The Evolution of Task Prices in Germany, 1980–2010

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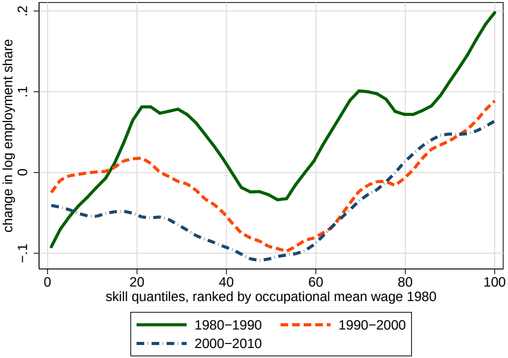
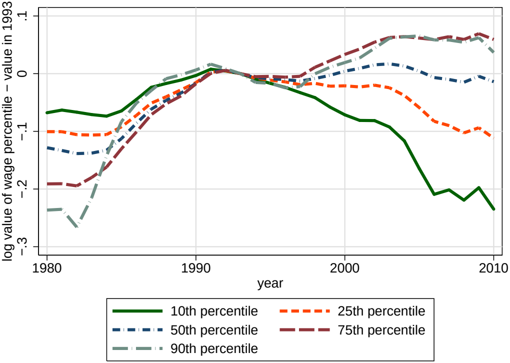
Job Polarization in Germany



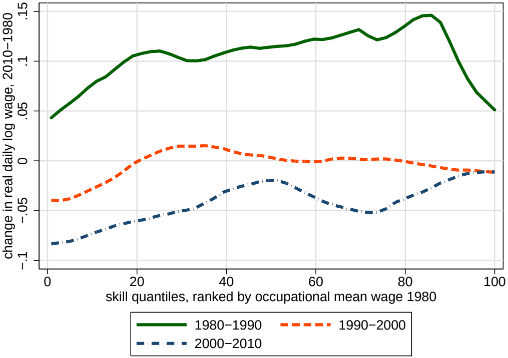
Similar in Dustmann, Ludsteck, Schoenberg (2009, QJE Figure 7b).

Increase in wage inequality across the board since 1990s



Same in Card, Heining, and Kline (2013, QJE Figure 1).

No occupational wage polarization or inequality increase



Different from Autor and Dorn (2013, AER Figure 1b), who find some occupational wage polarization in the US.

Are these facts connected? Prevailing view:

- Routine-Biased Technical Change (RBTC): new information & communication technologies substitute for work in routine tasks (e.g., assembly, record keeping).
- Occupations intense in routine tasks largely found in middle of wage distribution.

Seemingly clashes with the two pictures above. Series of papers find that over last decades

- employment polarized in US, Germany and most other advanced countries
- (occupational) wage distribution polarized only in US in 1990s.

Reconciling these facts

Böhm (2015) and Gottschalk, Green, Sand (2015):

- Changes in (occupational) wage distribution contain prices and composition effects.
- E.g., workers of different skills move across occupations, enter the labor market, and change position in wage distribution.
- Prices are determined by demand and supply for tasks, i.e., these composition effects are confounders.

Applications of task prices

- Assess importance of RBTC.
- Decompose changes in occupational wages into composition effects and market prices for tasks.
- Effect on overall wage inequality.
- Prices & quantities: learn about labor supply elasticities across tasks.

Also

- Decline of the gender wage gap (women more involved in price increasing tasks?)
- Educational decisions (increased share of university enrollees due to higher returns to cognitive/interpersonal tasks?)

Recent attempts to estimate task prices

- Firpo, Fortin, Lemieux (2013): decomposition of wages according to observables, remainder is task price.
- Gottschalk, Green, and Sand (2015): bounding based on different skill distributions in the Roy model.
- Cortes (2015): task fixed effects in panel data. Identification assumption that no switches due to changing skills.
- Böhm (2015): use sorting into tasks according observable talents and relate to changing returns to these talents.
- Yamaguchi (2012): dynamic structural Roy-type model estimated under normality of skill shocks in panel data.
- Heckman and Sedlacek (1985, classic): static structural Roy model estimated under normality of skill distribution.

This paper: propose a new way to estimate changing task prices

- Use static Roy framework.
- Exploit panel variation in workers' sorting into tasks and their wage growth (no demanding requirements on observables).
- Allow for multidimensional skills, changing skills, and endogenous sorting into tasks.
- Observable and unobservable components of skill matter.
- Allow for general distribution of unobservable skills and shocks.

Estimate in German IAB/BIBB data: evolution of task prices over time; decompose wages in tasks; assess wage distribution.

A K-task Roy model for panel data

K different occupations with (log) task prices $\pi = \{\pi_{1t}, \ldots, \pi_{Kt}\}$

Workers possess (log) skills $s = \{s_{1t}, \ldots, s_{Kt}\}$ and choose tasks that maximize their wage

$$W = max\{\pi_{1t} + s_{1t}, \ldots, \pi_{Kt} + s_{Kt}\}$$

Consider a marginal change in potential wages in t. By the envelope theorem:

$$dw_t = \begin{cases} dw_{1t} = d(\pi_{1t} + s_{1t}) & \text{if } I_{1t} = 1 \\ \quad \vdots & \\ dw_{Kt} = d(\pi_{Kt} + s_{Kt}) & \text{if } I_{Kt} = 1. \end{cases}$$

where $I_{kt} = 1[w_{kt} > w_{jt} \, \forall j \neq k]$ occupational choice indicator.

General worker's wage change

Marginally,

$$dw_t = l_{1t} dw_{1t} + \ldots + l_{Kt} dw_{Kt} = \sum_{k=1}^{K} l_{kt} dw_{kt}$$

Integrate both sides from $t-1$ to t to get worker's overall wage gain (imprecise notation!):

$$\Delta w_t = \sum_{k=1}^{K} \int_{w_{kt-1}}^{w_{kt}} l_{k\tau} dw_{k\tau}$$

Linearly approximate the integrals for $\tau \epsilon (t-1, t)$:

$$l_{k\tau} \approx l_{kt-1} + \frac{l_{kt} - l_{kt-1}}{w_{kt} - w_{kt-1}} (w_{k\tau} - w_{kt-1})$$

Leads to a very intuitive result

$$\Delta w_{it} = \bar{l}_{i1t} \Delta w_{i1t} + \ldots + \bar{l}_{iKt} \Delta w_{iKt} = \sum_{k=1}^{K} \bar{l}_{ikt} \Delta(\pi_{kt} + s_{ikt}),$$

where introduced individual index i and $\bar{l}_{ikt} \equiv \frac{l_{ikt} + l_{ikt-1}}{2}$.

- if worker stayed in some sector k, gets potential wage gain Δw_{ikt} from that sector.
- if he switched, gets half of potential wage gain from origin and half from destination sector.
- Gathmann and Schoenberg (2010) show that occupational mobility in Germany is higher than thought.

Time-invariant skills $s_{ikt} = s_{ik}$

$\beta_{kt} = \Delta\pi_{kt}$ identify the changing task prices from regression (under general multidimensional skill distribution):

$$\Delta w_{it} = \bar{I}_{i1t}\beta_{1t} + \ldots + \bar{I}_{iKt}\beta_{Kt} + u_{it}$$

- If workers do not switch jobs, related specification with task fixed effects (FE) also identifies $\Delta\pi_{kt}$.
- If workers do switch, "average" FE for destination and origin.
- Intuitive, as switching workers derive part of wage gain from origin and part from destination. Optimally use both info.
- Monte Carlo simulations show approximation of integrals no problem.
- Alternatively, worker-task FE (Cortes, 2015) or wage changes of only the stayers.

Time-varying skills s_{ikt} and endogenous switches

$$\Delta w_{it} = \sum_{k=1}^{K} \bar{I}_{ikt} \Delta \pi_{kt} + \sum_{k=1}^{K} \bar{I}_{ikt} \Delta s_{ikt},$$

where $\Delta s_{ikt} = f_K(I_{it-1}, age_{it-1}, educ_{it-1}, unobservables_{it-1})$.
Learning by doing on the job (e.g., Yamaguchi 2012).
If $\bar{I}_{ikt}$ endogenous to Δs_{ikt}, bias. Model Δs_{ikt} as flexible function:

$$\Delta s_{ikt} = (I_{it-1} \times age_{it-1} \times educ_{it-1})\gamma_k + \varepsilon_{ikt}$$

If remaining ε_{ikt} small, solves the problem. $\Delta \pi_{kt}$ versus γ_k identified from *restriction* that latter no time index (skill acquisition function time-invariant). Need multiple periods.

German IAB and BIBB data

SIAB data provided by the IAB

- Panel which contains full job histories (social security data) and wages.
- 2% sample from 1980–2010 (41 mio observations)
- Wages top coded at social security maximum. Impute using Tobit-model as described in Gartner (2005, IAB publication).
- Only West-German males age 18(25)–55 because other groups' labor market attachment transient (identification from within-person wage growth).
- Observables: education, age, occupation, industry, etc (model a worker's task specific skill accumulation)

Task data provided by the German Federal Institute for Vocational Training (BIBB)

- Surveys of individual workers about which tasks they do in their jobs, e.g. 'how often do you repair stuff'.
- 6 repeated cross sections from 1979 - 2012 where 20.000 workers were asked what tasks they perform
- Assess task content of occupations.
- Also model task profiles by age, education, profession, etc.

Difficulty: need to harmonize questions (task measures) across surveys.

