Function Approach II

- V_i, ε_{ai} and ε_{bi} are normally distributed with zero means and positive variances.
- possible correlation between error terms
- v_i is positive if an individual acquires higher education than expected conditional on observed characteristics

Second step: augmented wage equation

$$\ln Y_i = a_i + \beta S_i + \gamma_1 v_i + \gamma_2 V_i S_i + w_i$$

where:

- $\gamma_1 v_i$ and γ_2 are the **control functions**
  - $\gamma_1 = cov(\varepsilon_{ai}, v_i)/var(v_i)$
  - $\gamma_2 = cov(\varepsilon_{bi}, v_i)/var(v_i)$
- $E(w_i \mid X_i, S_i, v_i) = 0$ (as shown in Heckman / Robb, 1985)

Control Function Approach III

Interpretation of the coefficients of the control functions - γ_1 measures the effect of those unobserved factors that led to over- or under-achievement in education on the wage - Thus, if γ_1 is positive, the unobserved factors affect schooling *and* wages positively - γ_2 describes how this effect changes with increasing levels of education - Positive coefficient would indicate that those with unexpected educational "over-achievement" tend to earn higher wages

TODO: intuition for CF approach

Replication results

Set-up

- We use the same sample: West Germans (not foreign-born or self-employed) between 25 & 60 years who work full-time
- We have less observations than Gebel & Pfeiffer (2010) per survey year after we delete all observations with missing values
- Yet, we extend the observation period until 2016
- Three estimation methods: OLS, CMI & CF
- We are not able to replicate the estimation results of Gebel & Pfeiffer (2010) exactly, yet the trend / shape is similar

Results

- I'm not so sure how to add images / tables here but in the new do-file link https://1drv.ms/u/s!Ap1Tm8513oIthBjgyIALS8Zp3A7G you can just save the graph with all 3 approaches
- & then display on the other side the same graph from GP(2010, p.35)
- also: here is a table with the our & GP estimates for comparisons - your bootstrapped standard errors are already included

https://1drv.ms/x/s!Ap1Tm8513oIthBp5BPId0qO8h3Yj

Estimated returns on education

- Estimates from OLS & CMI are similar, yet, CMI produces lower estimates which points to a positive self-selection bias
- Generally, CF estimates are much more volatile and less precise

Differences between replicated & original estimations - Our OLS estimates are on average larger than those of Gebel & Pfeiffer (2010) by 0.004 percentage points - Our CMI estimates are on average larger than those of Gebel & Pfeiffer (2010) by 0.002 percentage points (first years lower, than larger) - Our CF estimates are on average significantly larger by 0.032 percentage points, though the divergence gets smaller from 2000 onwards

Control function estimates I

Instrumental variable in first stage - *Number of siblings* is significant at the 0.1% level for all years - As expected, the number of siblings has a negative impact on the years of schooling (the estimates range between -0.13 & -0.23) - We would assume that the instrument does not directly affect the error term in the wage equation

Coefficients of the control functions - γ_1 is negative for majority of years, yet very small and insignificant in all years - Gebel & Pfeiffer (2010) estimate a positive coefficient in the 1980s and 1990s - but also insignificant - γ_2 is negative and close to zero for most years - Indicates that those with unexpectedly high education have lower returns to education - Similarly, they are only slightly significant in the 1980s, and stronger significant in the early 2000s - The estimates are very similar to those of Gebel & Pfeiffer (2010)

- that both coefficients are (mostly) negative hints that educational expansion caused more "less able" to achieve higher education

Explanations for divergences between replication and Gebel & Pfeiffer (2010)

- sample not the same
- ...

Pro's & Con's of estimation methods

- CMI
- CF
    - requires further distributional assumptions on error terms

Results and Comparison I

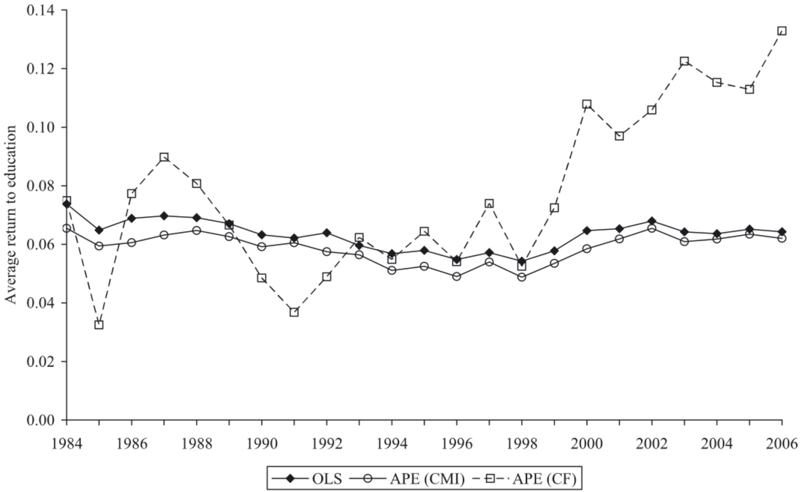


Figure 1: Original Results (GB 2010, pg.30)

Results and Comparison II

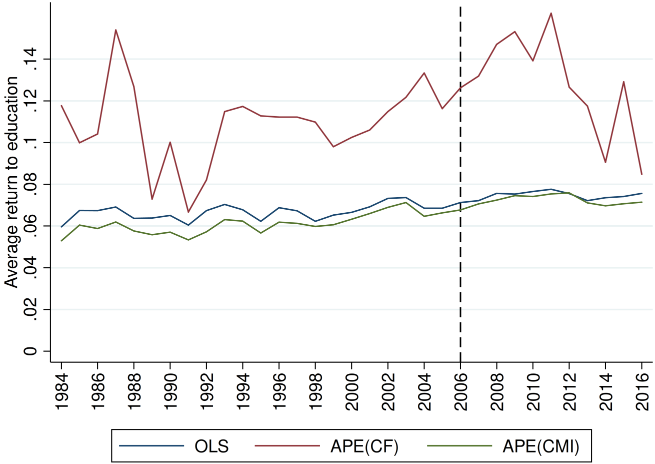


Figure 2: Replication results: Comparison between OLS, CMI and CF approaches

The end I