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

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Introduction

Outline

- Theoretical Framework
  - Gebel & Pfeiffer (2010)
  - Returns to education
- Empirical framework
  - Correlated random coefficients model
  - Conditional Mean approach
  - Control funtion approach
- Replication
  - Set-up
  - Code
  - Comparison of results

Theoretical Framework

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 I

Increase in educational attainment

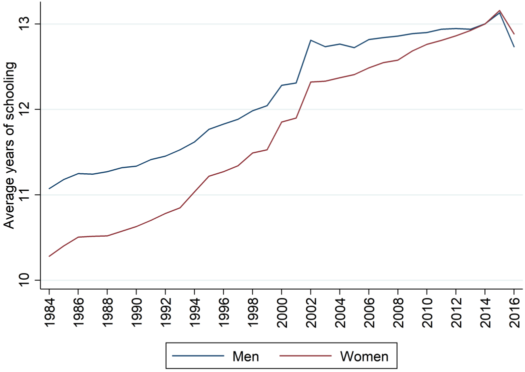

Figure 1: Source: SOEP 1984-2016, own estimations.

Background Information II

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
- If more less talented are accepted to higher education, this should decrease the average productivity levels of higher educated workers −> overall effect not clear

Problems in the estimation of returns to education

- 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

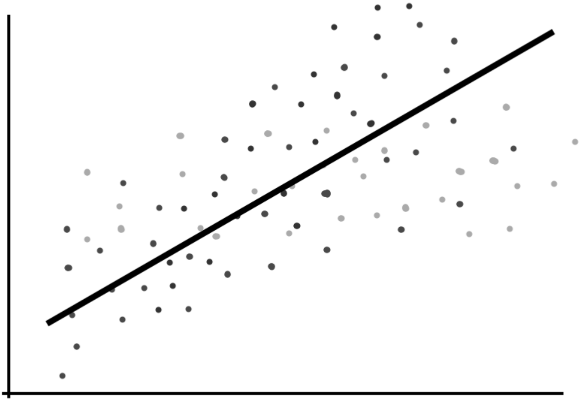

Figure 2: Simple OLS

Empirical Framework (Intuition) II

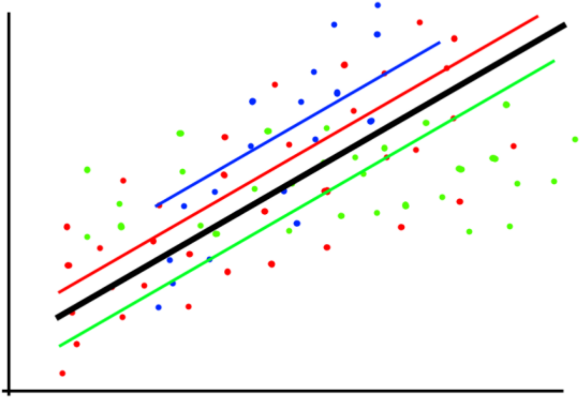

Figure 3: Multiple OLS with homogeneous return to Educ

Empirical Framework (Intuition) III

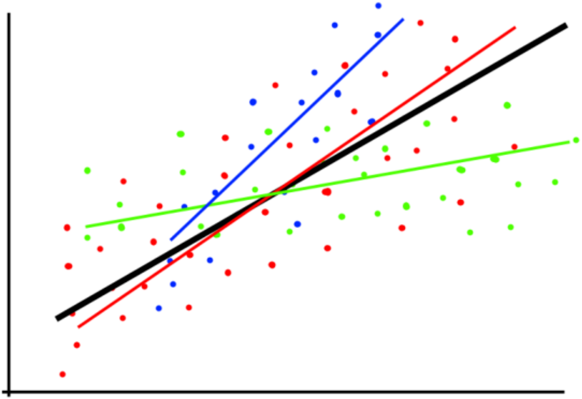

Figure 4: Correlated Random Coefficient Model

Distinction to conventional methods

- OLS
  - ability and “background” bias
- IV Methods:
  - suitable if assume homogeneous returns to education.
  - if education is correlated with **unobserved individual heterogeneity**, IV methods may fail to identity APE.
  - alternative: **L**ocal **A**verage **T**reatment **E**ffect if interested in effect of educational policy reforms.