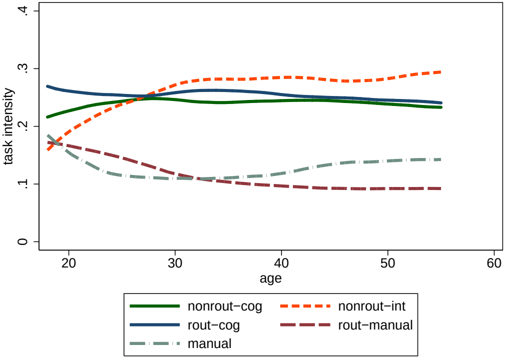
Occupation groups for which we estimate the task prices

1. Handcoded five occupation groups (“professions”, preferred)
   - Managers/Professionals/Technicians, Sales/Office, Crafts (e.g., carpenter, roofer, plumber), Production/Operator, Services.
   - Inspired by Acemoglu & Autor (2011 HoLE)
   - Check task content of groups using BIBB.
2. Occupation groups according to BIBB task content
   - Two: routine and nonroutine.
   - Five: nonrout-cog, nonrout-int, rout-cog, rout-manual and manual.

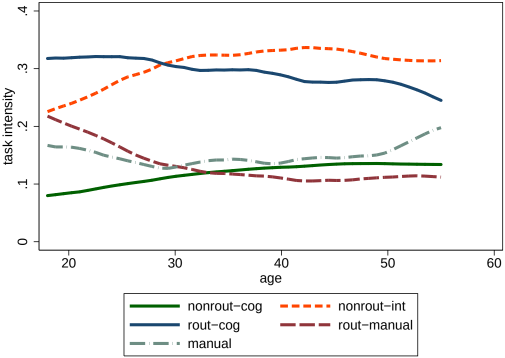
Correlations between profession dummies and BIBB task variables

	nonrout-cog	nonrout-int	rout-cog	rout-manual	manual
Man/Prof/Tech	.78	.39	.42	-.48	-.5
Sales/Off	.03	.38	.45	-.24	-.23
Prod/Op	-.46	-.52	-.39	.66	.11
Crafts	-.25	-.21	-.19	.13	.28
Services	-.07	.15	-.16	-.28	.38

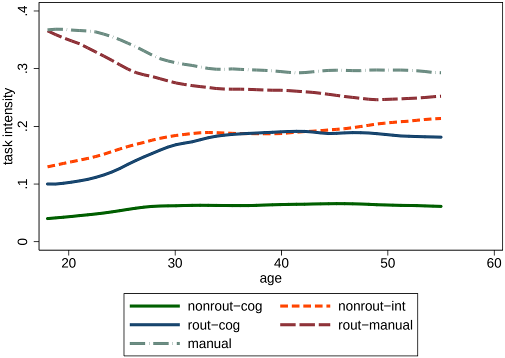
Task intensities by age in Mana., Prof., Tech.



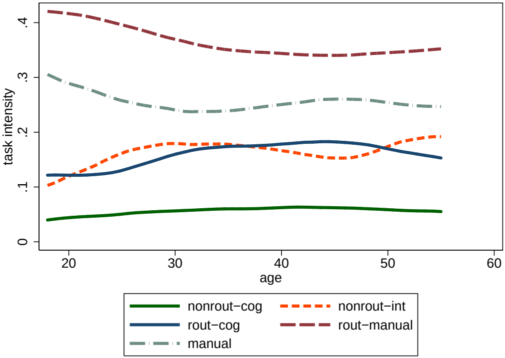
Task intensities by age in Sales, Office



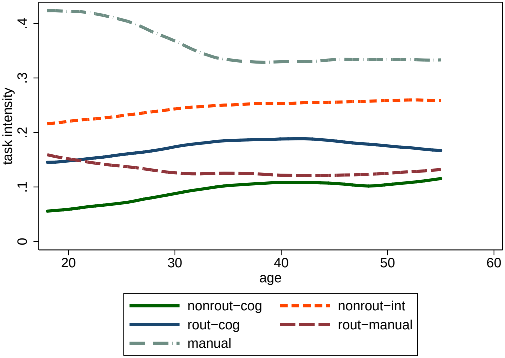
Task intensities by age in Craftspeople



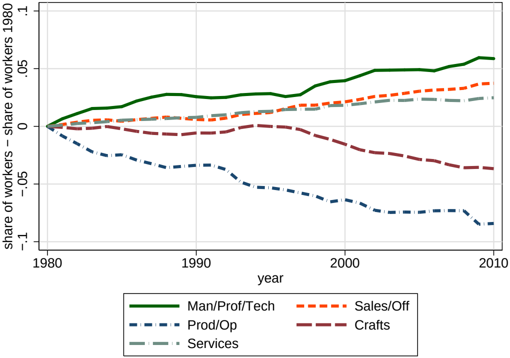
Task intensities by age in Production, Operate



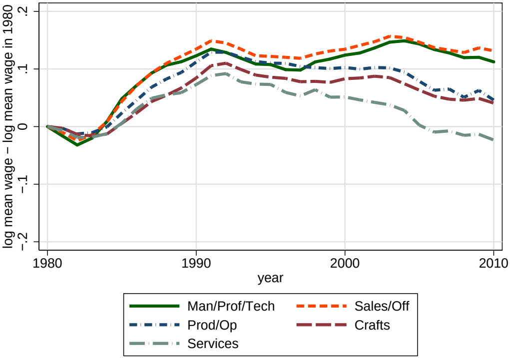
Task intensities by age in Service



Share of workers in professions relative to 1980

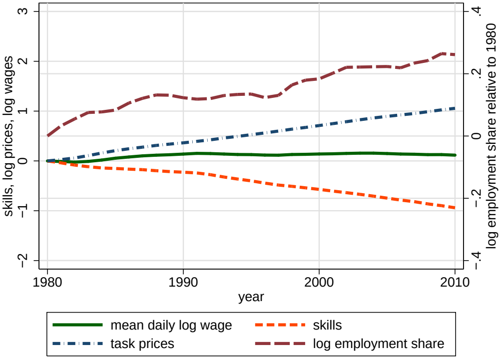


Real mean wages in professions relative to mean wages 1980



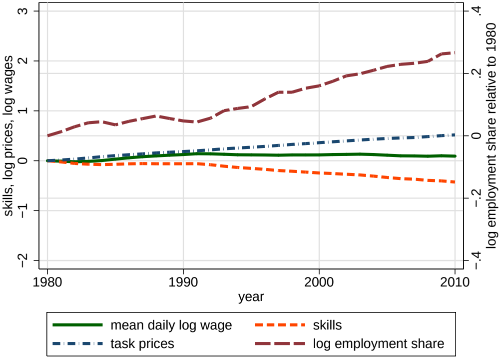
Results

Decomposition of log wages in Man/Prof/Tech



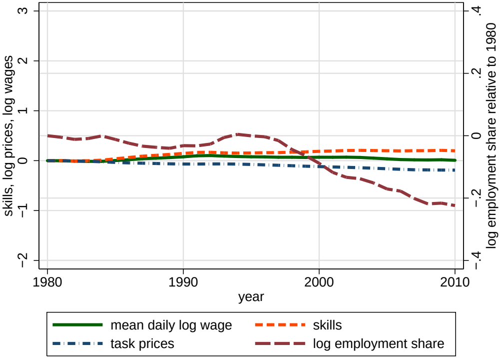
Suggests a large increase in task price (through employment demand) and a strongly deteriorating skill of professionals.

Decomposition of log wages in Sale/Off



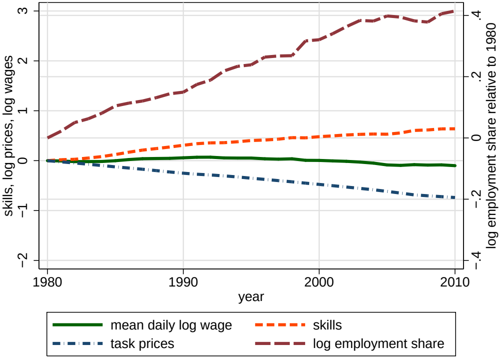
Again a positive demand shock, but very elastic labor supply response and only modest deterioration of skills.

Decomposition of log wages in Crafts



Continuous decline in demand with many leaving and the stayers slightly better skills than the leavers.

Decomposition of log wages in Services



Looks like large supply shock which increases employment and depresses prices. The skill composition actually improves!

Conclusion

- Propose method of estimating changing task prices from changing-over-time wage growth across jobs.
- Flexibly allow for systematic worker sorting.
- Estimate in German IAB data in context of task biased technological change and rising inequality.

Further steps:

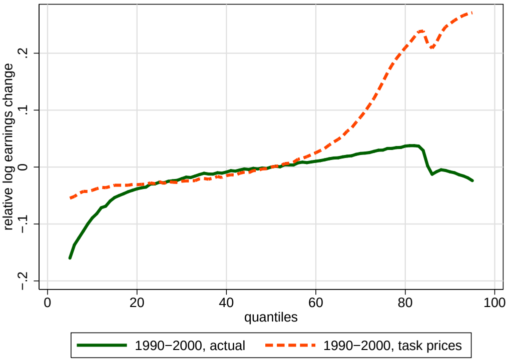
- Disentangling prices and skill accumulation doesn't seem to work yet.
- Decompose occupational wages; assess effect on wage distribution.
- Deal with confounders: leavers from employment; policy changes (Hartz reforms).

Thank you!

