Equal pay for equal task

Discovering heterogeneous returns to tasks across genders

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Background and motivation

A narrowing gender wage gap in the US has been documented because of:

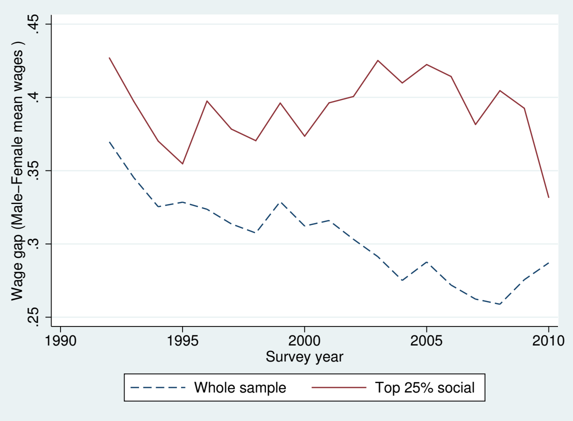
- *higher occurrence* of women in *cognitive* intensive occupations and *increase in returns* to cognitive skills (Bacolod and Bloom, 2010, JHR) , more valued with the diffusion of ICTs (Autor et. al, 2003, QJE; Black and Spitz-Oener, 2010, RESTAT)
- *substitution of men* with technological progress in motor-task intensive jobs, where they had a *higher relative ability* relative to women (Yamagutchi, 2015, JHR)
- increasing labour market *value of social activities* (Deming, 2015, JHR), for which *women* have higher *abilities/preferences* (Welch, 2001, AER, Grove at al, 2011, JHR; Kamas et al., 2015, JEBO).

Background and motivation

However, *social activities* (*coordination, persuasion*, Deming 2015) often characterise *managerial* positions, where women typically hit a *glass ceiling*

- Lower rewards due to career discontinuity and shorter work hours because of motherhood (Wood et al., 1993, JOLE; Bertand et. al, 2010, AEJ)
- wage gap up to 45% in top managerial positions, because women run smaller businesses (Bertrand and Hallock, 2001, ILRR; Munoz-Bullon, 2010, IR)

Figures from CPS



Current Population Survey. Top 25% social: occupations for which the value of the *social* measure (Deming, 2015) falls in the 4th quartile.

Contribution

- We rely on the task approach (Acemoglu and Autor, 2011, HLE; Autor and Handel, 2013, JOLE) that goes *beyond the human capital framework*:

  occupations as bundles of tasks - individuals choose the occupation giving the highest reward to the combination of their skills/preferences with the job task requirement;

- We use the Princeton Data Improvement Initiative (PDII), containing *individual* level task measures;
- We explore whether men and women perform different tasks between and within occupations;
- We explore whether *individual* tasks - with special attention to *social tasks*- differently predict wages of men and women across and within occupations.

Theoretical background

We extend Autor & Handel (2013). Let the production function of the aggregate output produced by all workers in occupation j be defined as

$$Y_j = \exp\left[\sum_{i \in I_j}\left(\alpha_j + \sum_{G=m,f}\sum_{k=1}^{K}\lambda_{jk}^{G}\phi_{jk}^{G} + \mu_i\right)\right], \text{ for } j = 1, \ldots, J$$

- I_j: set of workers in occupation j
- $\phi_i^G = \left[\phi_{i1}^G, \ldots, \phi_{iK}^G\right]$: vector of *skill endowments*: $\phi_{ik}^G > 0$, has continuous support, is the ability of worker i in performing task k, for $k = 1, \ldots, K$.
- $\lambda_{jk}^G \geq 0$: *task returns* are occupation and gender-specific
- μ_i is an error term; the output price is normalised to unity.

Wage equation and tasks as predictors of wages

Workers are paid their marginal product and the log-wage of worker i in occupation j will differ according to the gender

$$w_i^G = \alpha_j + \sum_{k=1}^{K} \lambda_{jk}^G \, \phi_{ik}^G + \mu_i. \tag{1}$$

yielding the following empirical model:

$$w_i = \alpha + \sum_{k=1}^{K} \beta_k^m T_{ik} + \sum_{k=1}^{K} \beta_k^f fem_i T_{ik} + \psi fem_i + \boldsymbol{x}_i' \gamma + \varepsilon_i \tag{2}$$

- T_{ik}: individual measures of tasks; ψ the wage gap independent of gender-specific task rewards; $\boldsymbol{x}_i$: education and demographics.

