# Discrimination

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# The plan

- Definition
- Basic models of discrimination
  - Taste-based
  - Statistical
- Useful workhorse models for broader range of questions (equalizing differences, worker/manager self-selection, racial profiling)
- Empirics
  - Field experiments on discrimination
  - Regressions (wage gaps)

# Discrimination: Definition

- Different sellers receive different prices or different customers pay different prices for the *same* good
- The "*same*" is the hard part
- In the labor market context:

$$\log w_i = \alpha + \beta X_i + \gamma M_i + \epsilon_i$$

$M_i$ ... dummy for a group (racial, gender, ethnic etc.)

- Discrimination: $\gamma < 0$
- Issues
  - Being able to control for all $X_i$'s (omitted variable bias)
  - $M_i$ directly affects productivity (consumer discrimination)
  - Minorities *choose* low $X_i$ in expectation of discrimination

# Taste-based discrimination

- Becker (1957): Some employers and employees have a taste for discrimination
- Employers: extra cost of employing minority workers (beyond paying the wage)
- Employees: costly to work with minority workers

# Employee taste-based discrimination

- Employers don't disciminate - simply hire workers with the lowest wage
- Worker types $A$ and $B$ ($B$ is minority)
- Wages:
  - $w_{AA}$, $w_{BB}$ wage to $A$ if she works with $A$ and vice versa
  - $w_{AB}$, $w_{BA}$ wage to $A$ if she works with $B$ and vice versa
- $B$'s don't care who they work with
- $A$'s dislike working with $B$'s - "as if" receiving a lower wage

$$w_{AB}^{*} = w_{AB}(1 - \delta)$$

- $\delta$ ... discrimination coefficient

# Employee discrimination

- $A$'s supply into the mixed jobs: they require $w_{AB} \geqslant w_{AA}/(1-\delta)$
- Demand for labor by employers:
    - Hire only $A$'s ... pay $w_{AA}$
    - Hire only $B$'s ... pay $w_{BB}$
    - Mix: pay $w_{BA} = w_{BB}$ to the $B$'s
    - But would have to pay $w_{AB} = w_{AA}/(1-\delta)$ to induce them to accept mixed jobs
- But employers have no reason to pay higher $w_{AB}$ wage if they can hire only $A$'s or only $B$'s for less

# Employee discrimination and segregation

- Equilibrium outcome:
  - perfect segregation
  - $w_{AA} = w_{BB}$ (demand condition on the firms's side)
- $A$'s make themselves less desirable
- What if some $A$'s have $\delta = 0$ and some $\delta > 0$?

# Employer taste-based discrimination

- Workers have no preferences as whom to work with
- Employers dislike employing $B$'s
- "Full" wage cost to employers (incl. discrimination taste):
  - Hire $A$'s ... $w_A$
  - Hire $B$'s ... $w_B^* = w_B(1+\delta)$
- Still willing to hire $B$'s if the wage discount is sufficiently attractive
- Reservation wage policy

$$\text{if } \frac{w_B}{w_A} > \frac{1}{1+\delta} = R \Rightarrow \text{hire only } A's$$

$$\text{if } \frac{w_B}{w_A} < \frac{1}{1+\delta} = R \Rightarrow \text{hire only } B's$$

# Employer discrimination: Market demand for labor

- Competitive labor market, all firms are of the same size
- The discrimination coefficient is distributed among firms:

$$f(\delta) \longleftrightarrow g(R)$$

- INSERT GRAPH - PDF AND CDF
- Firms with high $R$ (low $\delta$) hire $B$'s
- The demand for $B$'s labor as a function of $w_B/w_A$ determined by the distribution of $R$ in the population of employers
- INSERT GRAPH - DEMAND

# Employer discrimination: Equilibrium

- Supply of $B$ workers is inelastic
- Equilibrium $(w_B/w_A)^* = R^*$
- INSERT GRAPH - SUPPLY AND EQUILIBRIUM
- Equilibrium wage gap: given by the discrimination preference of the *marginal* employer
- $\uparrow$ relative supply of $B$ workers => $\uparrow$ observed discrimination ($\downarrow w_A/w_B$) even though the tastes do not change
- Perfect segregation

# Employer discrimination: Some special cases

- $\exists$ only one value of $\delta > 0$ in the population
- INSERT GRAPH FIXED $\delta$
- The distribution of $\delta$ has a spike at $\delta = 0$
- INSERT GRAPH SPIKE AT 0
  - Whether there is discrimination (and how much) depends on the share of non-discriminating employers

# Consumer (taste-based) discrimination

- (Some) consumers prefer to be served by $A$'s - willing to pay higher price
- Segregation - $B$'s serve non-discriminating consumers
- $A$'s obtain a wage premium
- Discrimination Virtually impossible to compete away

# Taste-based discrimination: implications and assessment

- Employee discrimination: perfect segregation, no discrimination
- Consumer markets (e.g., housing): segregation, multiple equilibria, critical levels of one type trigger the other type to segregate out
- Employer discrimination: actual wage gap
  - Still, near-complete segregation
  - $A$'s and $B$'s mix only in non-discriminating firms and in marginal firms
- Discrimination is costly for the discriminating employers
- There has to be not very elastic supply of non-discriminating employers for discrimination to persist
- Less discrimination in more competitive markets

# Limitations of the Becker model

- Predicts "too little" discrimination
- Apparently the discrimination exists (and existed) in the presence of mixed occupations
- Labor market frictions
- Or not taste-based discrimination

# Statistical discrimination

- Firms have no taste to discriminate as such
- Imperfect information problem: firms have only limited information about the workers' true productivity
- Use all available information to infer their best estimate of the true productivity
  - A signal about the individual productivity
  - Group (race, gender, ethnic)
  - The average true productivity differs between groups (this is known, correctly)

# Statistical discrimination - basic model

$$\theta_{ig} \quad \dots \quad \text{true productivity}$$

$$\widetilde{\theta_{ig}} = \theta_{ig} + u_i \quad \dots \quad \text{signal about the true productivity}$$

$$u_i \sim N(0, \sigma_u^2) \quad \dots \quad \text{pure white noise}$$

The average true productivity differs between groups

$$\overline{\theta_B} \quad < \quad \overline{\theta_A}$$

$$\theta_{iB} \sim N(\overline{\theta_B}, \sigma_\theta^2) \quad , \quad \theta_{iA} \sim N(\overline{\theta_A}, \sigma_\theta^2)$$

# Statistical discrimination - basic model

The signal observed by the firms is composed of

$$\begin{aligned} \widetilde{\theta_{ig}} &= \bar{\theta}_g + e_{ig} + u_i \\ e_i & \; \ldots \; \text{deviation of true productivity from group mean} \\ \text{high } \widetilde{\theta_{ig}} &\Rightarrow \text{can't tell if unusally good relative to } \bar{\theta}_g \text{ or just high noise} \end{aligned}$$

Firms are trying to obtain the best estimate of the true productivity

$$E[\theta_{ig}|g, \widetilde{\theta_{ig}}]$$

How?