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:

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

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

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

Control Function Approach {.allowframebreaks}

- 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 step: 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 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

Replication and Comparison

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)

Stata Implementation (CMI)

```
*** GLM regression with Poisson distribution
glm school sex age age_sq rural edu_f occ_f edu_m, family(poisson) link(log)

*** Predict conditional mean and extract pearson residuals
predict condMean, mu
predict res_pears, pearson

*** Calculate residual
gen resid = school - condMean

*** Estimate sigma^2
egen sigma_sq_pears = mean(res_pears^2)

*** generate APE
egen bCMI = mean((resid*lnw)/ (sigma_sq_pears*condMean))
```

Stata Implementation (Bootstrapping)

```
program define myCMI, rclass // return scalar as r() macro
  preserve    // using preserve/restore due to repeated sampling
    bsample   // setup for boostrap sampling

    ***************************************
    * run estimation as in previous slide *
    ***************************************

    *** Return variable of interest
    local bCMI=bCMI
    return scalar bCMI_return = `bCMI'
  restore
end

*** Run boostrapping
forv n = 1984/`endYear' {
  bootstrap r(bCMI_return), reps(`reps') seed(42): myCMI if syear == `n'
}
```

Stata Implementation (CF)

```
* First step: Estimate the reduced form of schooling, i.e. regress
* schooling  on all exogeneous variables including the instrument (siblings)
reg school sex age age_sq rural edu_f edu_m occ_f sibl ///
    if syear==`n'

* Obtain the residuals
predict v`n', res

* Second step:  Estimate the structural equation and include the
* residuals from  the reduced form as an additional regressor
reg lnw school sex age age_sq rural edu_f edu_m ///
    occ_f v`n' c.v`n'#c.school if syear==`n'
```

Results

Results Comparison I

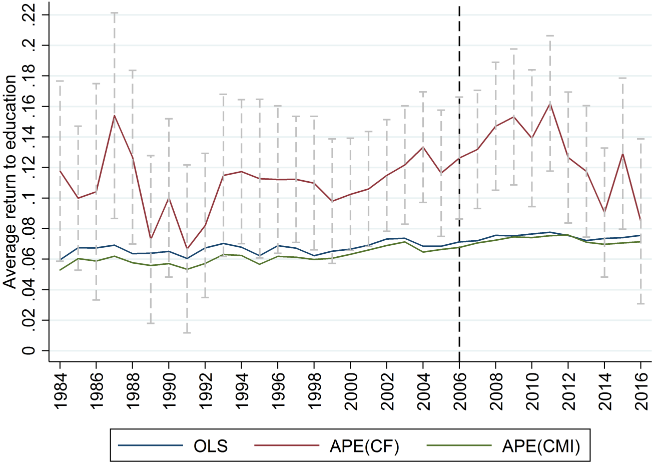

Figure 5: Replication results: Comparison between OLS, CMI and CF

Results Comparison II

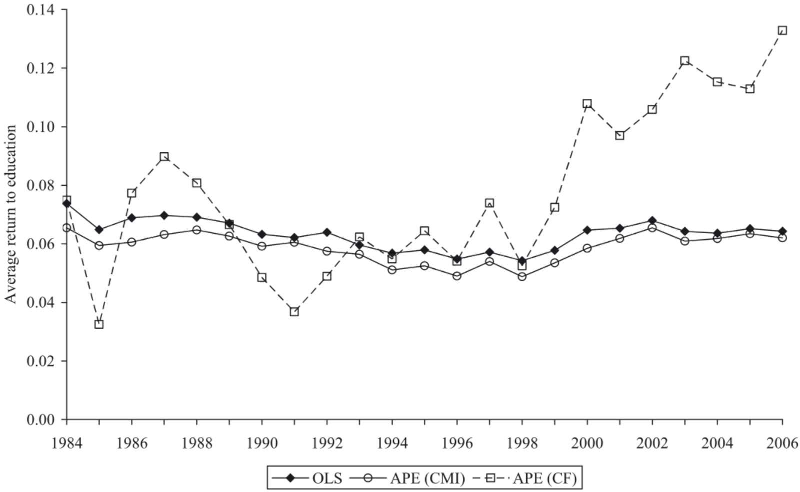

Figure 6: Original Results (GP 2010, pg.30)

