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

Luisa Hammer and Marcelo Avila

22 Nov 2018

Theoretical Part

Summary of Gebel and 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

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 and 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 higher expected 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)

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

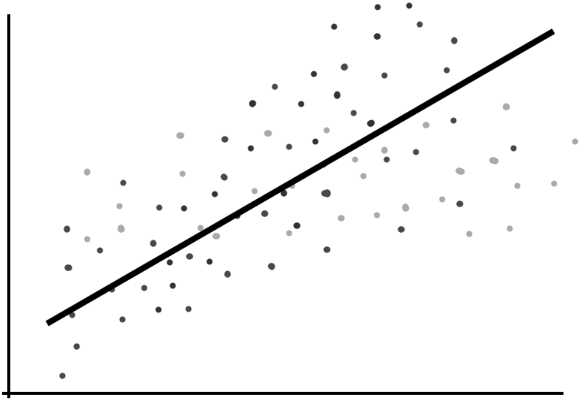
In case of homogeneous returns to education the wage equation reduces to:

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

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

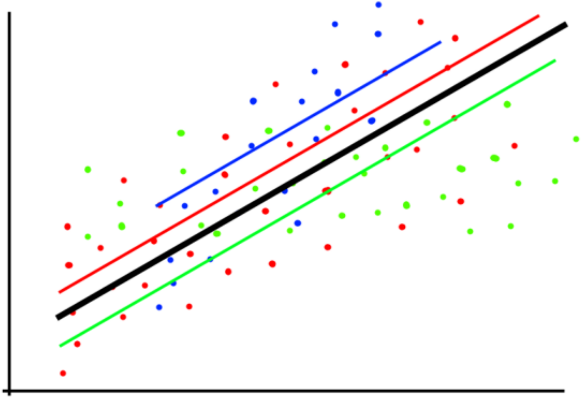
- still potential endogeneity if ε_{ai} correlates with S_i

Empirical Framework (Intuition) I



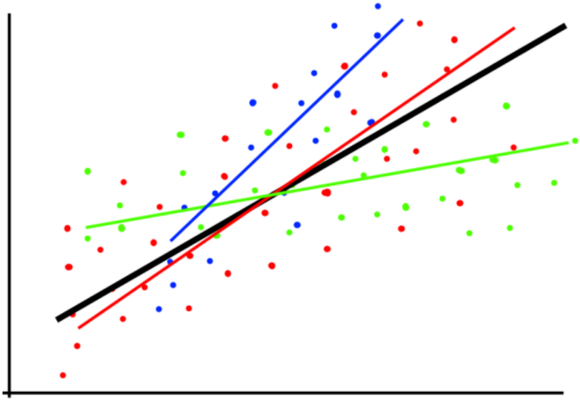
- Simple OLS

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:

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

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

- 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 and S_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

The **APE** can be estimated by:

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

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

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).
- CF approach can identify APE in heterogeneous returns while standard IV approach may not.
- Similar to Heckman two-step estimator.
- Models schooling choice explicitly in first step

First stage: modelling schooling choice

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

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, that are possibly correlated
- v_i is positive if an individual acquires higher education than expected conditional on observed characteristics

Second stage: augmented wage equation

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

where:

- γ_1 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

Replication and Comparison

CODES

```
*** Generalized linear regression model with Poisson distributio
    glm school sex age age_sq rural edu_f occ_f edu_m, family(po
```

TODO: play with codes

Set-up

- We use the same sample: West Germans (not foreign-born or self-employed) between 25 and 60 years who work full-time
- We have less observations than Gebel and 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
- control variables: age and age squared, gender, father's education, mother's education, father's occupation, rural or urban household, number of siblings (as instrument)

Results

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
- and then display on the other side the same graph from GP(2010, p.35)
- also: here is a table with the our and GP estimates for comparisons - your bootstrapped standard errors are already included

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

Estimated returns on education

- Estimates from OLS and 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 and original estimations - Our OLS estimates are on average larger than those of Gebel and Pfeiffer (2010) by 0.004 percentage points - Our CMI estimates are on average larger than those of Gebel and 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 and -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 and 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

Control function estimates II

- 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 and Pfeiffer (2010)

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

Divergences between replication and Gebel and Pfeiffer (2010)

- sample not the same
- ...