## Statistical discrimination - estimate of true productivity

Think of a regression

$$\theta_{ig} = a + b\widetilde{\theta_{ig}} + \epsilon_i$$

The estimate of the true productivity is

$$\widehat{\theta_{ig}} = \hat{a} + \hat{b}\widetilde{\theta_{ig}}$$

The employers hence infer

$$\begin{aligned} E[\theta_{ig}|g, \widetilde{\theta_{ig}}] &= (1-\gamma)\bar{\theta}_g + \gamma\widetilde{\theta_{ig}} \\ \gamma &= \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_u^2} \end{aligned}$$

INSERT DERIVATION AND GRAPHS

# Statistical discrimination - implications

$$
\begin{aligned}
E[\theta_{ig}|g,\widetilde{\theta_{ig}}] &= (1-\gamma)\bar{\theta_g} + \gamma\widetilde{\theta_{ig}} \\
\gamma &= \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_u^2}
\end{aligned}
$$

- The inferred productivity is a weighted average of the group mean and the signal
- Dependance on the signal variance
- No "discrimination", given observables
- Within group, average inferred productivity = actual average

# Statistical discrimination - implications

- Statistical discrimination is efficient, given
    - Limited information
    - Group means regarded as exogenous
    - Employers' correctly estimating the group means
- But
    - Prejudice (belief-driven statistical discrimination)
    - *Self-fulfilling expectations*
- Should wane over time

# Field experiments - audit/situation tests

- Carefully controlled field experiments using matched pairs of actors
  - Started in 1970s by British sociologists
  - Testing for discrimination on the labor, housing and product markets

1. Create matched pairs of actors that differ only in the tested characteristic (race, sex, disability)
2. Train these pairs to learn the same CV, respond in the same way to questions, match their behavior at interviews
3. Send them to the job interview
4. Measure average response of employers to minority/majority actors

# Field experiments - audit/situation tests

- Summary of results (Riach and Rich 2002):
  - Discrimination against non-whites, women, disabled and older people
  - Employment discrimination basedon race of over 25% found in Europe, North America, and Australia
  - Discrimination against women in male-dominated and high-paying occupations, discrimination against men in female-dominated and low-paying occupations

# Field experiments - audit/situation tests

- What problems do you see with these studies?

# Field experiments - audit/situation tests

- What problems do you see with these studies?
  - Objective selection of actors for matched pairs?
  - Minority actors might (un)consciously try to prove discrimination (Heckman, 1998)
  - Provide evidence mostly for entry-level jobs in low-skilled occupations (difficult to train for higher skill level)

# Field experiments - CV's

- Bertrand and Mullainathan (AER 2004)
    - Ficticious CV's with distinctively black and white names
    - Real job ads, subjects unaware of an experiment
    - Outcome measure: callback

# Bertrand and Mullainathan (2004 AER): Main result

TABLE 1—MEAN CALLBACK RATES BY RACIAL SOUNDINGNESS OF NAMES

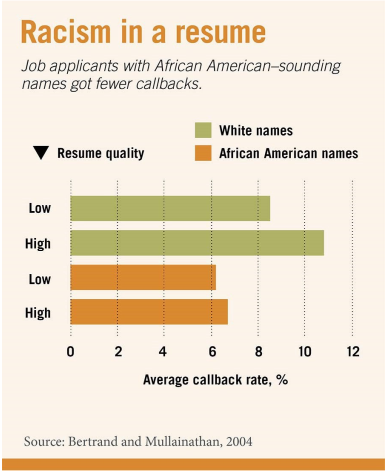
| | Percent callback for White names | Percent callback for African-American names | Ratio | Percent difference ($p$-value) |
|---|---|---|---|---|
| Sample: | | | | |
| All sent resumes | 9.65 | 6.45 | 1.50 | 3.20 |
| | [2,435] | [2,435] | | (0.0000) |
| Chicago | 8.06 | 5.40 | 1.49 | 2.66 |
| | [1,352] | [1,352] | | (0.0057) |
| Boston | 11.63 | 7.76 | 1.50 | 4.05 |
| | [1,083] | [1,083] | | (0.0023) |
| Females | 9.89 | 6.63 | 1.49 | 3.26 |
| | [1,860] | [1,886] | | (0.0003) |
| Females in administrative jobs | 10.46 | 6.55 | 1.60 | 3.91 |
| | [1,358] | [1,359] | | (0.0003) |
| Females in sales jobs | 8.37 | 6.83 | 1.22 | 1.54 |
| | [502] | [527] | | (0.3523) |
| Males | 8.87 | 5.83 | 1.52 | 3.04 |
| | [575] | [549] | | (0.0513) |

# Bertrand and Mullainathan (2004 AER): The slope

TABLE 5—EFFECT OF RESUME CHARACTERISTICS ON LIKELIHOOD OF CALLBACK

| Dependent Variable: Callback Dummy<br>Sample: | All resumes | White names | African-American names |
|---|---|---|---|
| Years of experience (*10) | 0.07 | 0.13 | 0.02 |
| | (0.03) | (0.04) | (0.03) |
| Years of experience$^2$ (*100) | −0.02 | −0.04 | −0.00 |
| | (0.01) | (0.01) | (0.01) |
| Volunteering? (Y = 1) | −0.01 | −0.01 | 0.01 |
| | (0.01) | (0.01) | (0.01) |
| Military experience? (Y = 1) | −0.00 | 0.02 | −0.01 |
| | (0.01) | (0.03) | (0.02) |
| E-mail? (Y = 1) | 0.02 | 0.03 | −0.00 |
| | (0.01) | (0.01) | (0.01) |
| Employment holes? (Y = 1) | 0.02 | 0.03 | 0.01 |
| | (0.01) | (0.02) | (0.01) |
| Work in school? (Y = 1) | 0.01 | 0.02 | −0.00 |
| | (0.01) | (0.01) | (0.01) |
| Honors? (Y = 1) | 0.05 | 0.06 | 0.03 |
| | (0.02) | (0.03) | (0.02) |
| Computer skills? (Y = 1) | −0.02 | −0.04 | −0.00 |
| | (0.01) | (0.02) | (0.01) |
| Special skills? (Y = 1) | 0.05 | 0.06 | 0.04 |
| | (0.01) | (0.02) | (0.01) |
| *Ho:* Resume characteristics effects are all zero (*p*-value) | 54.50<br>(0.0000) | 57.59<br>(0.0000) | 23.85<br>(0.0080) |
| Standard deviation of predicted callback | 0.047 | 0.062 | 0.037 |
| Sample size | 4,870 | 2,435 | 2,435 |