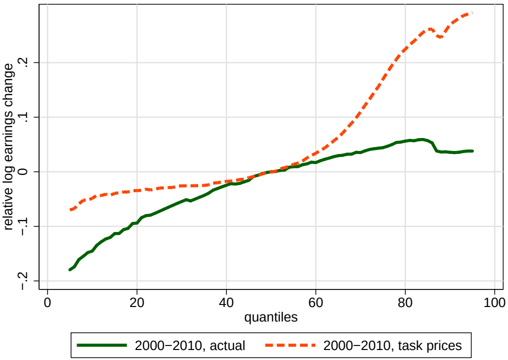
Postestimation

Professions: Changes in daily log wages relative to the median, 1980-1990

Professions: Changes in daily log wages relative to the median, 1990-2000

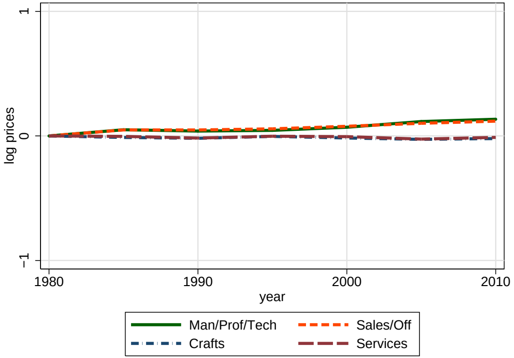


Professions: Changes in daily log wages relative to the median, 2000-2010

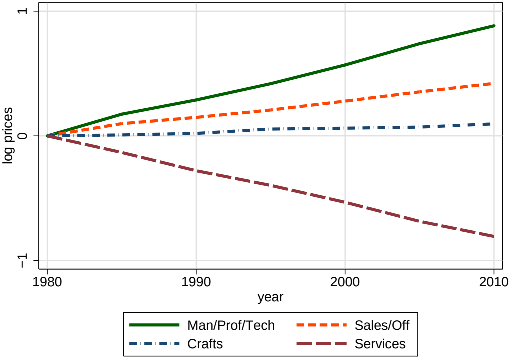


OLS Estimation Results for 40-55 year olds

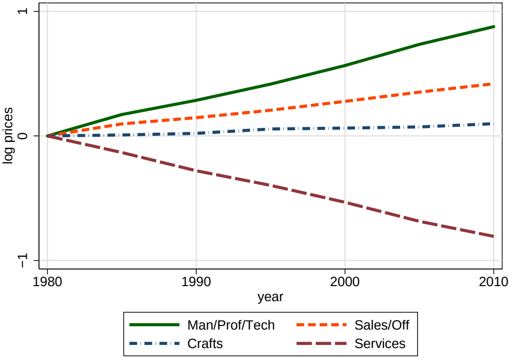
OLS - 5 years - professions - no controls - 40-55 year olds



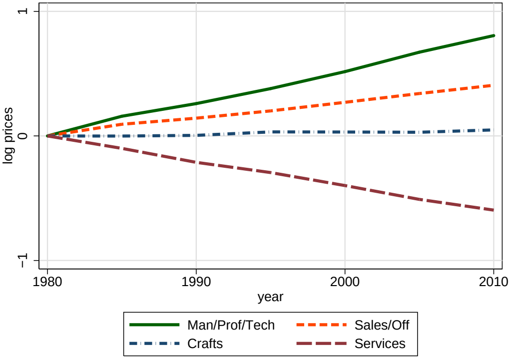
OLS - 5 years - professions - control for past task - 40-55 year olds



OLS - 5 years - professions - control for past task $\times$ age - 40-55 year olds



OLS - 5 years - professions - control for past task $\times$ educ $\times$ age - 40-55 year olds



OLS - 5 years - professions - control for past task $\times$ educ $\times$ age - 40-55 year olds

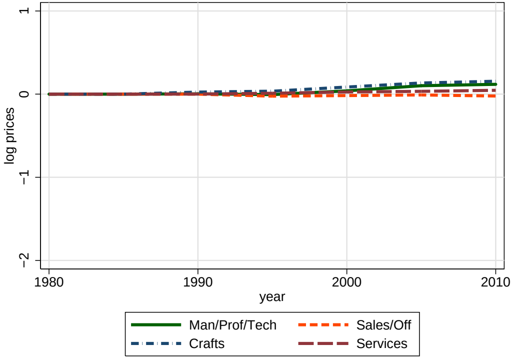
		$\Delta\pi_{\text{prod},t}$	$\Delta(\pi_{\text{mana},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{sale},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{craf},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{serv},t} - \pi_{\text{prod},t})$
1985	β:	.0107	.1582	.0938	-.001	-.0999
	σ_β:	.0019	.0049	.0055	.0046	.0069
1990	β:	.1094	.1015	.049	.0055	-.1122
	σ_β:	.0021	.0049	.0054	.0046	.007
1995	β:	.0055	.1204	.0584	.0277	-.0819
	σ_β:	.0021	.0049	.0055	.0047	.0071
2000	β:	.0122	.1363	.0689	-.0009	-.1045
	σ_β:	.0021	.0049	.0055	.0048	.007
2005	β:	-.0152	.156	.0706	-.0018	-.1109
	σ_β:	.0021	.0049	.0054	.0047	.0069
2010	β:	-.0117	.1332	.0664	.0189	-.0862
	σ_β:	.0021	.0048	.0054	.0047	.0068

Skill accumulation: control for past task ($\times$ age)

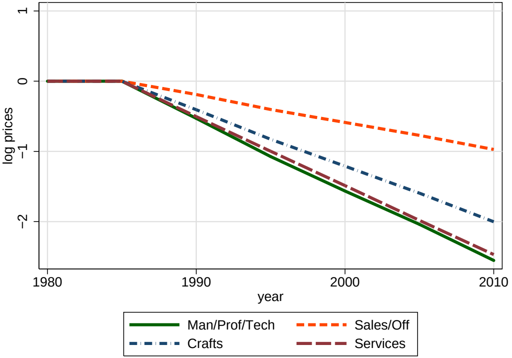
profession	all ages (40-55)	younger (40-47)	older (48-55)
Man/Prof/Tech	-.125	-.112	-.017
Sale/Off	-.05	-.039	-.016
Prod/Op			-.01
Crafts	-.019	-.017	-.004
Services	.135	.136	-.002

IV Estimation Results for all ages

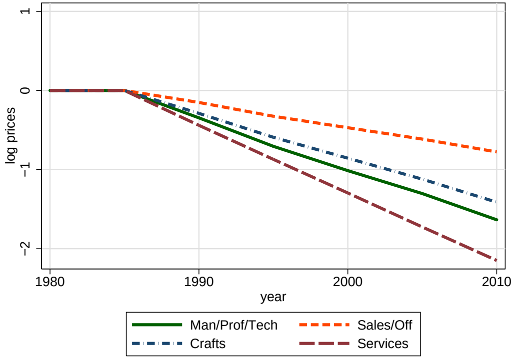
IV - 5 years - professions - no controls



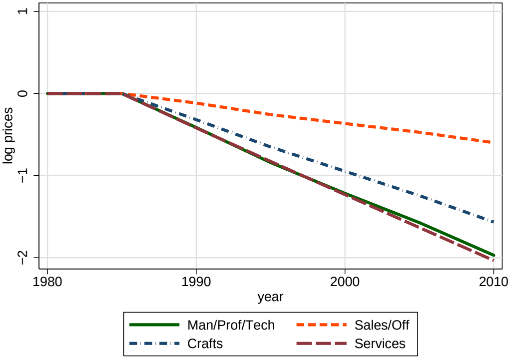
IV - 5 years - professions - control for past task



IV - 5 years - professions - control for past task × age



IV - 5 years - professions - control for past task × educ × age

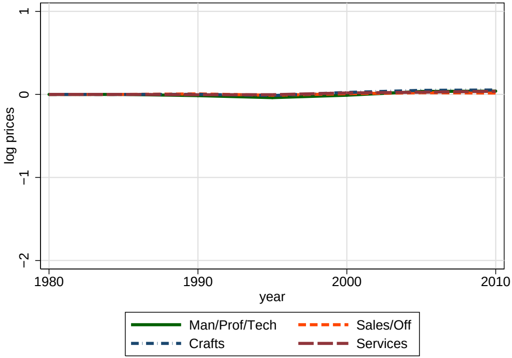


IV - 5 years - professions - control for past task $\times$ educ $\times$ age

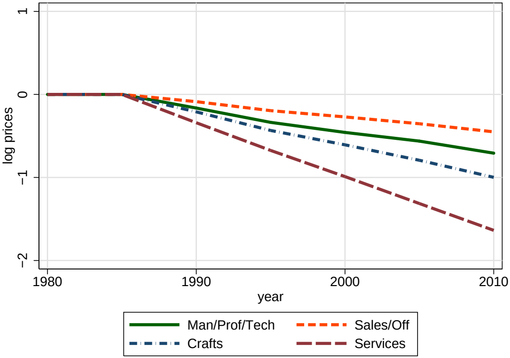
		$\Delta\pi_{\text{prod},t}$	$\Delta(\pi_{\text{mana},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{sale},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{craf},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{serv},t} - \pi_{\text{prod},t})$
1990	β:	.1003	-.414	-.1168	-.3185	-.4192
	σ_β:	.004	.033	.025	.0322	.0491
1995	β:	.0174	-.4273	-.1403	-.3328	-.4079
	σ_β:	.0041	.0331	.0249	.0321	.0489
2000	β:	-.0074	-.3752	-.1088	-.2956	-.4044
	σ_β:	.0041	.0331	.0249	.0321	.0488
2005	β:	-.0384	-.3565	-.1065	-.2966	-.4014
	σ_β:	.0041	.0331	.0249	.032	.0485
2010	β:	-.0182	-.3971	-.1263	-.322	-.4009
	σ_β:	.004	.0329	.0246	.0318	.0483

IV Estimation Results for 40-55 year olds

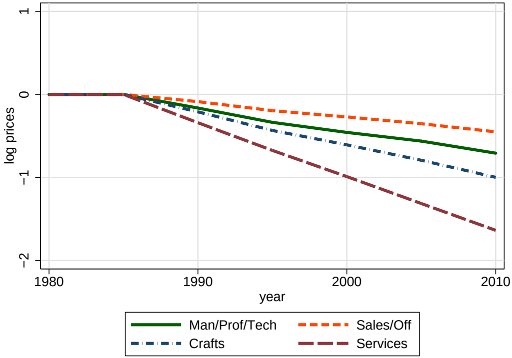
IV - 5 years - professions - no controls - 40-55 year olds



