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

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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)

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

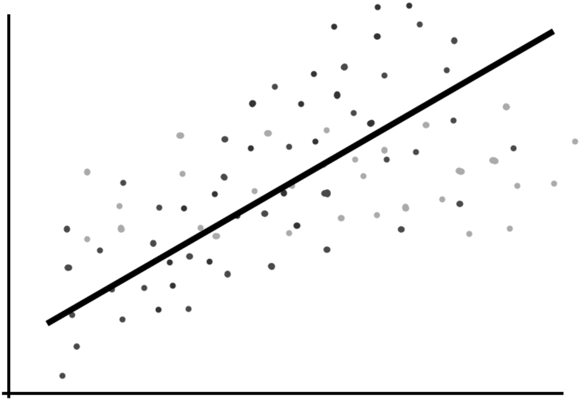
In case of homogeneous returns to education the wage equation reduces to:

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

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

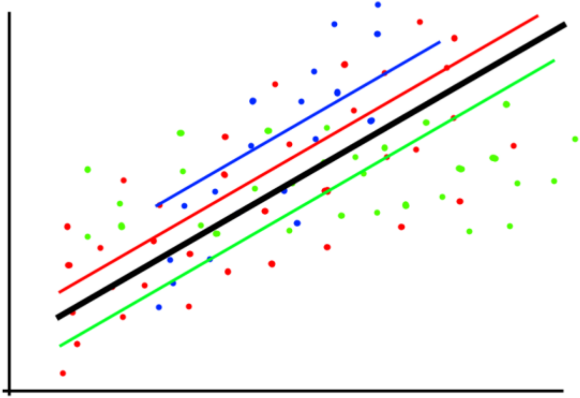
- still potential endogeneity if ε_{ai} correlates with S_i

Empirical Framework (Intuition) I



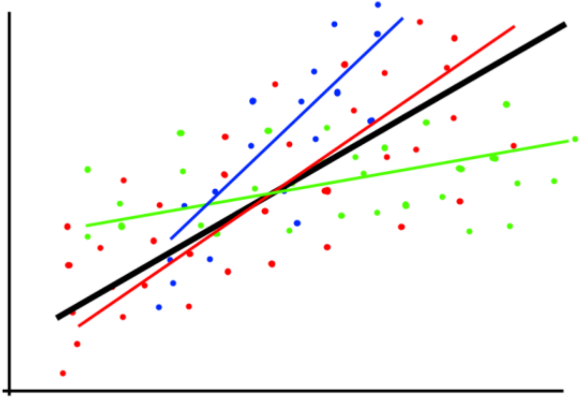
- Simple OLS

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:

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

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

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

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

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

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!Ap1Tm8513oIthBjgylALS8Zp3A7G 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

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

- sample not the same
- ...

Results and Comparison I

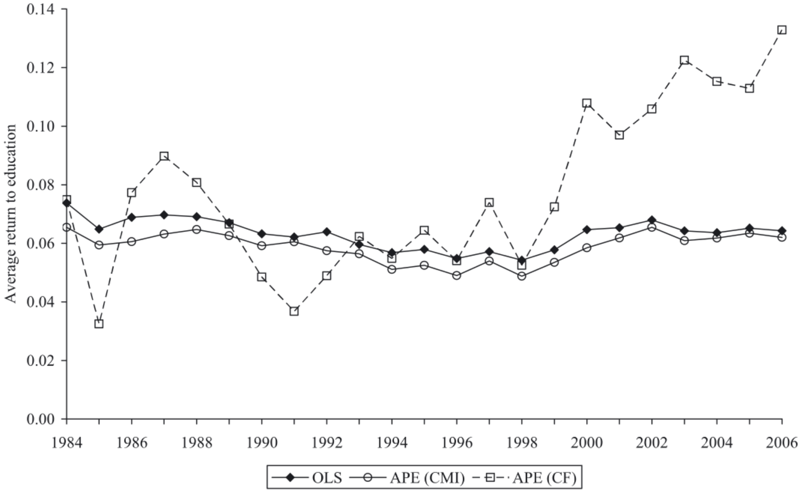


Figure 1: Original Results (GP 2010, pg.30)

Results and Comparison II

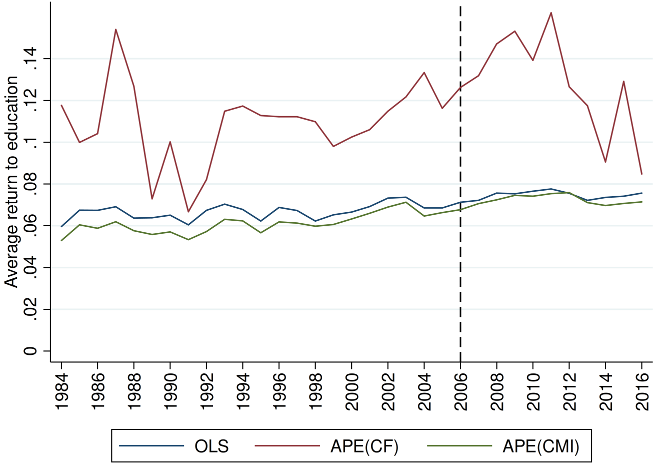


Figure 2: Replication results: Comparison between OLS, CMI and CF approaches

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)

%TODO: fix coefficients headers!

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