# Bertrand and Mullainathan (2004 AER): Summary of results



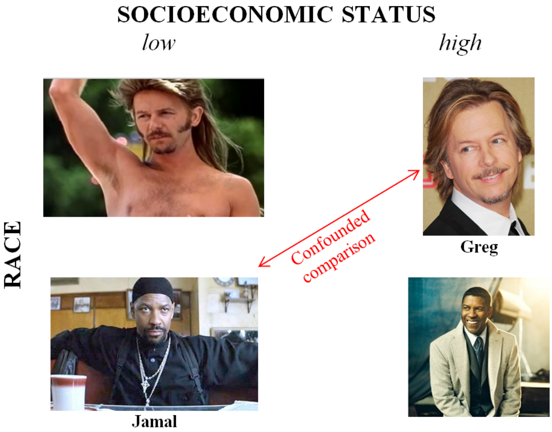
# Bertrand and Mullainathan (2004 AER)

- Main findings
  - Blacks have lower callback rate
  - Blacks benefit less from a better CV
- Methodological pros and cons
  - Undisputed evidence on differential treatment, holding *all* observables constant
  - Hence rejecting statistical discrimination?
  - Still, possibility of unequal variances in inferred productivity plus cutoff-policy by the firms
  - Cannot see "till the end" (i.e., job interview, wages)
  - Can names signal also something else? (see next slide)

# Bertrand and Mullainathan (2004 AER): Criticism

- Distinctively black names (Jamal and Lakisha) signal low socioeconomic status
  - Fryer Jr, R. G., & Levitt, S. D. (2004). The causes and consequences of distinctively black names. The Quarterly Journal of Economics, 119(3), 767-805.
- Typical White names (Greg and Emily) do not

# Bertrand and Mullainathan (2004 AER): Criticism



# Field experiments - CV's - some local examples

- Marek (VSE BA thesis 2012) Roma and Czech names, additional facts supporting statistical discrimination
- Onuferova (VSE BA thesis 2016) Ex-prisoners on the labor market
- Bartos, Bauer, Chytilova, Matejka (AER forthcoming) - Roma and Asian names on the Czech housing and labor markets
  - Deeper insights into the mechanism of statistical discrimination
  - Rational inattention
  - Less look-up of information about the minority applicant in selective (cherry picking) labor market
  - More attention would help (good) minority applicants
  - More look-up in non-selective (lemmons dropping) housing market

# Tyran and Hedegaard - Price of Prejudice

- Challenge in discrimination research: separating taste-based and statistical discrimination
- How much are people willing to pay for discrimination?
- Do they discriminate less if it is more costly for them?
- The idea of this experiment:
  - Payoff depends on collaborating with another person of same or different ethnicity
  - In T, subjects know the ethnicity *and productivity* of the person they are choosing (only taste-based)
  - In C, subjects know only the ethnicity (both taste-based and statistical)
  - Observing how much a subject loses by chosing a collaborator with lower productivity but same ethicity

# Tyran and Hedegaard - Experimental Design 1

1. 162 secondary school students from Copenhagen with Danish-sounding and Muslim-sounding names
2. Perform actual tasks (preparing letters for a large fundraising campaign)
3. Subjects unaware of being part of an experiment
4. Show up for work twice in two consecutive weeks
5. Week one: work alone, paid piece rates, researchers observe productivity
6. Week two: work in pairs, paid piece rates for joint output

# Tyran and Hedegaard - Experimental Design 2

- Assigning workers to pairs for the 2nd week:
    1. Pick a random worker and call him
    2. Pick two potential co-workers (one Danish- and one Muslim-sounding name)
    3. Pick until the own-ethnicity co-worker is less productive than other-ethnicity co-worker
    4. Give him choice over whether to work with “Frederik” or “Ahmed” (framed into timing choice)
    5. Treatment: inform about the first names and their productivity from last week
    6. Control: inform only about the names
    7. Week two: work in pairs, paid piece rates for joint output

# Tyran and Hedegaard - Price of Prejudice

- Explicit price of discrimination = difference between one's earnings if working with other-ethnicity worker and own-ethnicity worker (based on the first-week productivity)
- In T, all decision-makers face a positive price (by design)
- 38 % chose own ethicity, at a cost of €5 on average (8% of earnings)
- Willingness to discriminate declines with the price (€1 => 3.5 percentage points less)

# Discrimination choice regression

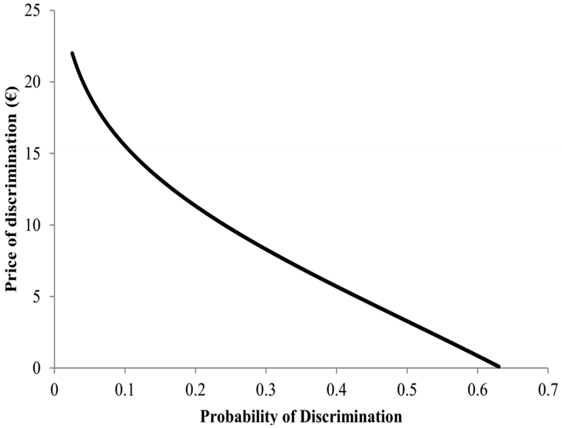
***Table 3:*** The demand for discrimination

| Dependent variable: Discr | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Price | -0.036** | -0.035** | -0.034** | -0.038* |
| | (0.016) | (0.017) | (0.016) | (0.020) |
| Danish-sounding | | 0.020 | | -0.045 |
| | | (0.160) | | (0.286) |
| Male | | -0.056 | | -0.022 |
| | | (0.152) | | (0.284) |
| Danish-sounding · Price | | | 0.005 | 0.011 |
| | | | (0.022) | (0.040) |
| Male · Price | | | -0.007 | -0.004 |
| | | | (0.018) | (0.036) |
| $R^2$ | 0.082 | 0.085 | 0.086 | 0.087 |
| *N* | 37 | 37 | 37 | 37 |