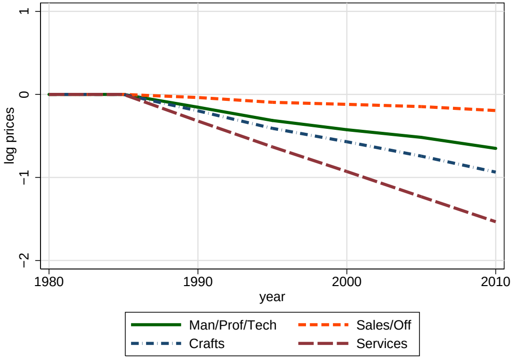
IV - 5 years - professions - control for past task - 40-55 year olds



IV - 5 years - professions - control for past task $\times$ age - 40-55 year olds



IV - 5 years - professions - control for past task $\times$ educ $\times$ age - 40-55 year olds



IV - 5 years - professions - control for past task $\times$ educ $\times$ age - 40-55 year olds

		$\Delta\pi_{\text{prod},t}$	$\Delta(\pi_{\text{mana},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{sale},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{craf},t} - \pi_{\text{prod},t})$	$\Delta(\pi_{\text{serv},t} - \pi_{\text{prod},t})$
1990	β:	.0909	-.154	-.0372	-.1979	-.3207
	σ_β:	.006	.0688	.0543	.0742	.1184
1995	β:	.0064	-.1598	-.0579	-.2107	-.311
	σ_β:	.0061	.0686	.054	.0738	.1173
2000	β:	-.0208	-.1115	-.0243	-.1615	-.2967
	σ_β:	.0065	.0691	.0544	.0739	.1176
2005	β:	-.0423	-.092	-.0273	-.1731	-.3039
	σ_β:	.0064	.0689	.0541	.0738	.1165
2010	β:	-.0223	-.1329	-.0473	-.1928	-.3011
	σ_β:	.0062	.0687	.0539	.0736	.1168

Thank you!

References I

Appendix

Literature

- Task changes and job polarization:
  - **Autor2003**
  - **Autor2006**
  - **Acemoglu2011**
  - **Goos2014**
- Occupational choice and change of tasks:
  - **Spitz2006**
  - **Gathmann2010**
  - **Yamaguchi2012**
- Measurement of task price polarization:
  - **Boehm2015**
  - **Cortes2015**

Empirical setup: Transition across occupations and task-age profiles

Correlation between BIBB tasks

	nonrout-cog	nonrout-int	rout-cog	rout-manual	manual
nonrout-cog	1				
nonrout-int	.36	1			
rout-cog	.5	.36	1		
rout-manual	-.58	-.69	-.5	1	
manual	-.57	-.29	-.57	-.05	1

Empirical Setup - Transitions

Table: Job switchers from previous year to 1985

	stay occ	manag	sale	prod	craft	serv
manag	.875	.014	.01	.016	.004	.006
sale	.851	.005	.025	.016	.009	.009
prod	.886	.007	.012	.01	.009	.011
craft	.851	.001	.003	.003	.03	.027
serv	.862	.001	.003	.003	.017	.029

Empirical Setup - Transitions

Table: Job switchers from previous year to 1990

	stay occ	manag	sale	prod	craft	serv
manag	.856	.016	.01	.016	.005	.007
sale	.829	.007	.026	.018	.011	.012
prod	.862	.008	.017	.011	.014	.014
craft	.801	.001	.003	.003	.039	.028
serv	.807	.001	.003	.003	.023	.033

Empirical Setup - Transitions

Table: Job switchers from previous year to 2000

	stay occ	manag	sale	prod	craft	serv
manag	.837	.026	.015	.024	.005	.009
sale	.816	.012	.025	.023	.011	.012
prod	.835	.014	.02	.015	.012	.018
craft	.814	.001	.004	.004	.032	.027
serv	.831	.001	.003	.003	.022	.03

Empirical Setup - Transitions

Table: Job switchers from previous year to 2010

	stay occ	manag	sale	prod	craft	serv
manag	.903	.011	.007	.01	.003	.004
sale	.85	.007	.02	.015	.006	.008
prod	.897	.007	.012	.007	.006	.009
craft	.848	.001	.003	.003	.025	.015
serv	.865	.001	.003	.002	.014	.02

Empirical Setup - Transitions

Table: Job switchers 5 years before to 1985

	stay occ	manag	sale	prod	craft	serv
manag	.606	.044	.023	.048	.011	.019
sale	.545	.017	.068	.053	.027	.03
prod	.623	.022	.035	.036	.033	.038
craft	.587	.001	.008	.009	.088	.071
serv	.61	.002	.008	.007	.052	.085

Empirical Setup - Transitions

Table: Job switchers 5 years before to 1990

	stay occ	manag	sale	prod	craft	serv
manag	.54	.049	.023	.041	.013	.022
sale	.506	.02	.066	.046	.027	.034
prod	.581	.023	.038	.031	.034	.042
craft	.502	.001	.007	.007	.075	.062
serv	.54	.002	.007	.005	.043	.067

Empirical Setup - Transitions

Table: Job switchers 5 years before to 2000

	stay occ	manag	sale	prod	craft	serv
manag	.529	.053	.031	.047	.015	.027
sale	.51	.024	.063	.051	.029	.034
prod	.57	.03	.041	.033	.034	.048
craft	.562	.002	.008	.009	.083	.067
serv	.582	.002	.007	.009	.054	.076

Empirical Setup - Transitions

Table: Job switchers 5 years before to 2010

	stay occ	manag	sale	prod	craft	serv
manag	.605	.048	.025	.046	.011	.018
sale	.528	.027	.061	.055	.023	.026
prod	.635	.028	.04	.028	.022	.033
craft	.607	.002	.008	.008	.071	.049
serv	.619	.003	.007	.008	.044	.065

Employment Facts

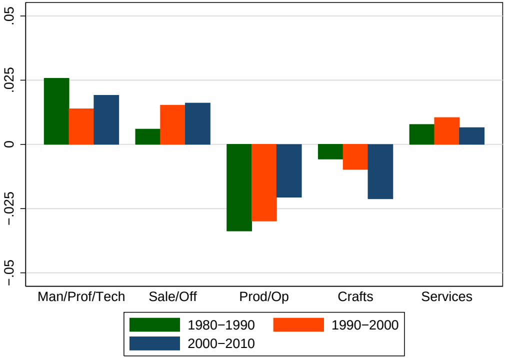
Partial employment routinization (1993–2010): Sales& Office are rising, Crafts are falling

Occupation group	Percent employment share in 1993	Percentage point change over 1993-2010
Man/Prof/Tech	.22	.04
Sales/Off	.13	.03
Prod/Op	.4	-.03
Crafts	.18	-.03
Services	.06	.01

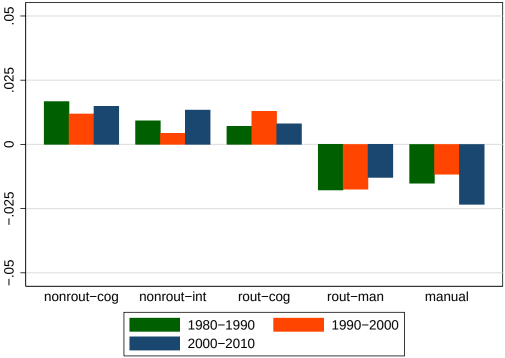
Partial employment routinization (1980–1993)

Occupation group	Percent employment share in 1980	Percentage point change over 1980-1993
Man/Prof/Tech	.2	.02
Sales/Off	.12	.01
Prod/Op	.45	-.05
Crafts	.18	0
Services	.05	.01

Employment changes in professions



Employment changes in five task groups



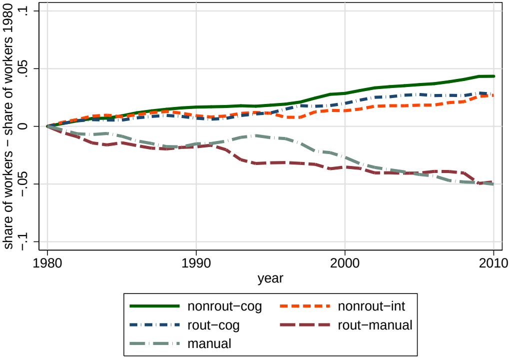
Partial employment routinization: both manual tasks are falling

Task group	Percent employment share in 1993	Percentage point change over 1993-2010
nonrout-cog	.08	.03
nonrout-int	.14	.02
rout-cog	.15	.01
rout-manual	.28	-.02
manual	.35	-.04

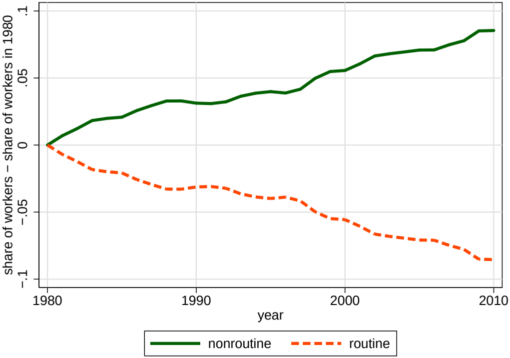
Partial employment routinization: both manual tasks are falling

Task group	Percent employment share in 1980	Percentage point change over 1980-1993
nonrout-cog	.07	.01
nonrout-int	.13	.01
rout-cog	.14	.01
rout-manual	.31	-.03
manual	.36	-.01

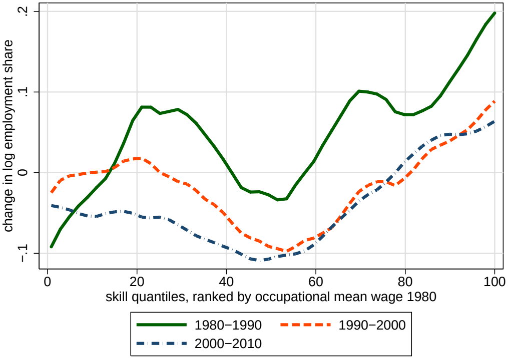
Share of workers in five task groups relative to 1980