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 step

- *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 abled" to achieve higher education

Heterogenous returns to education

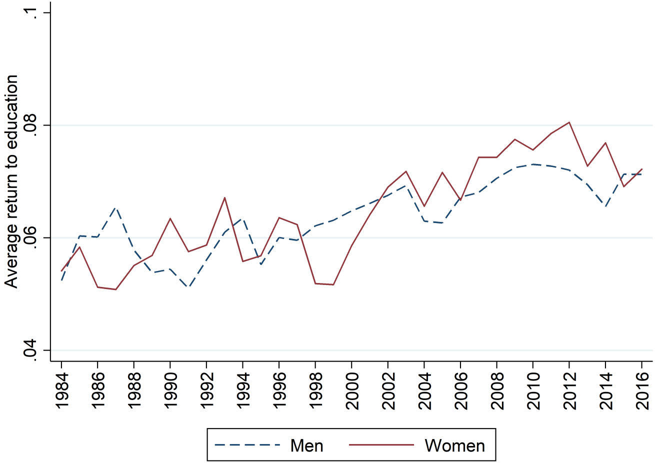

Figure 7: Replication results: **APE** by gender (CMI approach)

Heterogenous returns to education

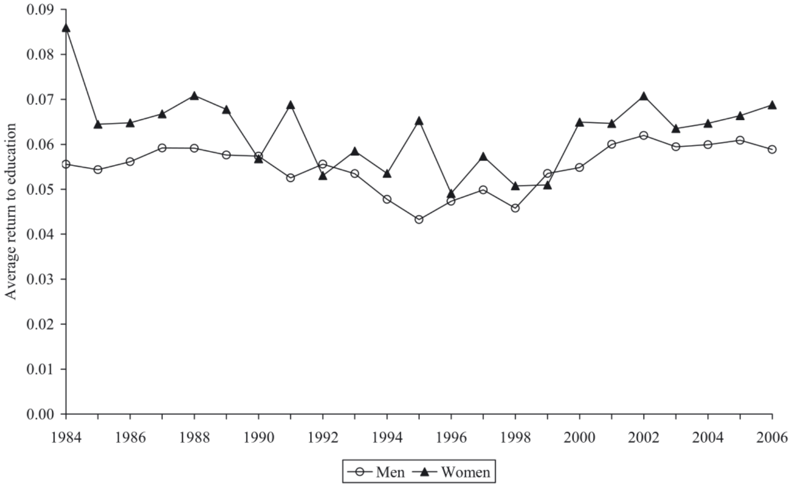

Figure 8: Original Results (GP 2010, pg.34

Results: Control Function (replication)

Table 1: Summary of Control Function estimates (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

Conclusion

Conclusion

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

The end

Appendix I

Table 2: Summary original results GB(2010).

year	OLS	s.e. (OLS)	CMI	s.e. (CMI)	CF	s.e. (CF)	obs
1984	0.074	0.004	0.066	0.004	0.075	0.079	1.545
1985	0.065	0.004	0.059	0.004	0.032	0.131	1.600
1986	0.069	0.004	0.061	0.004	0.077	0.091	1.682
1987	0.070	0.004	0.063	0.004	0.090	0.048	1.775
1988	0.069	0.004	0.065	0.004	0.081	0.041	1.798
1989	0.067	0.003	0.063	0.004	0.067	0.038	1.922
1990	0.063	0.003	0.059	0.004	0.048	0.031	2.007
1991	0.062	0.003	0.060	0.004	0.037	0.030	2.122
1992	0.064	0.003	0.057	0.004	0.049	0.027	2.107
1993	0.060	0.003	0.057	0.004	0.062	0.026	2.124
1994	0.057	0.003	0.051	0.004	0.055	0.022	2.082
1995	0.058	0.003	0.053	0.004	0.064	0.024	2.075
1996	0.055	0.003	0.049	0.004	0.054	0.025	2.057
1997	0.057	0.003	0.054	0.003	0.074	0.025	2.011
1998	0.054	0.003	0.049	0.003	0.053	0.021	2.145