*Notes*: The table shows average marginal effects estimated from Probit regressions. Numbers in parentheses are robust standard errors. *Discr* = 1 for a decision maker choosing *same* and 0 otherwise. *Male* and *Danish-sounding* are dummies characterizing the decision maker. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Demand for discrimination

***Figure 2:*** The demand for discrimination



# Backing down the discrimination coefficient

- Nice link to the original Becker model
- Discrimination coefficient $\delta$ distributed in the population by $F_\delta(\delta)$
- Given price $P_i$, worker $i$ chose discrimination => hence his own $\delta_i \geqslant P_i$

$$
\begin{aligned}
Prob(Disc = 1|P_i) &= Prob(\delta_i \geqslant P_i) \\
&= F_\delta(P_i)
\end{aligned}
$$

- Estimate the distribution function
- $\bar{\delta} = €3.2$, $\sigma_\delta = 9.6$

# Conclusions (so far)

- Taste-based and statistical theory of discrimination
- Equilibrium wage gap is determined by the relative supply of non-discriminating firms
- Field experiments can isolate finer aspects of discrimination
- Statistical discrimination appears empirically important

# Wage gap regressions

- Imagine you have individual-level data on hourly wage, gender, educational attainment, years of experience, and occupation.
- You want to test for presence of gender discrimination in wages.
- How would you proceed?

# Wage regressions

- Long tradition of wage regressions:

$$\log w_i = \alpha + X_i'\beta + \gamma M_i + \epsilon_i$$

- Coefficient $\gamma$ captures the wage difference between men and women that is not explained by characteristics $X$
- Is the positive coefficient on male ($M_i$) an evidence of discrimination of women? Why not?

# Wage regressions

- Long tradition of wage regressions:

$$\log w_i = \alpha + X_i'\beta + \gamma M_i + \epsilon_i$$

- Coefficient $\gamma$ captures the wage difference between men and women that is not explained by characteristics $X$
- Is the positive coefficient on male ($M_i$) an evidence of discrimination of women? Why not?
  - Omitted variables (e.g. industry, field of education, type of job)
  - Unobserved differences (e.g. productivity)
  - Selection - do not observe wages for non-working!

# Decomposition of wage gap

- Blinder (1973) and Oaxaca (1973): decompose the average wage gap into the explained part (caused by observable productive characteristics) and unexplained part
- From the wage regression run on men and women, we can write the average wage as: $\overline{\log w_g} = \overline{X_g}'\hat{\beta}_g$, where $g = f, m$
- If we think the proper counterfactual average wage is that women would have earned at male returns $\overline{X_f}'\hat{\beta}_m$, we can decompose the average wage gap:

$$\overline{\log w_m} - \overline{\log w_f} = \overline{X_m}'\hat{\beta}_m - \overline{X_f}'\hat{\beta}_f - \overline{X_f}'\hat{\beta}_m + \overline{X_f}'\hat{\beta}_m =$$

$$(\overline{X_m} - \overline{X_f})'\hat{\beta}_m + \overline{X_f}'(\hat{\beta}_m - \hat{\beta}_f) \quad (1)$$

# Decomposition of wage gap

- Similarly, we can think the proper counterfactual average wage is that men would have earned at female returns $\overline{X_m}'\hat{\beta}_f$, leading to similar decomposition:

$$\overline{\log w_m} - \overline{\log w_f} = (\overline{X_m} - \overline{X_f})'\hat{\beta}_f + \overline{X_m}'(\hat{\beta}_m - \hat{\beta}_f)$$

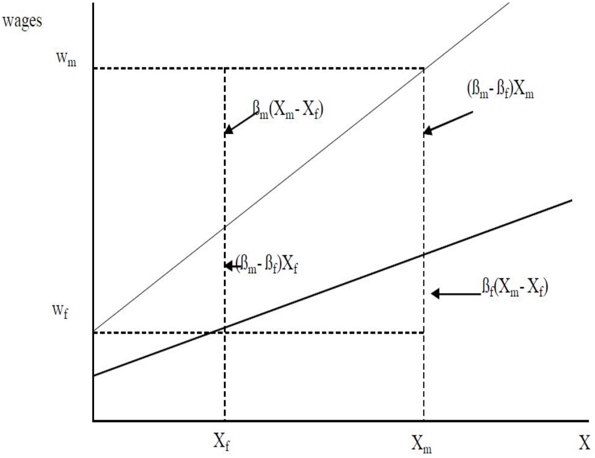
- Alternatively, we can evaluate the gender wage gap at the pooled returns (from a pooled regression of men and women: $\overline{\log w} = \bar{X}'\tilde{\beta}$), which leads to the following decomposition:

$$\overline{\log w_m} - \overline{\log w_f} = (\overline{X_m} - \overline{X_f})'\tilde{\beta} + [\overline{X_f}'(\tilde{\beta} - \hat{\beta}_f) + \overline{X_m}'(\hat{\beta}_m - \tilde{\beta})]$$

# Decomposition of wage gap

- What is the interpretation of these decompositions?
- Using $\beta_f$ or $\beta_m$ instead of $\tilde{\beta}$ corresponds to estimating ATU and ATT (instead of ATE)

# Decomposition of wage gap

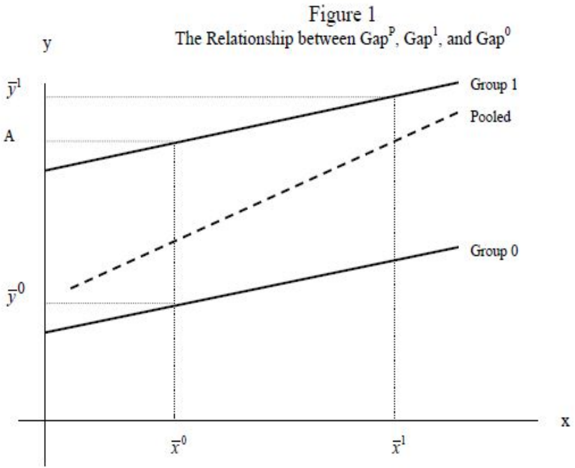



Oaxaca-Blinder decomposition

# Decomposition of wage gap - comparison of approaches

- Elder, T. E., Goddeeris, J. H., & Haider, S. J. (2010). Unexplained gaps and Oaxaca–Blinder decompositions. *Labour Economics*, 17(1), 284-290.
- Comparison of four approaches for wage gap decompositions:
  1. Gap 1 (using majority coeff):
     $\overline{\log w_m} - \overline{\log w_f} = (\overline{X_m} - \overline{X_f})'\hat{\beta}_m + \overline{X_f}'(\hat{\beta}_m - \hat{\beta}_f)$
  2. Gap 0 (using minority coeff):
     $\overline{\log w_m} - \overline{\log w_f} = (\overline{X_m} - \overline{X_f})'\hat{\beta}_f + \overline{X_m}'(\hat{\beta}_m - \hat{\beta}_f)$
  3. Gap p (using pooled coeff):
     $\overline{\log w_m} - \overline{\log w_f} = (\overline{X_m} - \overline{X_f})'\tilde{\beta} + [\overline{X_f}'(\tilde{\beta} - \hat{\beta}_f) + \overline{X_m}'(\hat{\beta}_m - \tilde{\beta})]$
  4. Gap OLS: $\log w_i = \alpha + X_i'\beta + \gamma M_i + \epsilon_i$