Share of workers in two task groups relative to 1980



Employment change by occupational skill quantile



Wage Facts

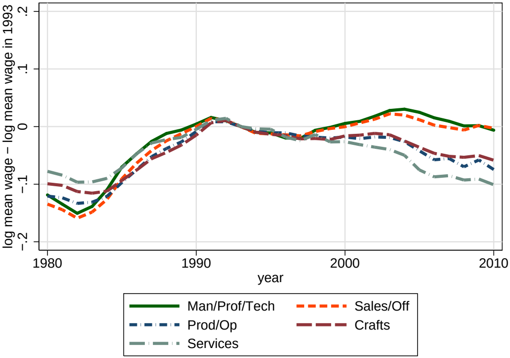
Partial wage polarization (1993–2010): production and crafts wages drop but also service wages plummet

Occupation group	$\frac{\text{mean wage in occupation 1993}}{\text{overall mean wage 1993}}$	change of this ratio between 1993–2010
Man/Prof/Tech	1.39	.01
Sales/Off	1.11	.01
Prod/Op	.85	-.05
Crafts	.85	-.04
Services	.78	-.06

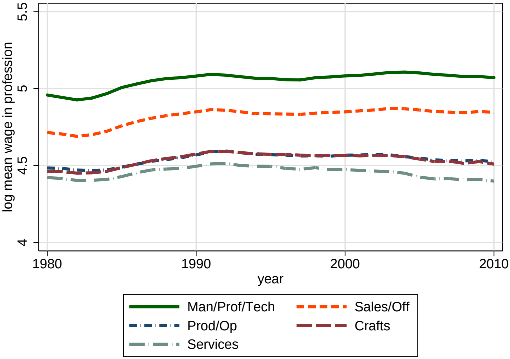
No wage polarization (1980–1993)

Occupation group	$\frac{\text{mean wage in occupation 1980}}{\text{overall mean wage 1980}}$	change of this ratio between 1980–1993
Man/Prof/Tech	1.41	-.02
Sales/Off	1.11	0
Prod/Op	.86	-.01
Crafts	.88	-.03
Services	.83	-.05

Real mean wages in professions relative to mean wages 1993



Log mean wages in professions



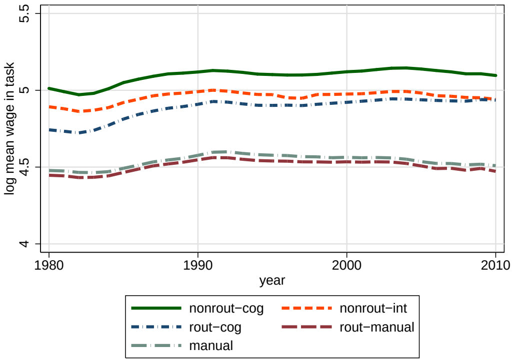
No Wage Polarization

Task group	$\frac{\text{mean wage in occupation 1993}}{\text{overall mean wage 1993}}$	change of this ratio between 1993 - 2010
nonrout-cog	1.45	-.01
nonrout-int	1.26	-.03
rout-cog	1.18	.04
rout-manual	.82	-.05
manual	.85	-.05

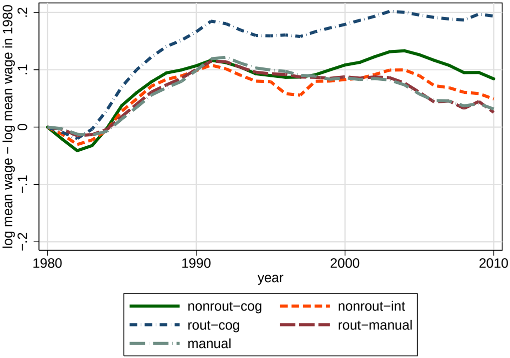
No Wage Polarization

Task group	$\frac{\text{mean wage in occupation 1980}}{\text{overall mean wage 1980}}$	change of this ratio between 1980 - 1993
nonrout-cog	1.49	-.05
nonrout-int	1.32	-.09
rout-cog	1.14	.08
rout-manual	.85	-.08
manual	.87	-.07

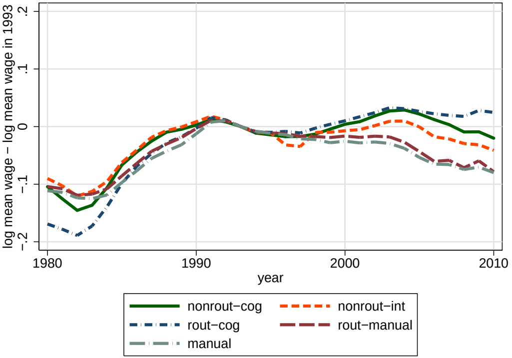
Log mean wages five task groups



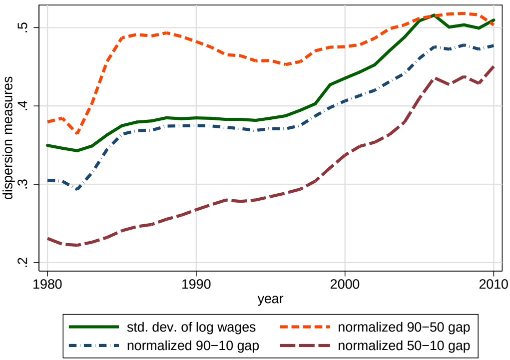
Real mean wages in five task groups relative to mean wages 1980



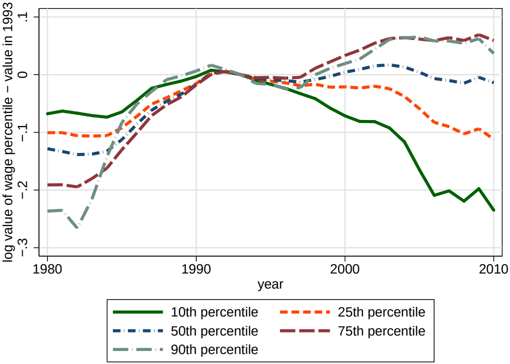
Real mean wages in five task groups relative to mean wages 1993



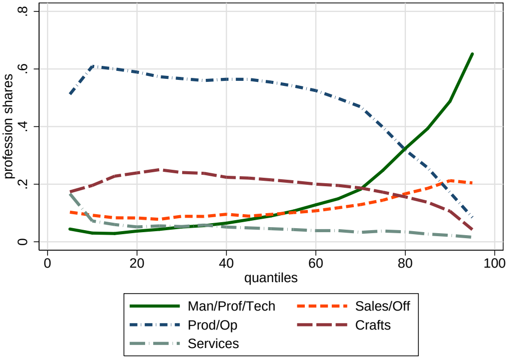
Evolution of wage dispersion measures



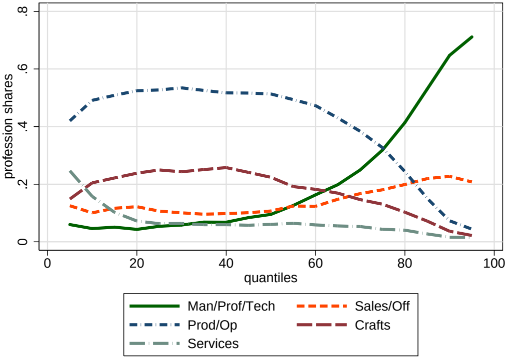
Evolution of wage percentiles



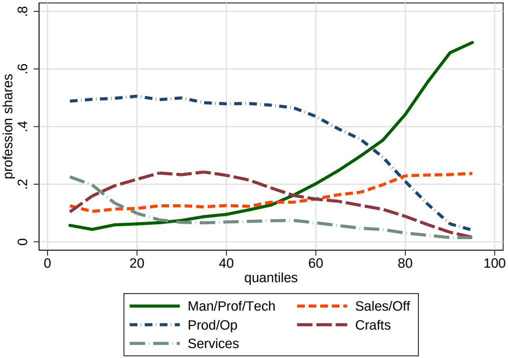
Share of workers in professions in wage quantiles 1980



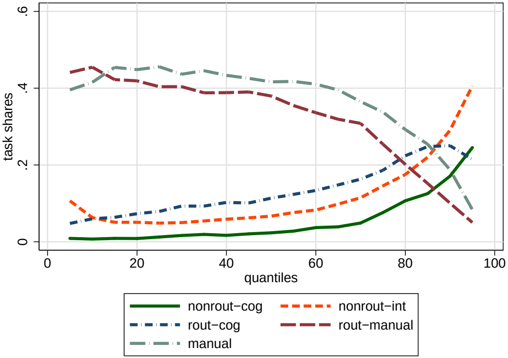
Share of workers in professions in wage quantiles 2000



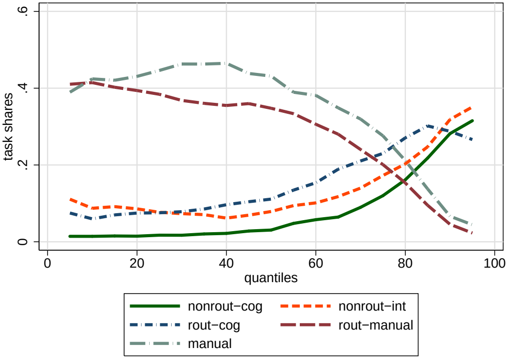
Share of workers in professions in wage quantiles 2010



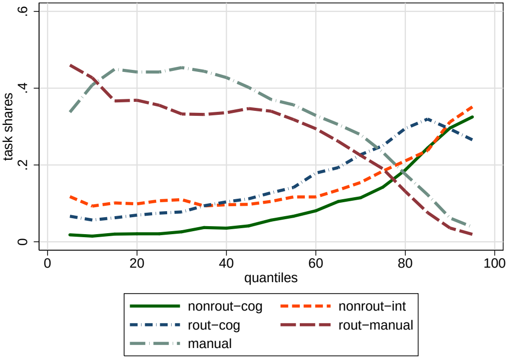
Share of workers in five tasks in wage quantiles 1980



Share of workers in five tasks in wage quantiles 2000



Share of workers in five tasks in wage quantiles 2010

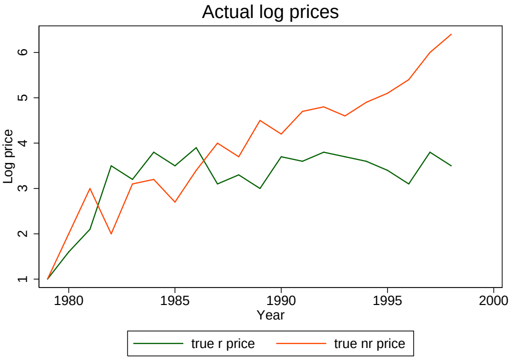


ADD MONTE CARLO SIMULATIONS HERE OR AFTER MODEL OR INTO APPENDIX?