Appendix II

1999	0.058	0.003	0.054	0.003	0.072	0.023	2.163
2000	0.065	0.002	0.059	0.003	0.108	0.024	3.965
2001	0.065	0.002	0.062	0.003	0.097	0.022	3.961
2002	0.068	0.003	0.066	0.003	0.106	0.030	3.668
2003	0.064	0.003	0.062	0.003	0.123	0.028	3.476
2004	0.064	0.003	0.062	0.003	0.115	0.030	3.366
2005	0.065	0.003	0.064	0.003	0.113	0.032	3.220
2006	0.064	0.003	0.063	0.003	0.133	0.033	3.477

Appendix III

Table 3: Summary replication results.

year	OLS	s.e. (OLS)	CMI	s.e. (CMI)	CF	s.e. (CF)	obs
1984	0.060	0.004	0.030	0.118	0.053	0.006	1.448
1985	0.067	0.003	0.024	0.100	0.060	0.005	1.412
1986	0.067	0.004	0.036	0.104	0.059	0.006	1.463
1987	0.069	0.004	0.034	0.154	0.062	0.005	1.489
1988	0.064	0.003	0.029	0.127	0.058	0.005	1.476
1989	0.064	0.003	0.028	0.073	0.056	0.005	1.553
1990	0.065	0.003	0.026	0.100	0.057	0.005	1.571
1991	0.060	0.004	0.028	0.067	0.053	0.005	1.602
1992	0.067	0.003	0.024	0.082	0.057	0.005	1.555
1993	0.070	0.004	0.027	0.115	0.063	0.005	1.527
1994	0.068	0.003	0.024	0.117	0.062	0.005	1.491
1995	0.062	0.003	0.026	0.113	0.057	0.005	1.444
1996	0.069	0.003	0.025	0.112	0.062	0.005	1.383
1997	0.067	0.003	0.021	0.112	0.061	0.005	1.285
1998	0.062	0.003	0.022	0.110	0.060	0.005	1.452

Appendix IV

1999	0.065	0.003	0.021	0.098	0.061	0.005	1.452
2000	0.067	0.003	0.019	0.102	0.063	0.004	2.701
2001	0.069	0.003	0.019	0.106	0.066	0.004	2.659
2002	0.073	0.003	0.019	0.115	0.069	0.004	2.818
2003	0.074	0.003	0.020	0.122	0.071	0.004	2.741
2004	0.069	0.003	0.018	0.133	0.065	0.004	2.558
2005	0.069	0.003	0.021	0.116	0.066	0.004	2.457
2006	0.071	0.003	0.020	0.126	0.068	0.004	2.525
2007	0.072	0.003	0.020	0.132	0.071	0.004	2.462
2008	0.076	0.003	0.021	0.147	0.072	0.005	2.316
2009	0.075	0.003	0.023	0.153	0.075	0.004	2.367
2010	0.077	0.003	0.023	0.139	0.074	0.005	2.183
2011	0.078	0.003	0.023	0.162	0.075	0.004	2.523
2012	0.076	0.003	0.022	0.127	0.076	0.004	2.493
2013	0.072	0.003	0.022	0.117	0.071	0.004	2.477
2014	0.074	0.003	0.022	0.091	0.070	0.004	2.353
2015	0.074	0.003	0.025	0.129	0.071	0.005	2.147
2016	0.076	0.003	0.028	0.085	0.071	0.005	1.971