# Decomposition of wage gap - comparison of approaches




Source: Elder et al. (2010)

# Decomposition of wage gap - comparison of approaches

- Elder et al. (2010) use three examples of decompositons: male-female and white-black wage gap, white-black test score gap in kindergarten
- Data: Current Population Survey (1985, 2001) and Early Childhood Longitudinal Study (1998) data
- $X$ includes age, education, and occupation; parental characteristics for the test score gap

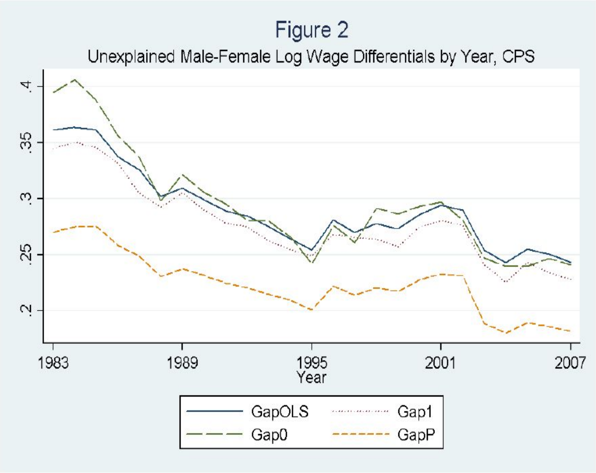
# Decomposition of wage gap - comparison of approaches

**Table 1: Empirical results**

| | White-black log wage gap | | Male-female log wage gap | | White-black test score gap | |
|---|---|---|---|---|---|---|
| | 1985 | 2001 | 1985 | 2001 | Math | Reading |
| N | 28,163 | 40,949 | 48,499 | 76,747 | 13,040 | 12,374 |
| Total gap | 0.254 | 0.216 | 0.372 | 0.285 | 14.660 | 11.352 |
| Share in group 1 | 0.927 | 0.902 | 0.598 | 0.570 | 0.871 | 0.865 |
| $Gap^1$ | 0.130 | 0.105 | 0.346 | 0.280 | 0.380 | -0.272 |
| $Gap^0$ | 0.126 | 0.129 | 0.388 | 0.297 | 4.103 | 2.800 |
| $Gap^P$ | 0.127 | 0.105 | 0.276 | 0.233 | 0.680 | 0.109 |
| $Gap^{OLS}$ | 0.131 | 0.108 | 0.361 | 0.294 | 0.782 | 0.124 |
| Auxiliary $R^2$ | 0.034 | 0.028 | 0.238 | 0.208 | 0.131 | 0.122 |

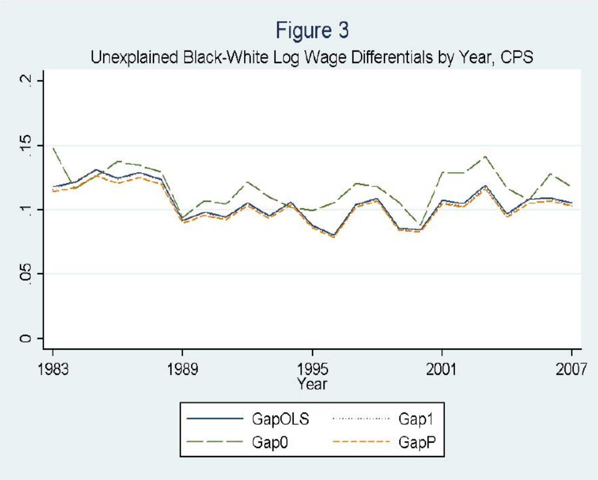
Source: Elder et al. (2010)

# Decomposition of wage gap - comparison of approaches




Source: Elder et al. (2010)

# Decomposition of wage gap - comparison of approaches




Source: Elder et al. (2010)

# Decomposition of wage gap - comparison of approaches

- Elder et al. findings:
  - Gap p overstates the contribution of $X$ to the mean outcome, understating the unexplained differences (group indicators are not used in estimation of $\tilde{\beta}$)
  - Gap OLS is close to Gap 0 and Gap 1, but larger than Gap p (caused by differences in mean $X$ across groups)
  - Pooling approach (Gap p) is problematic if you want to assess the extent of unexplained gap

# Empirical issues in wage gap regressions

1. How well can you control for the $X$'s
2. Occupational segregation (vertical and horizontal)
3. Selection - by the researcher
4. Selection - employment in the economy

- Usually purely descriptive (though informative)

# 1. Controlling for $X$'s

TABLE 1

LOG WAGE REGRESSIONS BY SEX

| | MEN ($N$ = 1,593) | | | WOMEN ($N$ = 1,446) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Black | −.244 | −.196 | −.072 | −.185 | −.155 | .035 |
| | (.026) | (.025) | (.027) | (.029) | (.027) | (.031) |
| Hispanic | −.113 | −.045 | .005 | −.028 | .057 | .145 |
| | (.030) | (.029) | (.030) | (.033) | (.031) | (.032) |
| Age | .048 | .046 | .040 | .010 | .009 | .023 |
| | (.014) | (.013) | (.013) | (.015) | (.014) | (.015) |
| AFQT | ... | ... | .172 | ... | ... | .228 |
| | | | (.012) | | | (.015) |
| AFQT$^2$ | ... | ... | −.013 | ... | ... | .013 |
| | | | (.011) | | | (.013) |
| High grade by 1991 | ... | .061 | ... | ... | .088 | ... |
| | | (.005) | | | (.005) | |
| $R^2$ | .059 | .155 | .168 | .029 | .191 | .165 |

NOTE.—The dependent variable is the log of hourly wages. The wage observations come from 1990 and 1991. All wages are measured in 1991 dollars. If a person works in both years, the wage is measured as the average of the two wage observations. Wage observations below $1.00 per hour or above $75 are eliminated from the data. The sample consists of the NLSY cross-section sample plus the supplemental samples of blacks and Hispanics. Respondents who did not take the ASVAB test are eliminated from the sample. Further, 163 respondents are eliminated because the records document a problem with their test. All respondents were born after 1961. Standard errors are in parentheses.