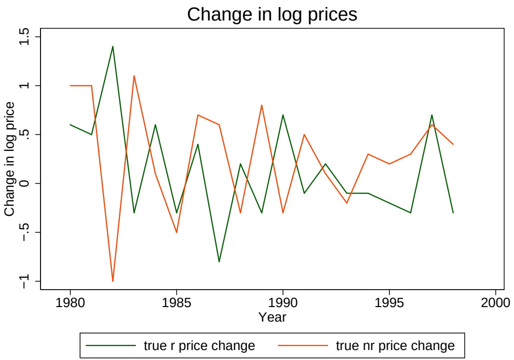
Empirical Setup - Monte Carlo Simulations

- How big is the bias due to the endogeneity in our estimation equation? And in what direction does it go?
- Is there an additional problem because of the linear approximation of the integral?
- Construct an artificial panel dataset (agent - time) by explicitly specifying prices and skills, so we know the true values
- Then apply our estimation strategy and see how great the bias is for this artificial dataset
- Can artificially also get rid of endogeneity by using $\Delta w^*_{it} = \Delta w_{it} + \bar{N}_{it}\varepsilon_{Rit} - \bar{N}_{it}\varepsilon_{Nit}$ instead of Δw_{it} on the left side
    - Increasing price polarization
    - Normal log skill shocks, no learning at all
    - 2000 agents, 20 periods, 400 simulations

Empirical Setup - Monte Carlo Simulations

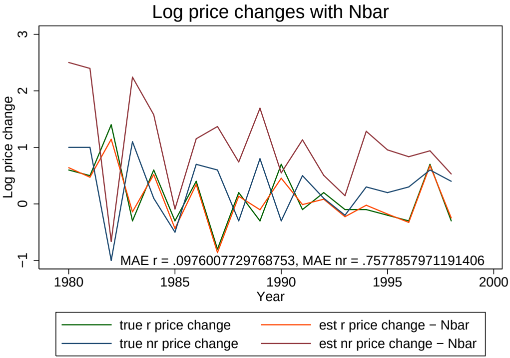


Empirical Setup - Monte Carlo Simulations

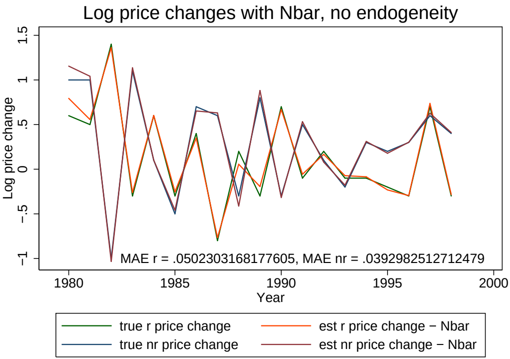


Empirical Setup - Monte Carlo Simulations

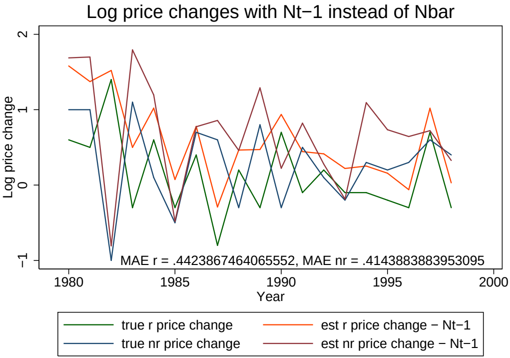
Empirical Setup - Monte Carlo Simulations



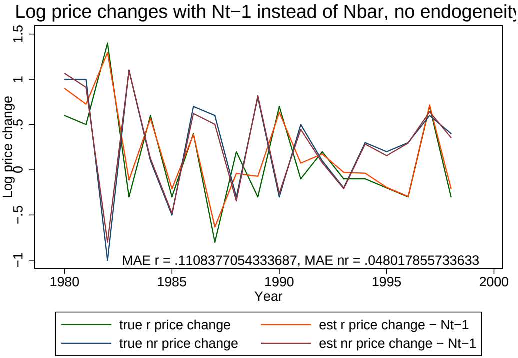
Empirical Setup - Monte Carlo Simulations



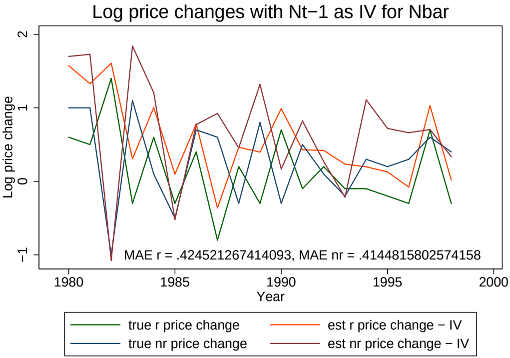
Empirical Setup - Monte Carlo Simulations



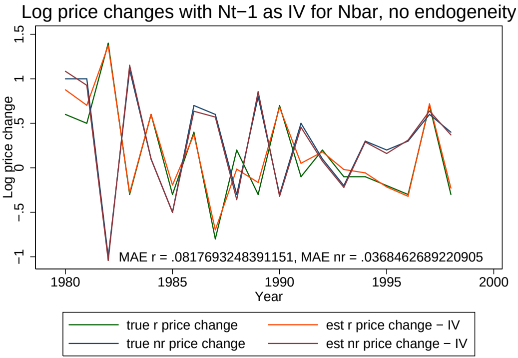
Empirical Setup - Monte Carlo Simulations



Empirical Setup - Monte Carlo Simulations

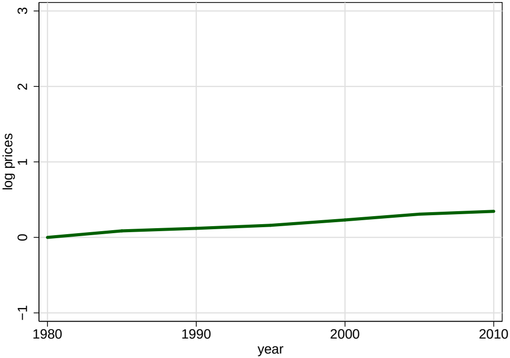


Empirical Setup - Monte Carlo Simulations

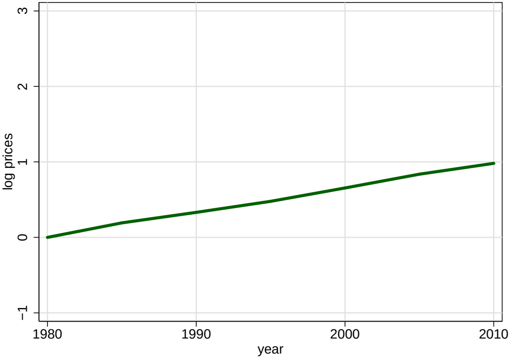


Estimation Results for 5 year periods

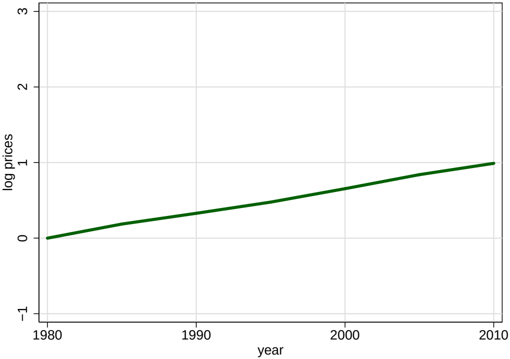
OLS - 5 years - two tasks - no controls



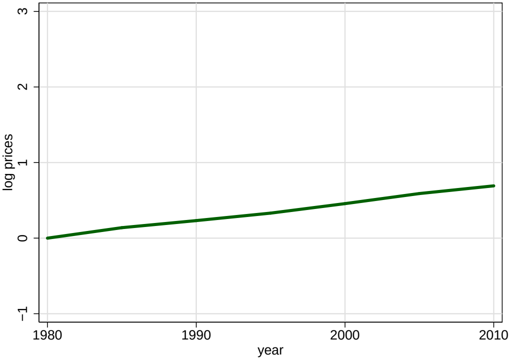
OLS - 5 years - two tasks - control for past task



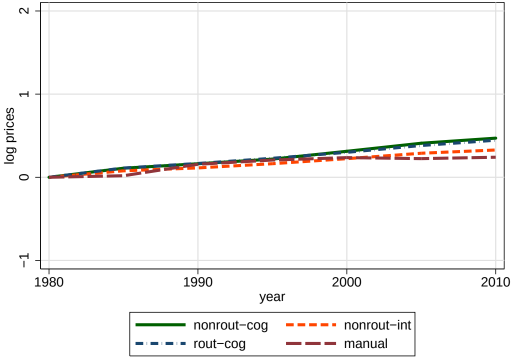
OLS - 5 years - two tasks - control for past task × age