Results and Comparison I

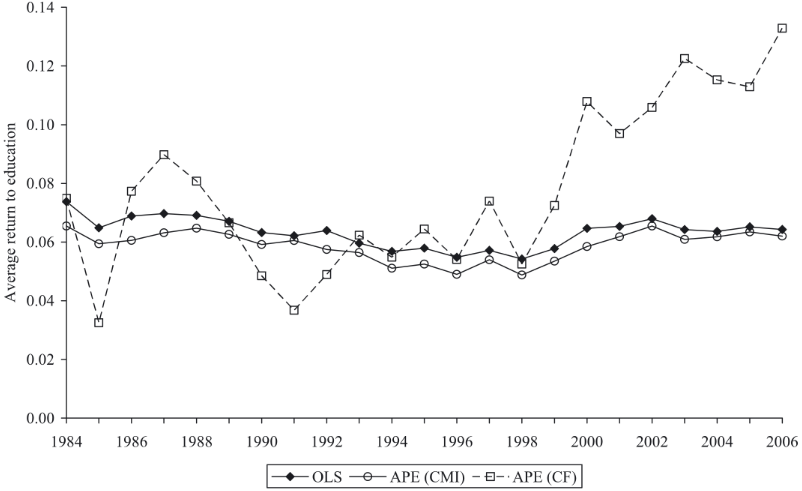


Figure 1: Original Results (GP 2010, pg.30)

Results and Comparison II

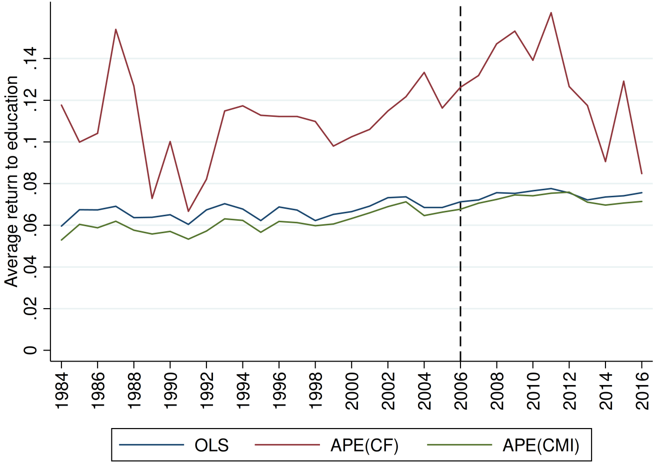


Figure 2: Replication results: Comparison between OLS, CMI and CF approaches

Results: Control Function (replication)

	First Stage		Second Stage					
	IV: Nr. of Siblings		v_i			$v_i S_i$		
year	coef.	s.e.	coef.	s.e.	p	coef.	s.e.	p
1984	-0.163	0.035	-0.019	0.036	0.601	-0.003	0.001	0.027
1985	-0.191	0.036	0.005	0.030	0.864	-0.003	0.001	0.024
1986	-0.129	0.034	-0.039	0.041	0.344	-0.001	0.001	0.681
1987	-0.133	0.033	-0.064	0.039	0.105	-0.002	0.001	0.141
1988	-0.150	0.034	-0.031	0.034	0.365	-0.003	0.001	0.038
1989	-0.153	0.033	0.018	0.033	0.590	-0.002	0.001	0.056
1990	-0.164	0.032	-0.027	0.032	0.404	-0.001	0.001	0.341
1991	-0.167	0.033	0.014	0.034	0.685	-0.002	0.001	0.152
1992	-0.178	0.032	-0.007	0.030	0.808	-0.001	0.001	0.298
1993	-0.162	0.033	-0.033	0.033	0.311	-0.001	0.001	0.264
1994	-0.176	0.034	-0.035	0.029	0.233	-0.001	0.001	0.225
1995	-0.172	0.036	-0.026	0.032	0.422	-0.002	0.001	0.077
1996	-0.195	0.037	-0.015	0.031	0.624	-0.003	0.001	0.058
1997	-0.214	0.038	-0.030	0.027	0.268	-0.002	0.001	0.225

Results: Control Function (replication)

Pro's and Con's of estimation methods

- CMI
  - no analytical standard errors
- CF
  - requires further distributional assumptions on error terms
  - valid and relevant "instrument"

The end I

TODO: add