1 Discrimination: Definition

When $\gamma < 0$ in the following equation:

$$\ln w_i = \alpha + \beta' x_i + \gamma M_i + \epsilon_i,$$

where M is an indicator of minority status.

Caveats:

- Productivity depends on M? (Customer preferences)
- Is β exogenous? (Japanese fire-fighting equipment.)
- Expectations of γ reduce x for minority group.

1.1 Taste-Based Discrimination

Becker (1957): some employers have a 'taste for discrimination'. Let d be the "coefficient of discrimination." Firms maximize

$$U = pF(N_b + N_a) - w_a N_a - w_b N_b - dN_b.$$

Prejudiced employers ($d > 0$) only hire b group members if $w_a - w_b \geq d$.

If there are enough non-discriminating employers, minority workers don't work for discriminating employers. A wage differential will arise iff the fraction of discriminating employers is sufficiently large that the demand for b workers when $w_b = w_a$ is less than the supply. Then some b group members will work at $d > 0$ employers. The strength of prejudice *at the margin* (that is d for the marginal employer of b workers) is what determines the size of the wage gap.

Order firms based on their d – a there will be a cut-off firm, below which all firms employ black workers and above which they employ white workers. The cut-off must satisfy: $w_a - w_b = d$.

Competition: In the short run, minority workers must 'compensate' employers by accepting a lower wage for equivalent productivity. But with free entry, discriminating employers may be competed out of business: In a competitive market, each worker must earn his marginal product and discriminating employers must fund the cost of their distaste out of their own pockets.

But note that if discrimination starts with customer preferences, then it will not be competed away.

Segregation: Discriminatory tastes create incentives for segregation. It is potentially Pareto improving for minority workers to work in their own businesses — then no one bears the cost of the distaste.

1.2 Statistical Discrimination

Starting with Phelps (1972) and Arrow (1973): firms have limited information about the skills of job applicants. They thus use observable characteristics such as race or gender to infer the expected productivity of applicants (if these characteristics are correlated with productivity). Statistical discrimination is the solution to a signal extraction problem.

Noisy signal $\widetilde{\eta}^i$ of applicant's i true productivity η^i.

$\eta_a^i \sim N(\overline{\eta}_a, \sigma_\eta^2)$ and $\eta_b^i \sim N(\overline{\eta}_b, \sigma_\eta^2)$ and $\overline{\eta}_a > \overline{\eta}_b$.

$\widetilde{\eta}_x^i = \overline{\eta}_x + \epsilon_i + \nu_i$, where ν is noise around true η_x^i and $\epsilon_i = \eta_x^i - \overline{\eta}_x$

Employers form $E[\eta|x, \widetilde{\eta}] = \overline{\eta}_x(1-\gamma) + \widetilde{\eta}\gamma$, where $\gamma = \sigma_\eta^2/(\sigma_\eta^2 + \sigma_\nu^2)$.

The expected productivity of b applicants is below that for a applicants, even though $\widetilde{\eta}$ is an unbiased signal of true productivity for each applicant.

There is equal pay for equal *expected* productivity, but not equal pay for equal work, because 'work' is not fully observable. For some workers, there is discrimination, but within each group, expected productivity equals true average productivity.

The less noise there is for a particular group, the lower the importance of the group average productivity. Similarly, if employers are risk averse, they will hate to hire from high variance groups. If the signal $\widetilde{\eta}$ corresponds to education and non-whites' education 'counts' less, they will not invest in schooling as much.

Unlike taste-based discrimination, statistical discrimination is not competed away in equilibrium.

Statistical discrimination is 'efficient.' It is the optimal solution to an information extraction problem, it is profit-maximizing, it is not motivated by animus. Of course, it is 'efficient' only if the averages for each group are correctly estimated. Otherwise, we are talking about prejudice...

But statistical discrimination is illegal (in the US, EU). You should not be punished for the fact that others in your group are not productive. If we allow your fate to be determined not just by what you do but by what people like you do, this can lead to self-fulfilling expectations that are discriminatory in nature.

