

Gender wage gap 2008-2020

September 2021

Conclusions

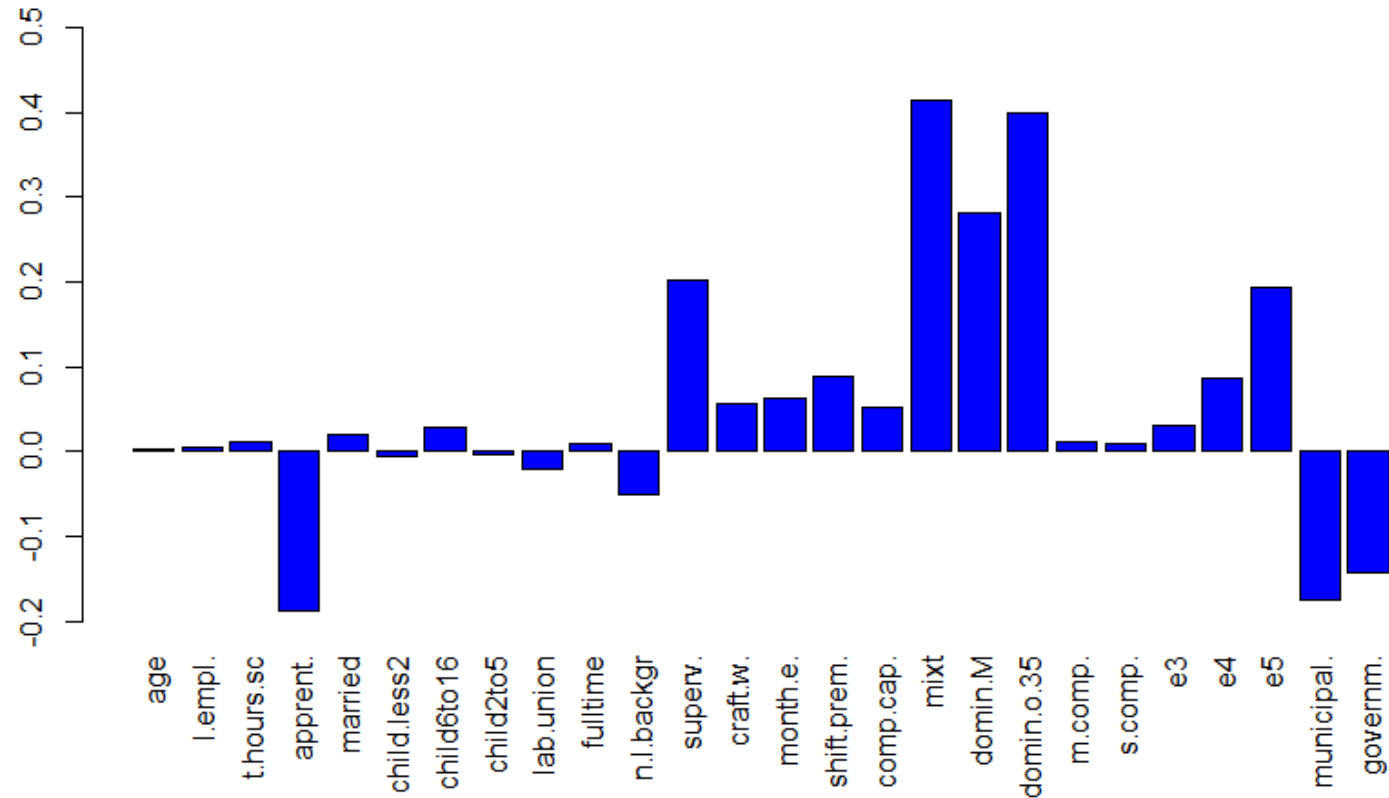
- Gain: modelling and understanding wages and wage differences
- Findings:
 - Decreasing gap(s), through time
 - Some characteristics have *same* influence on wages of men and women:
 - Icelandic background
 - Balanced mixture of men/women in an occupation
 - Proportion of employees older than 35
 - Some characteristics have better effect on *women's* wages (e.g. education)
 - Some characteristics have better effect on *men's* wages (the gap still grows with age and employment length)