Source: Neal and Johnson (1996)

# 1. Controlling for $X$'s

- Classical omitted variable bias
- Adding more $X$'s usually reduces the estimated wage gap
- E.g. Ichino and Moretti (2009) - explain extra 14% of the gap in Italy by detailed data on sick leave absences
- We rarely observe actual productivity (room for contribution)?
- Where would it stop if one could include all?
- Interpretation:
  - Never "prove" discrimination (**"prove"** is the f-word in empirical research!)
  - How much raw gap is left unexplained, after including available $X$'s
- The minority has worse $X$'s - What if they expect discrimination and act on that? Is that not part of the problem?

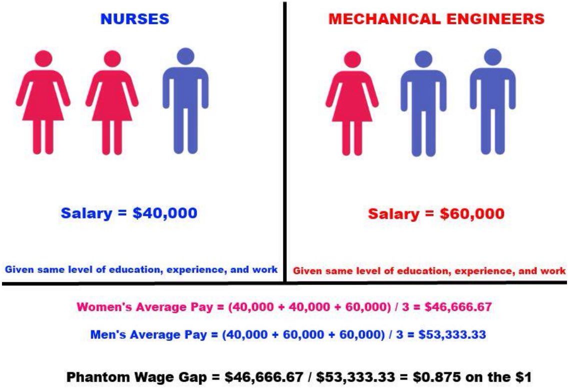
# 2. Segregation - firm, occupation, etc. dummies

Estimated log wage differentials by sex: WLS regressions

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | Czech public sector | | |
| Female | −0.241 | −0.180 | −0.155 | −0.156 | −0.103 |
| | (0.044) | (0.04) | (0.021) | (0.023) | (0.006) |
| $R^2$ | 0.073 | 0.571 | 0.586 | 0.621 | 0.726 |
| Number of workers | 178,209 | 178,209 | 178,209 | 178,209 | 163,072 |
| Number of firms | 92 | 92 | 92 | 92 | 913[a] |
| | | | Czech non-public sector | | |
| Female | −0.297 | −0.315 | −0.266 | −0.247 | −0.200 |
| | (0.014) | (0.013) | (0.011) | (0.009) | (0.009) |
| $R^2$ | 0.107 | 0.385 | 0.490 | 0.596 | 0.715 |
| Number of workers | 548,381 | 548,381 | 548,381 | 548,381 | 530,807 |
| Number of firms | 571 | 571 | 571 | 571 | 6648[a] |
| | | | Slovak public sector | | |
| Female | −0.152 | −0.082 | −0.076 | −0.078 | −0.069 |
| | (0.023) | (0.023) | (0.019) | (0.018) | (0.016) |
| $R^2$ | 0.025 | 0.530 | 0.653 | 0.676 | 0.823 |
| Number of workers | 13,709 | 13,709 | 13,709 | 13,709 | 13,662 |
| Number of firms | 35 | 35 | 35 | 35 | 438[a] |
| | | | Slovak non-public sector | | |
| Female | −0.227 | −0.231 | −0.204 | −0.179 | −0.161 |
| | (0.014) | (0.014) | (0.008) | (0.007) | (0.008) |
| $R^2$ | 0.064 | 0.287 | 0.476 | 0.600 | 0.703 |
| Number of workers | 98,989 | 98,989 | 98,989 | 98,989 | 94,130 |
| Number of firms | 408 | 408 | 408 | 408 | 3832[a] |
| Fixed effects | No | No | No | Firm | Job cell |
| Worker controls[b] | No | Yes | Yes | Yes | Yes |
| Firm controls[c] | No | No | Yes | Yes | Yes |

Source: Jurajda (2003)

# 2. Horizontal segregation and impact on the wage gap



# 2. Segregation - firm, occupation, etc. dummies

- Regression mechanics: including a (for example) firm dummy
  - Take deviations from the firm mean
  - Estimate $Y_{iF} - \overline{Y_F} = \beta(X_{iF} - \overline{X_F}) + (\epsilon_{iF} - \bar{\epsilon_F})$
  - Identify $\beta$ out of differences *within* a firm
  - Remove all variation between firms
- Adding dummies for industries, firms, job types, etc usually reduces the estimated wage gap
- Women tend to work in industries, firms, job types etc that pay lower wages (even to men)
- Particularly large absence of women among top managers (Jurajda and Paligorova 2009)

# 2. Segregation - firm, occupation, etc. dummies

- What are the potential reasons for occupational segregation?

# 2. Segregation - firm, occupation, etc. dummies

- What are the potential reasons for occupational segregation?
- Alternative interpretations of findings
  - Discriminating employers do not let women into better-paying jobs
  - "Female" jobs are inherently low-value jobs yet women have comparative advantage in those jobs
  - "Female" jobs offer non-wage characteristics preferred by women (sorting)

# 2. Segregation already in the educational system

## COLLEGE MAJORS WITH THE HIGHEST/LOWEST EARNINGS

| MAJORS W/ HIGHEST EARNINGS | MEDIAN EARNINGS | PERCENT FEMALE |
|---|---|---|
| Petroleum engineering | $136K | 14% |
| Pharmacy, pharmaceutical sciences | $113K | 59% |
| Metallurgical engineering | $98K | 23% |
| Mining and mineral engineering | $97K | 13% |
| Chemical engineering | $96K | 32% |
| Electrical engineering | $93K | 12% |
| Aerospace engineering | $90K | 14% |
| Mechnical engineering | $87K | 12% |
| Computer engineering | $87K | 10% |
| Geological/geophysical engineering | $87K | 40% |

| MAJORS W/ LOWEST EARNINGS | MEDIAN EARNINGS | PERCENT FEMALE |
|---|---|---|
| Early childhood education | $39K | 96% |
| Human/community services | $41K | 85% |
| Studio arts | $42K | 69% |
| Social work | $42K | 88% |
| Teacher education | $42K | 82% |
| Visual/performing arts | $42K | 67% |
| Theology/religious vocations | $43K | 32% |
| Elementary education | $43K | 91% |
| Drama/theater arts | $45K | 63% |
| Family/consumer sciences | $45K | 90% |

**SOURCE:** JEC.senate.gov; National Center for Education Statistics; 2014 Digest of Education Statistics; US Census Bureau; American Community Service micro data (2009–2013); Georgetown University Center

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# 3. Wage gap regressions - sensitivity to selection

- Weichselbaumer and Winter-Ebmer (2005) - Meta-Study of 263 papers (1535 estimates) of the female wage gap
- The estimated gap is smaller if the regressions limited to
  - New labor market entrants
  - Narrowly-defined jobs
  - Public sector
  - Medium and high-prestige jobs
- The estimated gap is higher if
  - Married (household specialization)
- Little sensitivity to econometric techniques

# 4. Wage gap regressions - sensitivity to employment

- Which countries have the smallest gender wage gap?