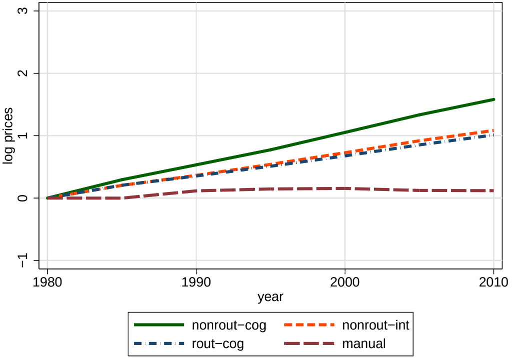
OLS - 5 years - two tasks - control for past task $\times$ educ $\times$ age



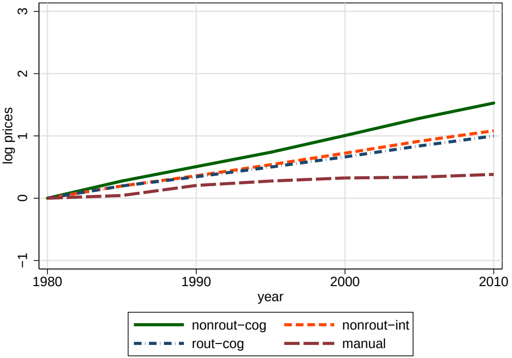
OLS - 5 years - five tasks - no controls



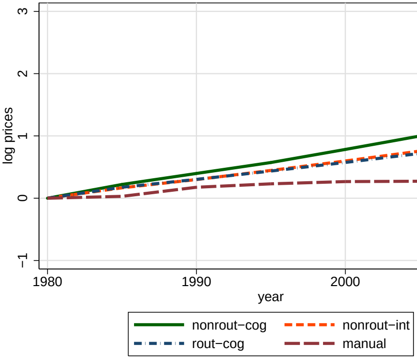
OLS - 5 years - five tasks - control for past task



OLS - 5 years - five tasks - control for past task $\times$ age

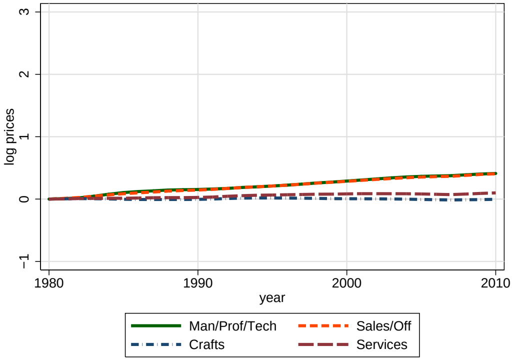


OLS - 5 years - five tasks - control for past task $\times$ educ $\times$ age

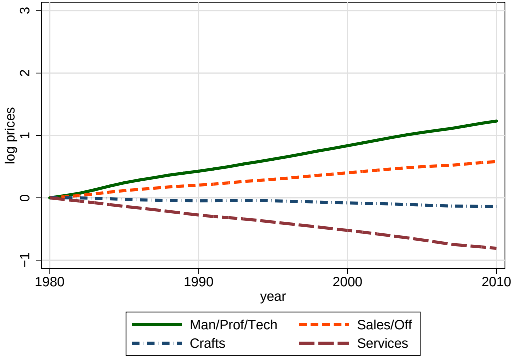


Estimation Results for 1 year periods

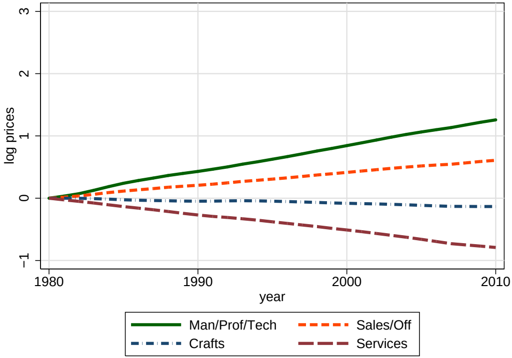
OLS - yearly - professions - no controls



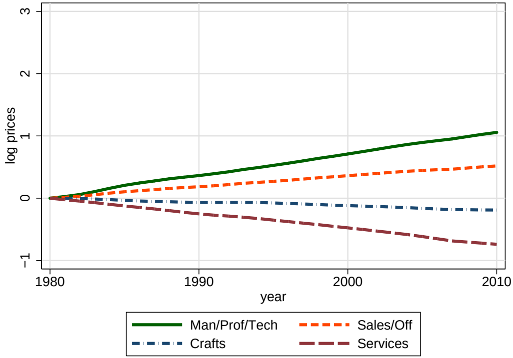
OLS - yearly - professions - control for past task



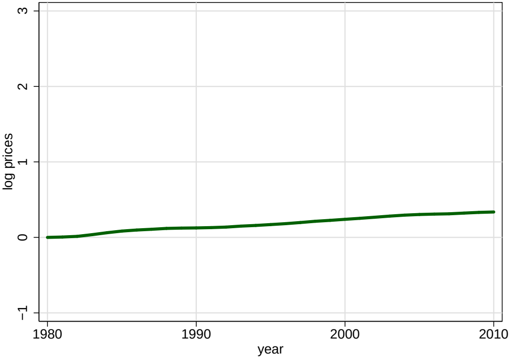
OLS - yearly - professions - control for past task $\times$ age



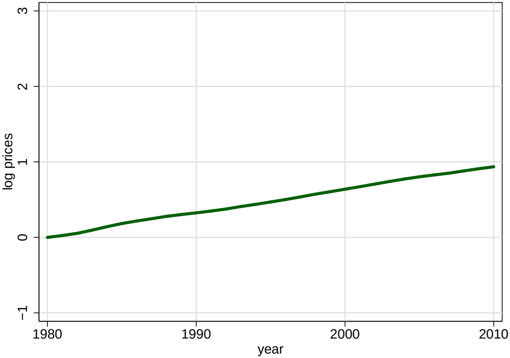
OLS - yearly - professions - control for past task × educ × age



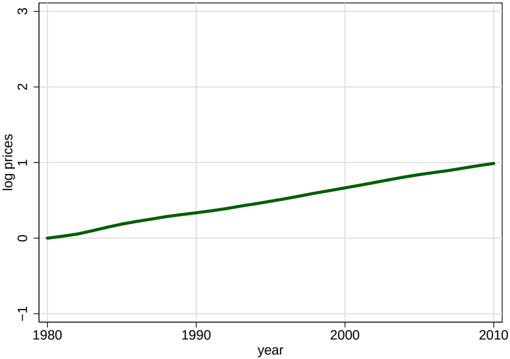
OLS - yearly - two tasks - no controls



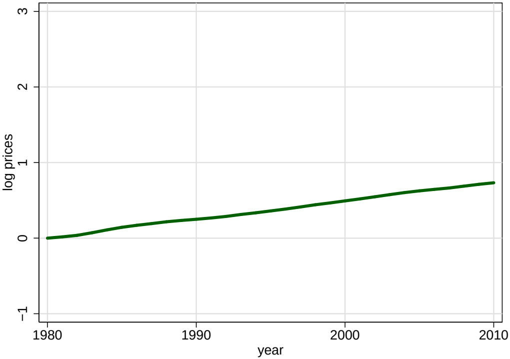
OLS - yearly - two tasks - control for past task



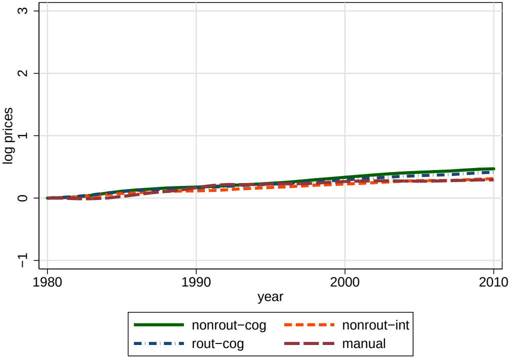
OLS - yearly - two tasks - control for past task $\times$ age



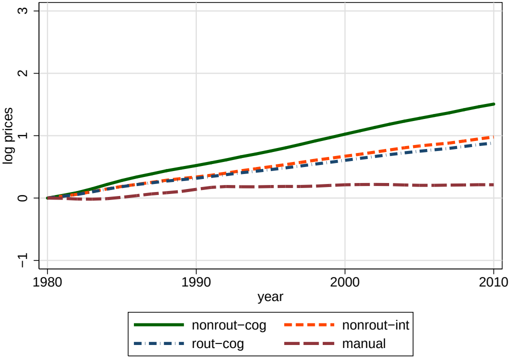
OLS - yearly - two tasks - control for past task × educ × age



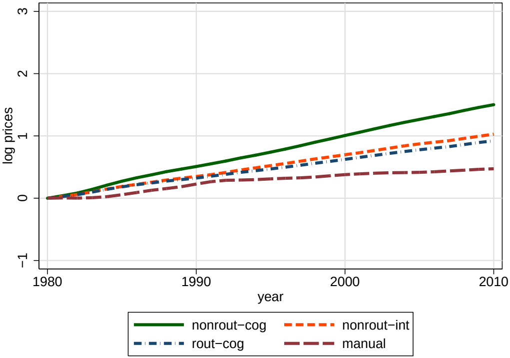
OLS - yearly - five tasks - no controls



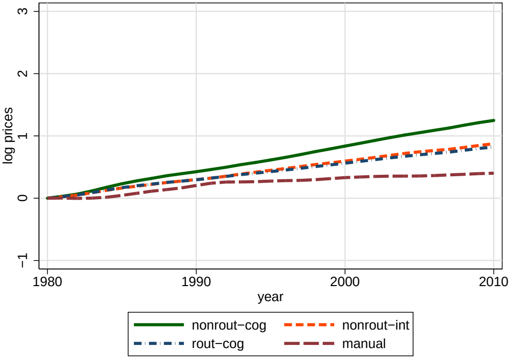
OLS - yearly - five tasks - control for past task