Results

- New models:
 - type (MLM-fixed time, MLM-time dependent)
 - set of characteristics
- Comparisons
 - additive <-> *adjusted gap*
 - interactive <-> *explaining* the gap based on differences in:
the effects of/and model characteristics
 - restricted, optimum, maximal (sets of characteristics)

What matters for regular, hourly *wages*

after accounting for correlations within companies or due to common occupation and economic activity
(see: units and reference values of covariates)



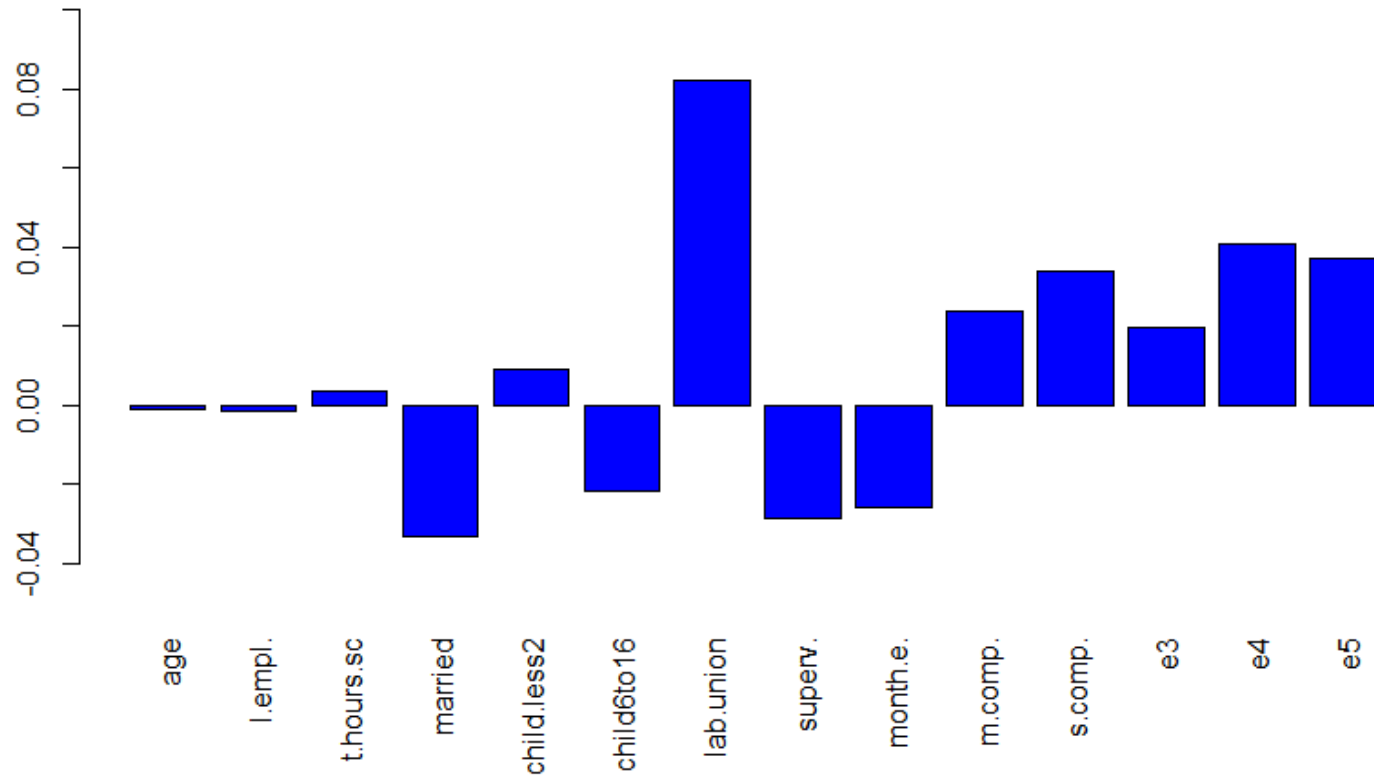
What “matters for wages” *depends on* gender