# Wage gap and female employment

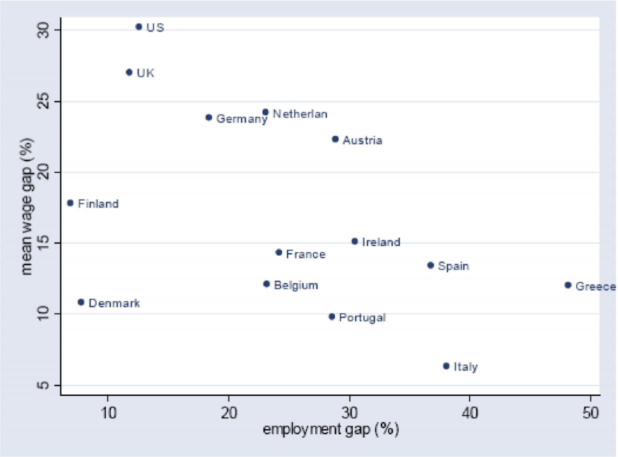



Figure 1: Gender gaps in median hourly wages and in employment, 1994-2001

# 4. Wage gap regressions - sensitivity to employment

- Large differences between countries in female LFP
- In low LFP countries, the non-working women tend to have lower skills (observable and unobservable)
- This employment margin has huge effect on the gender wage gap (both raw and unexplained)
- Hunt (2002): East Germany in 1991, low-wage women stopped working - drop in female wage gap
- To what extent is non-employment due to discrimination?
- U.S. - opposite story (increasing LFP and falling wage gap) - potentially opposite selection of women in the past (or actually improving the wage gap)

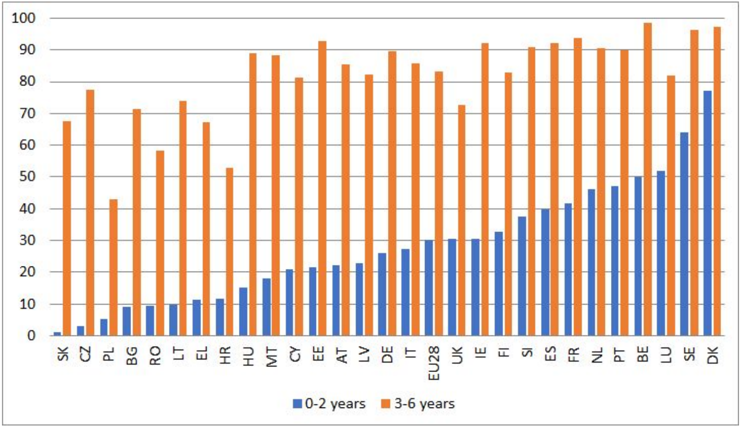
# Wage gap regressions - summing up

- The raw gender wage gap is meaningless
- Wage gap regressions quantify some factors behind the wage gap
- Wage gap regressions cannot “prove” discrimination
- Employment margin is very important

# Position of women on the Czech labor market

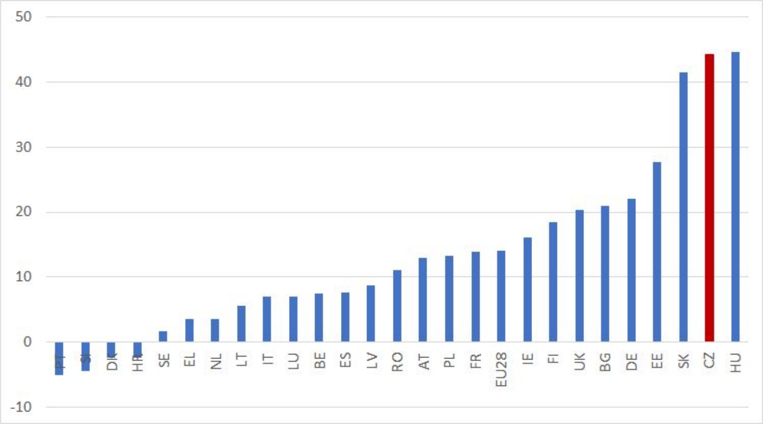
- CZ has the highest employment rate of women without children and with children above 12 in the EU (88% and 91% in 2015, respectively) -> higher GPG.
- Very low share of part-time employment (9% in CZ compared to 32% EU average) -> lower GPG.
- But, coverage of pre-school children by childcare is very low in the CZ and parental leave very long, so Czech women face the second largest drop in employment caused by motherhood in the EU -> long career breaks due to childbirth may substantially increase GPG.

# Share of children attending childcare.




Source: EUROSTAT: Formal child care by duration and age group, 2015.

# Employment impact of motherhood

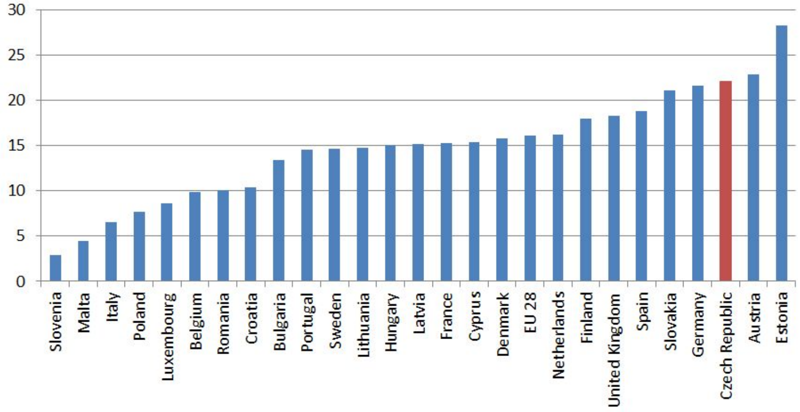



Source: Eurostat, 2015. Employment impact of motherhood is calculated as the precentage point difference in employment rates of women without children and women with children aged below 6.

