

REPLICATION OF “EDUCATIONAL
EXPANSION AND ITS HETEROGENEOUS
RETURNS FOR WAGE WORKERS”
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THEORETICAL FRAMEWORK

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OUTLINE

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:
 - Wooldridge'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

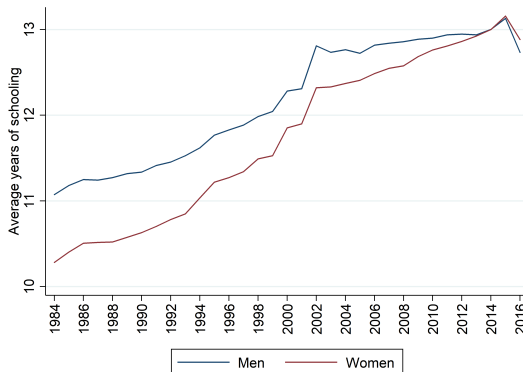


FIGURE 1: Source: SOEP 1984-2016, own estimations.

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 \rightarrow Individuals with higher expected benefits from education are more likely to remain longer in education $\rightarrow b_i$ 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

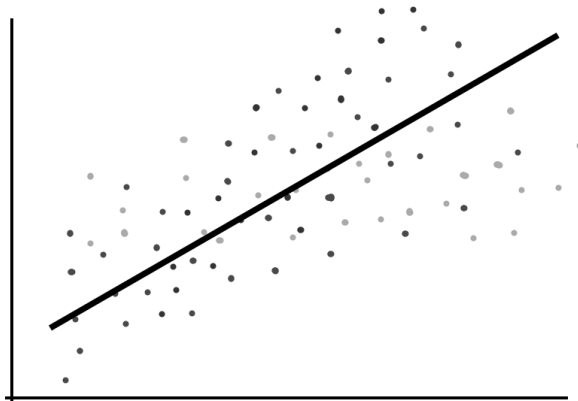


FIGURE 2: Simple OLS

EMPIRICAL FRAMEWORK (INTUITION) II

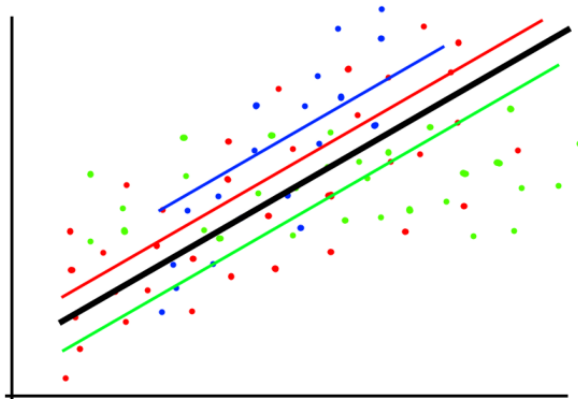


FIGURE 3: Multiple OLS with homogeneous return to Educ

EMPIRICAL FRAMEWORK (INTUITION) III

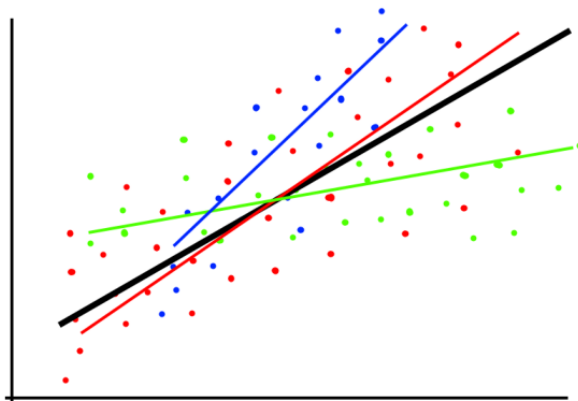


FIGURE 4: Correlated Random Coefficient Model

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 identify APE.
 - alternative: **Local Average Treatment Effect** if interested in effect of educational policy reforms.

CONDITIONAL MEAN INDEPENDENCE

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

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

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

- 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 \rightarrow “Staying longer in Education is determined by X covariates”.

ESTIMATOR FOR β AND GLM

The **APE** can be estimated by:

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

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

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

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

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**
 - $\gamma_1 = \text{cov}(\varepsilon_{ai}, v_i) / \text{var}(v_i)$
 - $\gamma_2 = \text{cov}(\varepsilon_{bi}, v_i) / \text{var}(v_i)$
- $E(w_i \mid X_i, S_i, v_i) = 0$ (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

REPLICATION AND COMPARISON

CODES

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

RESULTS

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 $\hat{\alpha}$ less able $\hat{\alpha}$ to achieve higher education

DIVERGENCES BETWEEN REPLICATION AND GEBEL AND PFEIFFER (2010)