...see Table 3. Here is part of it, for illustration:

	2016		2017		2018		2019		2020	
Predictors	Estimates	SE	Estimates	SE	Estimates	SE	Estimates	SE	Estimates	SE
educ1e3	0.014	0.003	0.014	0.003	0.019	0.002	0.020	0.002	0.019	0.002
educ1e4	0.067	0.003	0.065	0.003	0.063	0.003	0.061	0.003	0.061	0.003
educ1e5	0.179	0.004	0.170	0.004	0.165	0.004	0.161	0.004	0.154	0.004
econSectM	-0.176	0.033	-0.218	0.031	-0.221	0.030	-0.212	0.028	-0.186	0.028
econSectR	-0.137	0.021	-0.177	0.020	-0.163	0.020	-0.172	0.020	-0.181	0.020
gender1:l(age – mean(age))	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
gender1:l((age – mean(age))^2)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
gender1:l(lenEmployComp – mean(lenEmployComp))	-0.002	0.000	-0.002	0.000	-0.002	0.000	-0.002	0.000	-0.001	0.000
gender1:l((lenEmployComp – mean(lenEmployComp))^2)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
gender1:l(totalHoursScaled – mean(totalHoursScaled))	0.002	0.001	0.002	0.001	0.003	0.001	0.004	0.001	0.003	0.001
gender1:regapprentice1	0.130	0.049	0.138	0.032	0.103	0.026	0.109	0.026	0.088	0.028
gender1:marital1	-0.037	0.003	-0.037	0.003	-0.034	0.003	-0.033	0.003	-0.029	0.003
gender1:childage0to2_1	0.018	0.005	0.016	0.005	0.015	0.005	0.010	0.005	0.013	0.005
gender1:childage6to16_1	-0.019	0.004	-0.025	0.004	-0.025	0.003	-0.022	0.003	-0.024	0.003
gender1:inlabunion1	0.106	0.008	0.096	0.008	0.081	0.008	0.083	0.008	0.100	0.008
gender1:supervisor1	-0.031	0.006	-0.039	0.006	-0.019	0.006	-0.025	0.006	-0.033	0.006
gender1:monthlyEarn1	-0.048	0.004	-0.045	0.004	-0.034	0.004	-0.038	0.004	-0.038	0.004
gender1:equalpaycert1							0.001	0.003	-0.001	0.004
gender1:sizeCompanycatgmedium	0.024	0.005	0.024	0.004	0.018	0.004	0.022	0.004	0.018	0.004
gender1:sizeCompanycatgsmall	0.025	0.011	0.038	0.011	0.034	0.010	0.033	0.009	0.033	0.010
gender1:educ1e3	0.022	0.004	0.020	0.003	0.016	0.003	0.016	0.003	0.016	0.003
gender1:educ1e4	0.033	0.004	0.029	0.004	0.032	0.004	0.033	0.004	0.029	0.004
gender1:educ1e5	0.017	0.005	0.017	0.005	0.020	0.005	0.026	0.004	0.026	0.004
gender1:econSectM	0.045	0.004	0.046	0.004	0.039	0.004	0.038	0.004	0.036	0.003
gender1:econSectR	0.040	0.004	0.039	0.004	0.031	0.004	0.035	0.004	0.034	0.004

„What matters for wages“ *depends on* gender:

after accounting for correlations within companies or due to common occupation and economic activity
(Is the effect of covariates the same for men and women? *Sometimes, yes!*)



Thank you!

The computing R-code, at:

<https://github.com/violetacln/GIW>

More beautiful pictures and details at:

<http://hagstofan.s3.amazonaws.com/media/public/2021/2b7b1b12-47b5-4dfd-b1af-97437a20c243.pdf>