# The unadjusted gender wage gap

- Q: What is the unadjusted GPG in CZ compared to EU average?

# The unadjusted gender wage gap in the EU




Source: Eurostat, 2014. The unadjusted gender pay gap (GPG) represents the difference between average gross hourly earnings of male paid employees and of female paid employees as a percentage of average gross hourly earnings of male employees.

# What Xs mostly matter for the gender wage gap in the CZ?

- Nowadays, educational attainment of men and women is very similar. In young cohorts, there is even more tertiary educated women than men -> education not an important factor of GPG.
- Gender occupation segregation (both horizontal and vertical) is important, but not outstanding in the EU.
- Children are an important determinant. Drop in employment caused by motherhood negatively affects careers of women and increases wage gap especially for older women, but also for young.
- This is closely related to family policy - if women bear the budren of care (childcare is not available, fathers do not participate), the gender wage gap is higher (see below).

# Parental leave and gender wage gap


*Gender pay gap is defined as the difference between male and female median earnings divided by male median earnings. Parental leave data is based on OECD estimates and reflects leave available to either parent, as opposed to maternity leave (only available to moms) or paternity leave (only available to dads). Due to ongoing changes in family leave policies, these estimates may not reflect present policies in all nations.
Source: OECD Family Database 2012; OECD Database on Earnings Distribution

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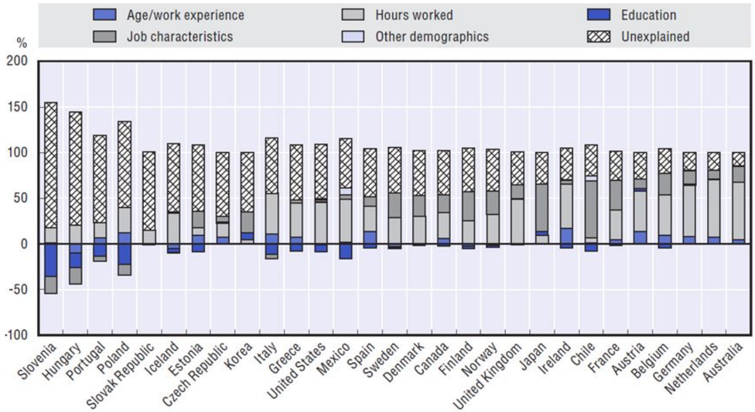
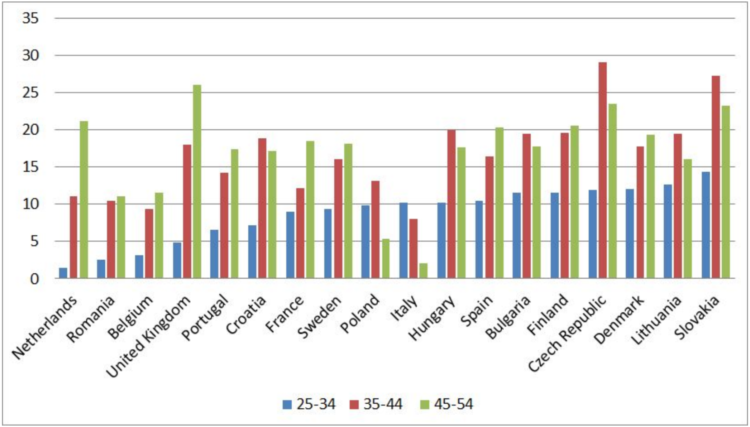
# Decomposition of gender wage gap



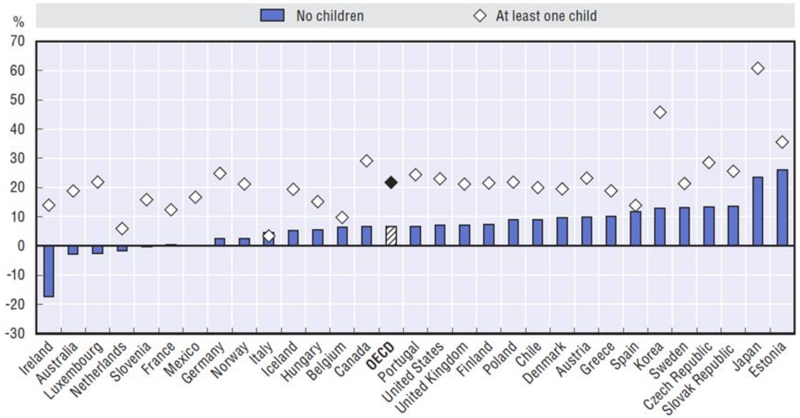

Source: OECD (2012), Closing the Gender Gap: Act Now, OECD Publishing

# Gender wage gap by age



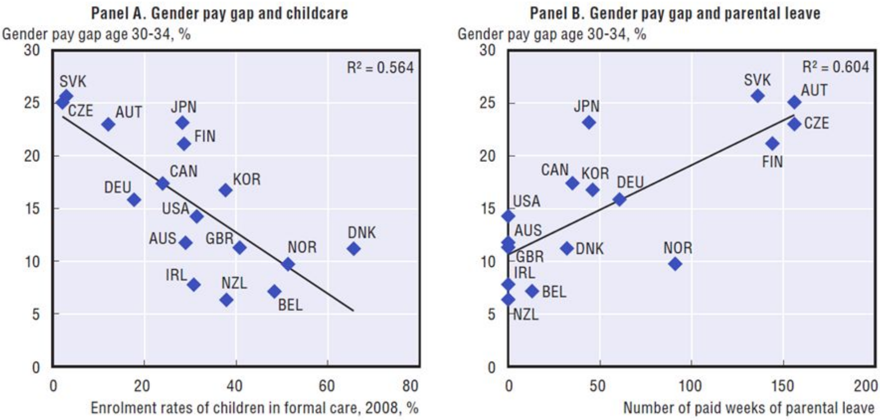

Source: Eurostat: Gender pay gap by age in an unadjusted form, 2014.

# Gender wage gap by presence of children




Source: OECD (2012), Closing the Gender Gap: Act Now, OECD Publishing

# Gender wage gap and family policy




Source: OECD (2012), Closing the Gender Gap: Act Now, OECD Publishing

# Conclusions

- Taste-based and statistical theory of discrimination
- Equilibrium wage gap is determined by the relative supply of non-discriminating firms
- Wage gap empirics - what they don't and do measure, sensitivity to the selection of workers into employment
- Field experiments can isolate finer aspects of discrimination

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