- sample not the same
- large variance of CF approach

RESULTS COMPARISON I

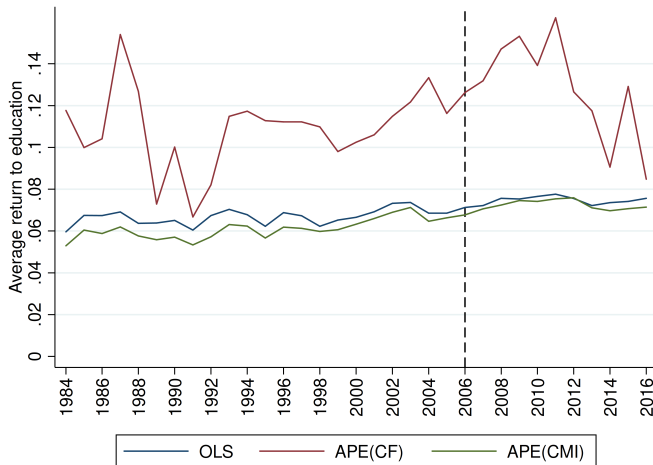


FIGURE 5: Replication results: Comparison between OLS, CMI and CF approaches

RESULTS COMPARISON II

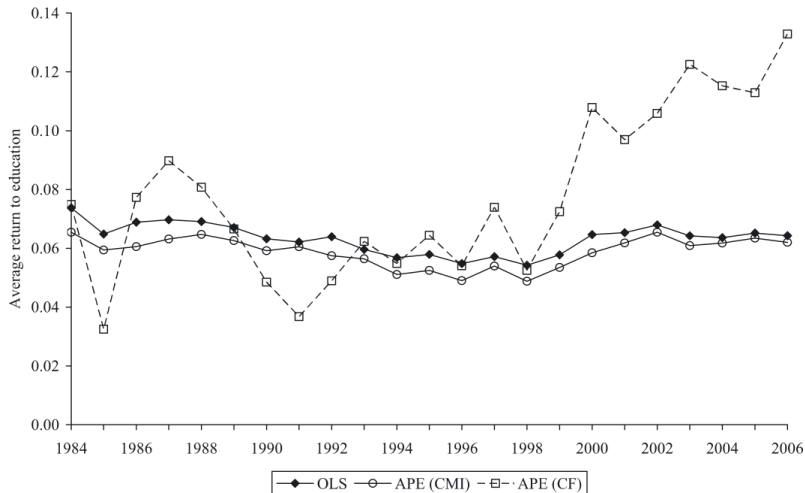


FIGURE 6: Original Results (GP 2010, pg.30)

RESULTS COMPARISON III

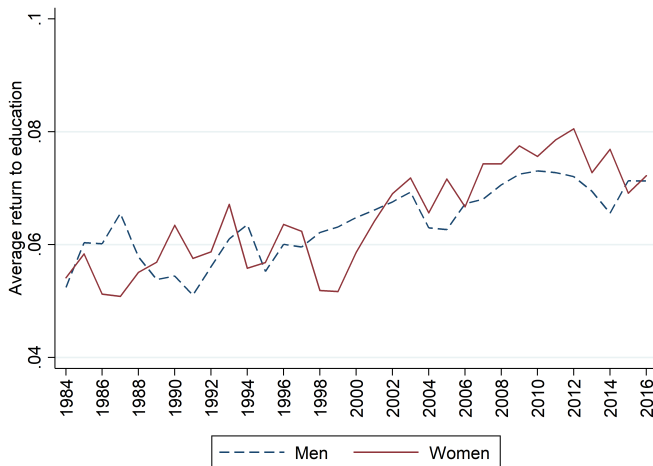


FIGURE 7: Replication results: **APE** by gender (CMI approach)

RESULTS COMPARISON IV

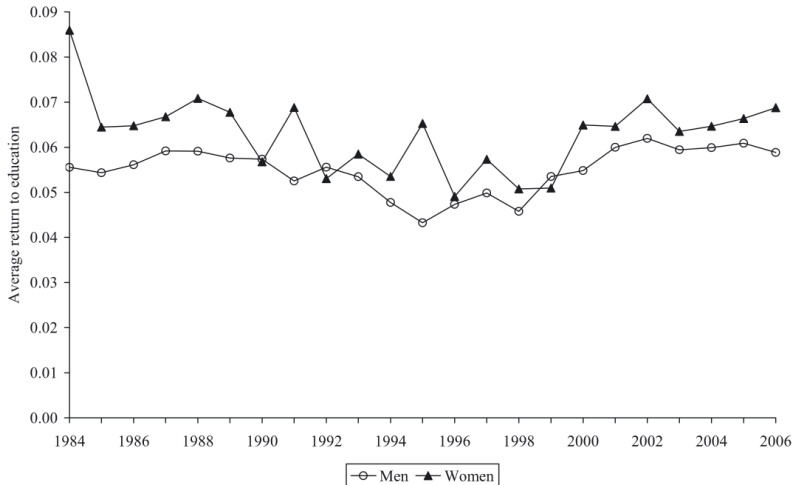


FIGURE 8: Original Results (GP 2010, pg.34)

RESULTS: CONTROL FUNCTION (REPLICATION)

TABLE 1: Summary of Control Function estimates (replication)

year	First Stage		Second Stage					
	IV: Nr. of Siblings		v_i			$v_i S_i$		
	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

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