But consider the case of racial profiling: screening at airports or anti-drug police stopping cars on the highway. The police will stop cars such that they will equate the *marginal* return to stopping a driver from each of the two race groups (i.e., the marginal car stopped has the same expected probability of criminality for both groups). Of course, this will mean that innocent group b drivers will be stopped (checked) a lot more often. Statistical discrimination is inequitable on average, even if it is 'fair' at the margin.

1.3 Descriptive Empirics

The relative position of a minority group, say women, on the labor market:

- pre-market productive characteristics (education, its field)
- employment gaps (10% in the US, UK and Scandinavian countries, 15-25% in northern and central EU, 30-40% in southern EU and Ireland)
- wage gaps
- representation in occupations (vertical, horizontal segregation) or neighborhoods (Scandinavian countries have high segregation thanks to high employment rates.)

1.3.1 Oaxaca-Blinder Decomposition

Use Least Squares to "account" for observable sources of the gap. Use the fact that fitted regressions pass through the sample means:

$$\overline{\ln w_g} = \widehat{\beta_g}' \overline{X_g}, \quad g \in \{f, m\},$$

Mean wage decomposition:

$$\overline{\ln w_m} - \overline{\ln w_f} = (\overline{X_m} - \overline{X_f})' \widetilde{\beta} + [\overline{X_m}' (\widehat{\beta_m} - \widetilde{\beta}) + \overline{X_f}' (\widetilde{\beta} - \widehat{\beta_f})],$$

where $\widetilde{\beta}$ represents a counter-factual non-discriminatory wage structure.

Using $\beta_m$or β_f for $\widetilde{\beta}$ corresponds to estimating the ATU or ATT.

Matching is an alternative when support (X) is not perfectly overlapping.