PDII

- Main data source: a module of PDII survey, conducted in 2008, which provides information on *job activities* regularly performed by workers, hourly wage and workers personal characteristics.
- Same dataset used in Autor and Handel (2013)
- Initial sample 2, 513. we keep individuals: currently working; between 18 and 64; non-military; without missing information in relevant variables. Drop occupations with only men/women. Final sample 1,185

Task measures: items in PDII

Manual	Time spent performing physical tasks *almost none . . . almost all the time*
Cognitive[1] PCA[3] 1st COMP	How often solve problems take more than 30 minutes How often solve problems using advance mathematics *never . . . every day* The longest document typically read *never . . . more than 25 pages*
Social[2] PCA[3] 1st COMP	Time spent supervising and managing others *all the time . . . none of the time* Work performed in a group or alone *group, varies, alone* Face to face contact with people (non colleagues nor super) *none . . . a lot*

[1] Bacolod and Bloom (2010); [2]Deming (2015); [1] [3]Ingram and Neumann (2006)

Comparing PDII and O*NET tasks

	PDII *(person level)*		
	Social	*Cognitive*	*Manual*
PDII *Social (person level)*	1		
PDII *Cognitive (person level)*	0.17	1	
PDII *Manual (person level)*	0.04	-0.33	1
O*NET *Manual*	-0.04	-0.24	**0.49**
O*NET *Cognitive*	0.17	**0.38**	-0.43
O*NET *Social*	**0.21**	0.3	-0.46

PDII occupation level task means and O*NET occupation level task measures

	PDII *(occ mean)*		
	Social	*Cognitive*	*Manual*
PDII *Social (occ mean)*	1		
PDII *Cognitive (occ mean)*	0.11	1	
PDII *Manual (occ mean)*	0.04	-0.49	1
O*NET *Manual*	0.03	-0.26	**0.59**
O*NET *Cognitive*	0.24	**0.47**	-0.53
O*NET *Social*	**0.28**	0.32	-0.56

Task Usage Difference between Men and Women

Task	Women	Men	Diff(W-M)	Within Occ.	Between Occ.
	3-Digit SOC - 57 occupations, 1187 obs				
Manual	0.0892	0.1804	-0.0912	-0.0946	0.0034
Cognitive	-0.1550	0.0186	-0.1736	0.0116	-0.1852
Social	0.0116	0.1627	-0.1511	-0.1428	-0.0083
	6-Digit SOC - 133 occupations, 905 obs.				
Manual	0.1069	0.1577	-0.0508	-0.0641	0.0133
Cognitive	-0.1618	-0.0758	-0.0860	0.0102	-0.0961
Social	0.0562	0.2024	-0.1462	-0.1499	0.0037

An example of SOC

11-2000	**Advertising, Marketing, Promotions, Public Relation and Sales Managers**
11-2010	Advertising and Promotions Managers
11-2011	Advertising and Promotions Managers
11-2020	Marketing and Sales Managers
11-2021	Marketing Managers
11-2022	Sales Managers
11-2030	Public Relations Managers
11-2031	Public Relations Managers