OLS - yearly - five tasks - control for past task $\times$ age

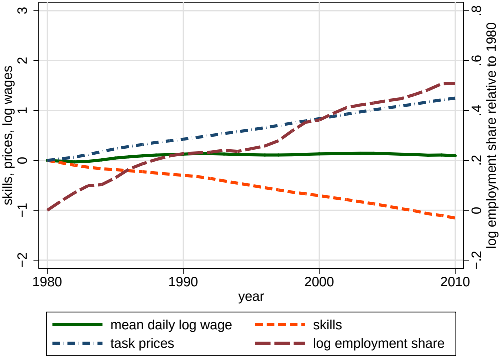


OLS - yearly - five tasks - control for past task $\times$ educ $\times$ age

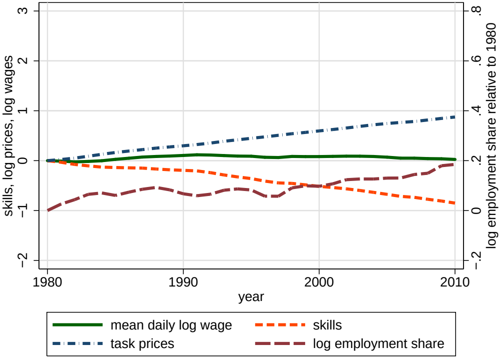


Postestimation

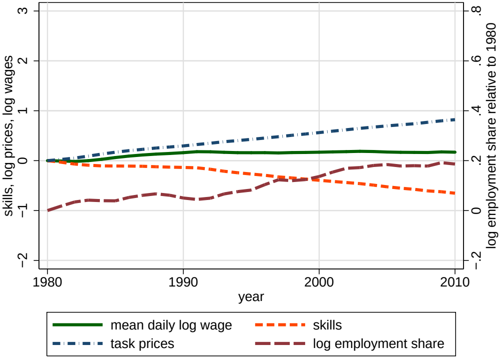
Decomposition of log wages in nonrout-cog



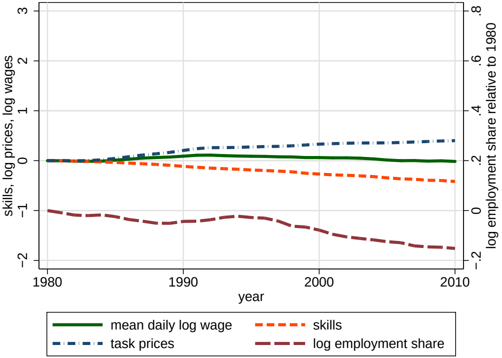
Decomposition of log wages in nonrout-int



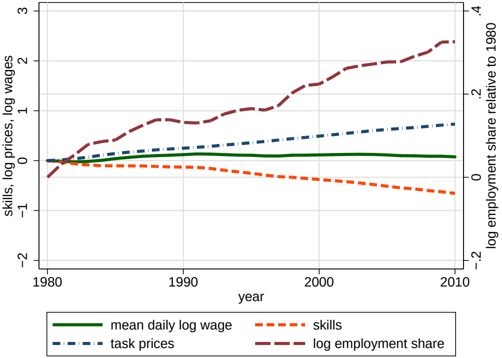
Decomposition of log wages in rout-cog



Decomposition of log wages in manual

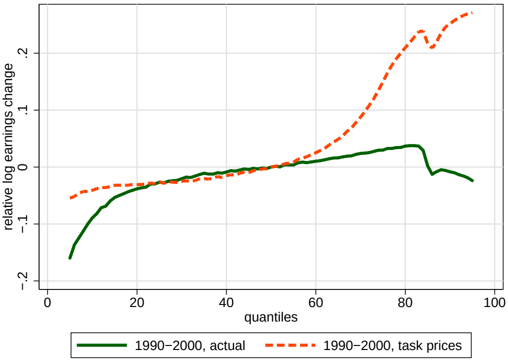


Decomposition of log wages in nonroutine

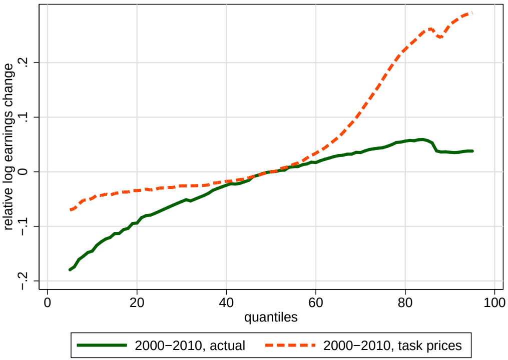


Professions: Changes in daily log wages relative to the median, 1980-1990

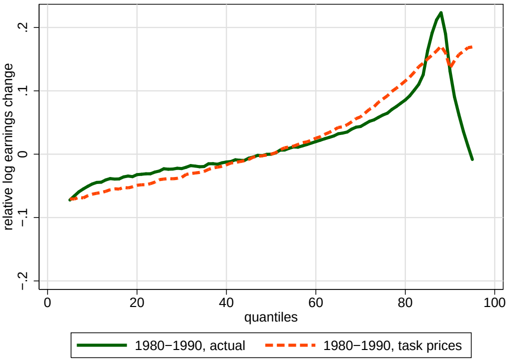
Professions: Changes in daily log wages relative to the median, 1990-2000



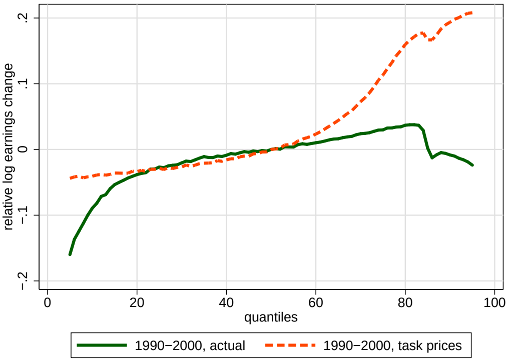
Professions: Changes in daily log wages relative to the median, 2000-2010



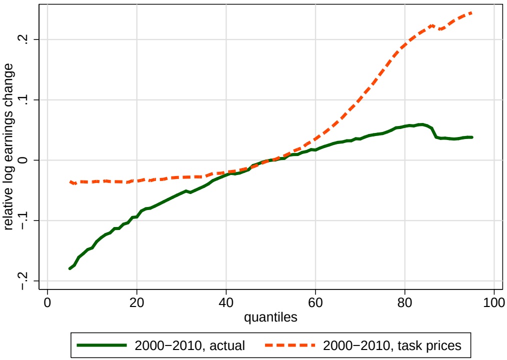
Five tasks: Changes in daily log wages relative to the median, 1980-1990



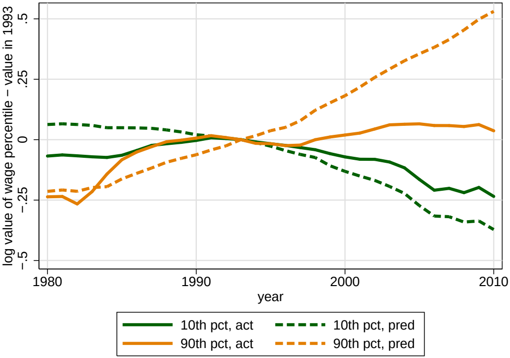
Five tasks: Changes in daily log wages relative to the median, 1990-2000



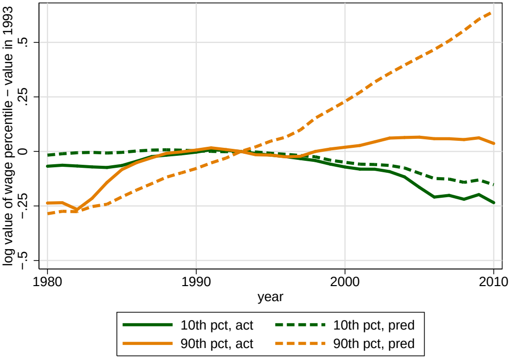
Five tasks: Changes in daily log wages relative to the median, 2000-2010



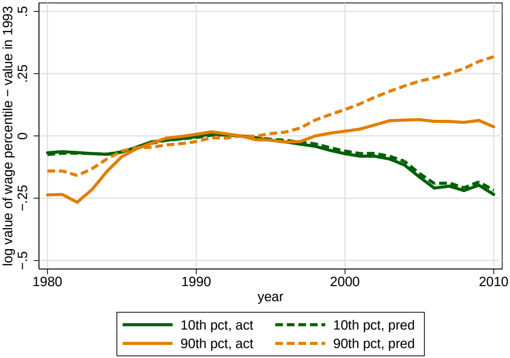
Professions: Evolution of predicted wage percentiles



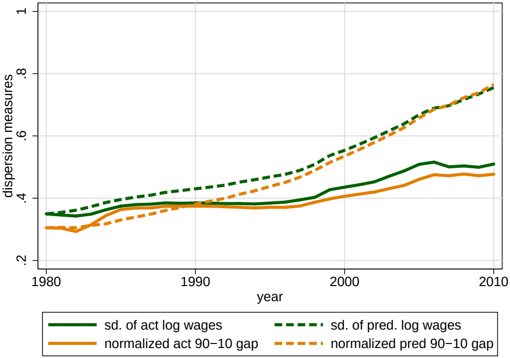
Five tasks: Evolution of predicted wage percentiles



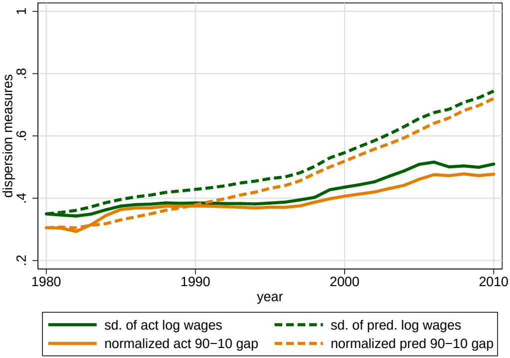
Two tasks: Evolution of predicted wage percentiles



Professions: Evolution of predicted wage dispersion measures



Five tasks: Evolution of predicted wage dispersion measures



Two tasks: Evolution of predicted wage dispersion measures