Task measures: descriptive regressions

	Manual		Cognitive		Social	
fem	0.014	0.072	-0.280***	-0.061	-0.144*	-0.074
	[0.062]	[0.062]	[0.071]	[0.074]	[0.079]	[0.075]
lesshigh	-0.053	0.005	-0.027	-0.109	0.484**	0.13
	[0.140]	[0.132]	[0.147]	[0.128]	[0.193]	[0.152]
somecoll	-0.370***	-0.054	0.477***	0.245**	0.06	0.031
	[0.100]	[0.087]	[0.116]	[0.108]	[0.126]	[0.103]
coll	-0.579***	-0.225***	0.607***	0.189**	0.314***	0.106
	[0.086]	[0.075]	[0.100]	[0.094]	[0.100]	[0.084]
postcoll	-0.955***	-0.505***	1.066***	0.461***	0.397***	0.222**
	[0.102]	[0.101]	[0.105]	[0.118]	[0.108]	[0.109]
potexp	-0.028***	-0.008	0.029**	0.002	0.015	0.021*
	[0.010]	[0.009]	[0.012]	[0.011]	[0.013]	[0.012]
potexp2	0.001*	0	-0.001***	0	-0.001*	-0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
spanish	0.259*	0.056	-0.518***	-0.278	-0.579**	-0.218
	[0.156]	[0.162]	[0.195]	[0.191]	[0.286]	[0.219]
black	0.083	0.009	-0.189*	-0.191*	0.245**	0.146
	[0.097]	[0.084]	[0.114]	[0.109]	[0.125]	[0.109]
hispanic	0.143	0.059	0.008	0.048	0.034	0.067
	[0.113]	[0.109]	[0.126]	[0.121]	[0.155]	[0.121]
asian	-0.261	-0.096	-0.194	-0.14	-0.524***	-0.25
	[0.264]	[0.225]	[0.333]	[0.267]	[0.194]	[0.215]
married	-0.291***	-0.135**	0.027	-0.114	-0.027	-0.035
	[0.077]	[0.060]	[0.086]	[0.078]	[0.093]	[0.079]
child_cohab	0.074	-0.044	0.056	0.138	0.13	0.117
	[0.083]	[0.062]	[0.105]	[0.087]	[0.114]	[0.091]
OCC. FEs:	NO	YES	NO	YES	NO	YES

1185 obs. All models include an intercept term, 3-digit industry dummies and use sampling

Wage equation and tasks

	BETWEEN OCC		WITHIN OCC		
manual	-0.248***	-0.137***	-0.164***	-0.115***	-0.114***
	[0.022]	[0.020]	[0.022]	[0.022]	[0.023]
cognitive	0.188***	0.109***	0.075***	0.062**	0.057**
	[0.021]	[0.022]	[0.025]	[0.025]	[0.022]
social	0.063***	0.042**	0.016	0.013	0.021
	[0.020]	[0.017]	[0.020]	[0.019]	[0.019]
fem		-0.266***		-0.162***	-0.130***
		[0.038]		[0.040]	[0.037]
Observations	1,185	1,185	1,186	1,185	1,185
R-squared	0.307	0.464	0.522	0.574	0.642
CONTROLS	NO	YES	NO	YES	YES
OCC FEs	NO	NO	YES	YES	YES
IND FEs	NO	NO	NO	NO	YES

Wage equation and heterogeneous tasks

	BETWEEN OCC	WITHIN OCC	
manual	-0.183***	-0.148***	-0.142***
	[0.031]	[0.031]	[0.032]
cognitive	0.060**	0.019	0.026
	[0.027]	[0.030]	[0.029]
social	0.071***	0.056**	0.074***
	[0.025]	[0.024]	[0.024]
femXman	0.087**	0.062*	0.054
	[0.041]	[0.038]	[0.036]
femXcogn	0.099***	0.094**	0.068*
	[0.037]	[0.036]	[0.035]
femXsocial	-0.065*	-0.091***	-0.107***
	[0.034]	[0.032]	[0.033]
fem	-0.264***	-0.147***	-0.117***
	[0.036]	[0.038]	[0.036]
occ. dummies	NO	YES	YES
ind. dummies	NO	NO	YES

All models include an intercept term, explanatory variables used in descriptive regressions and use sampling weights. Standard errors in squared brackets.

	WITHIN OCC		
manual	-0.132***	-0.142***	-0.141***
	[0.031]	[0.033]	[0.032]
cognitive	0.027	0.036	0.038
	[0.029]	[0.029]	[0.029]
femXman	0.036	0.049	0.054
	[0.035]	[0.037]	[0.036]
femXcogn	0.061*	0.048	0.047
	[0.036]	[0.035]	[0.034]
managerial	0.077***		
	[0.026]		
femXmanagerial	-0.082**		
	[0.034]		
face		0.020	
		[0.026]	
femXface		-0.018	
		[0.037]	
team			0.032
			[0.023]
femXteam			-0.079**
			[0.031]

All models include an intercept term, explanatory variables used in descriptive regressions, occupation and industry fixed effects and use sampling weights. Standard errors in squared brackets.

Robustness checks

- PDII: We consider task measures at the *occupation level* derived from O*NET, previously DOT, mostly used in the literature (Bacolod and Bloom, Yamaguchi, Deming)
- CPS: We build similar task measures for *manual, cognitive, and social* and apply them to the Current Population Survey CPS using available cross-walks for occupation classifications and estimate the wage equations using 2-digit occupation dummies (*3-digit variation* instead of individual level)
- We find similar results to our PDII based *within-occupation* regressions

Conclusions and further extensions

- We explored task usages across genders
- We exploited *individual-level* task measures that allow us to carry out a *within-occupation* analysis
- individual tasks heterogeneously predict wages across gender
- We observed a wage *penalty* for women in *social* tasks, mainly driven by managerial and team tasks
- Further analyses could be carried out using more representative surveys with task measures at the individual level or . . .
- using CPS + O*NET dataset, although further research is warranted in order to tackle the *identification of average task returns* in presence of endogenous self-selection.

Identification Issues

- The conceptual model of Autor and Handel (2013) embeds *endogenous self-selection* into task-intensities because of workers' *comparative advantages*
- We explore - heterogeneous - endogenous task/occupation selection.

Distribution of task returns

- The *cross-occupation covariance* between task returns *cannot be uniformly positive*
- Tasks returns must negatively covary across the set of occupations, otherwise some workers could be made strictly better off by changing occupations.
- It is a *necessary but not sufficient* condition for self-selection of workers into occupations: workers with a higher ability in performing a certain task will choose occupations that give a higher reward for that task.

$$w_i = \alpha + \sum_{k=1}^{K} \beta_k^m T_{ik} + \sum_{k=1}^{K} \beta_k^f fem_i T_{ik} + \psi fem_i + \boldsymbol{x}_i' \gamma + \varepsilon_i$$

- The sign of $\hat{\beta}_k$ could depend on the not uniformly positive *cross-occupation covariance* between task returns, even though $\lambda_{jk} \geq 0$.
- If relevant cross occupation correlations among task rewards exists, estimates of average returns can be biased.

Testing for cross-occupation covariance

- With *individual-level* task measures, we can *test* for the absence of cross-occupation covariance between tasks returns
- This is a *necessary condition* for self-selection
- If we failed to reject, we could interpret β_k as *average task returns*

For 89 occupations: $w_{ij} = \alpha_j + \beta_{j1} Manual + \beta_{j2} Cognitive + \beta_{j3} Social + \varepsilon_{ij}$

Separate bivariate regressions to recover the correlations between task returns

$$\begin{aligned}
\hat{\beta}_{jm} &= \alpha_{mc} + \delta_{mc}\hat{\beta}_{jc} + e_{mc} \\
\hat{\beta}_{jm} &= \alpha_{ms} + \delta_{ms}\hat{\beta}_{js} + e_{ms} \\
\ldots & \quad \ldots
\end{aligned}$$

Testing for cross-occupation covariance of task returns

	All			Men			Women		
	$\beta_{Cognitive}$	β_{Social}	*Intercept*	$\beta_{Cognitive}$	β_{Social}	*Intercept*	$\beta_{Cognitive}$	β_{Social}	*Intercept*
$\beta_{Cognitive}$			0.436			0.948**			-0.440
			[0.266]			[0.365]			[0.273]
β_{Social}	-.092		-0.041	0.171		-0.084	-0.151		0.654***
	[0.145]		[0.494]	[0.280]		[0.644]	[0.195]		[0.176]
β_{Manual}	-0.170	-0.192	-0.524*	-0.10	0.303	-.232	0.240	0.182	0.269
	[0.130]	[0.098]	[0.200]	[0.084]	[0.375]	[0.468]	[0.288]	[0.131]	[0.252]

We fail to reject, *with this data*, the null hypothesis of absence of cross-occupation covariance of task returns → we could interpret OLS estimates as average task returns.