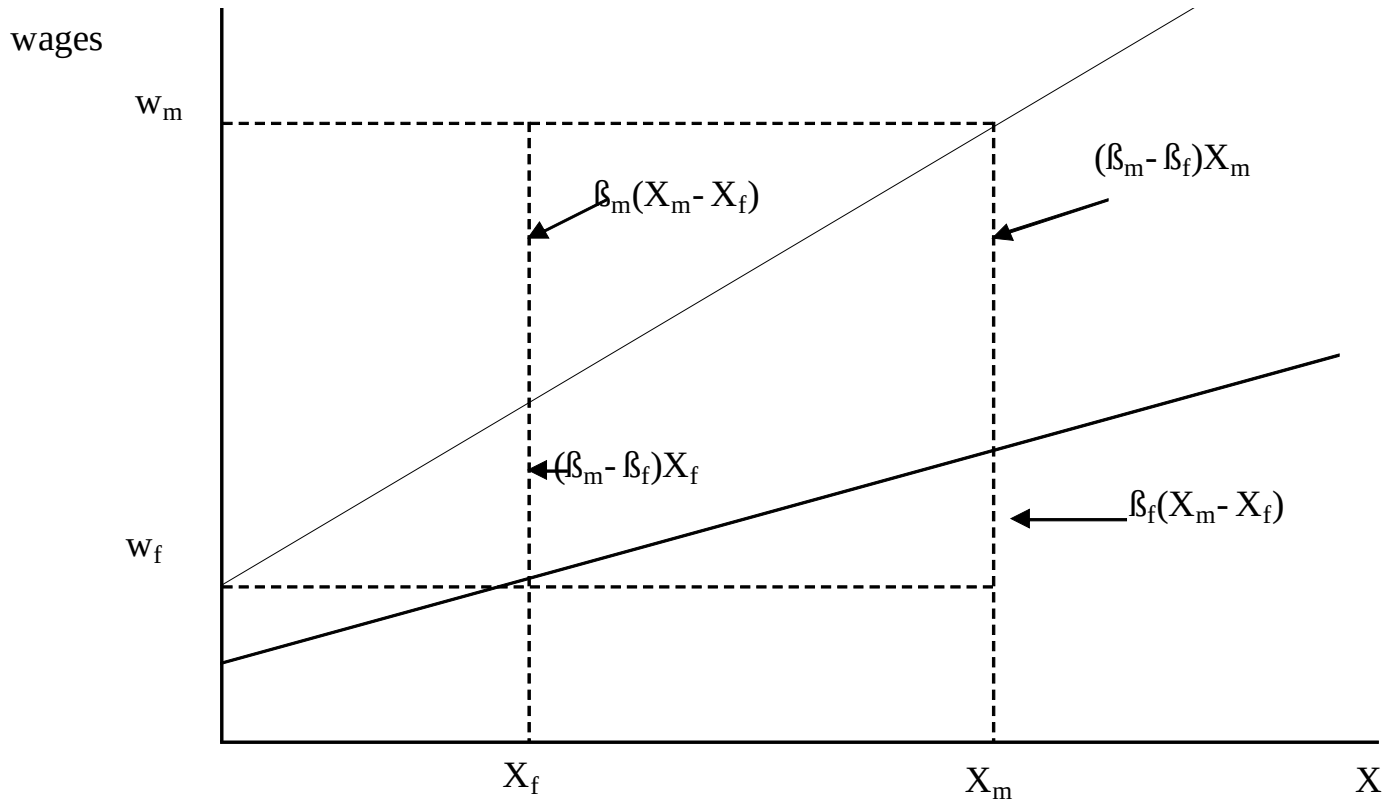


Figure 1: Oaxaca-Blinder Decomposition

1.3.2 Wage Gap Studies

Not very useful. Try measure the wage gap, gender or racial, for comparable workers (the conditional or 'unexplained' gap). (Differences: Women have babies. Ethnic minorities often geographically concentrated.)

Recently, employed men and women are similar, so X does not explain much.

The EU cares about the (raw) gender gap: compare across countries, over time.

Misleading when there are differences/changes in the skill structure (*observable as well as unobservable*) of female employment participation.

Hunt (2002): East Germany in 1991: low-wage women stop working, wage gap shrinks (even the conditional gap). This is not good new. Kazakova (2005) etc.

The same story applies in cross-country comparisons:

Is position of women in southern Europe really much better than in Northern Europe, the US?

Problem of sample selection (Petrongolo and Olivetti, 2005) – proportion of (low-wage) women working in southern Europe is much lower. (next graph)

Where does female labor-market participation come from? Could be related to discrimination, labor-market institutions or culture / history.

Some stories seem clear: in the second half of the 20th century female participation increased and wage gap shrank in US, UK. (Graphs.)

Female/Male Ratios, Median Weekly Earnings of Full-Time Workers

Country	*1979–81*	*1989–90*	*1994–98*	*Change 1979–81 to 1994–98*
Australia	0.800	0.814	0.868	0.068
Austria	0.649	0.674	0.692	0.043
Belgium	na	0.840	0.901	na
Canada	0.633	0.663	0.698	0.065
Finland	0.734	0.764	0.799	0.065
France (net earnings)	0.799	0.847	0.899	0.100
Germany (west)	0.717	0.737	0.755	0.038
Ireland	na	na	0.745	na
Italy	na	0.805	0.833	na
Japan	0.587	0.590	0.636	0.049
Netherlands	na	0.750	0.769	na
New Zealand	0.734	0.759	0.814	0.080
Spain	na	na	0.711	na
Sweden	0.838	0.788	0.835	−0.003
Switzerland	na	0.736	0.752	na
United Kingdom	0.626	0.677	0.749	0.123
United States	0.625	0.706	0.763	0.138
Non-US Average				
1979–81 sample	0.712	0.731	0.774	0.063
full sample	0.712	0.746	0.778	0.067

Notes: The years covered for each country are as follows: Australia: 1979, 1989, 1998; Austria: 1980, 1989, 1994; Belgium: 1989, 1995; Canada: 1981, average of 1988 and 1990, 1994; France: 1979, 1989, 1996; W. Germany: 1984, 1989, 1995; Italy: 1989, 1996; Japan: 1979, 1989, 1997; Netherlands: 1990, 1995; New Zealand: average of 1988 and 1990, 1997; Sweden: average of 1978 and 1980, 1989, 1996; Switzerland: 1991, 1996; United Kingdom: 1979, 1989, 1998; United States: 1979, 1989, 1996.

Source: Authors' calculations from unpublished OECD data.

Figure 2: Variation in Gender Pay Gap Across Countries (Blau-Kahn, 2000)

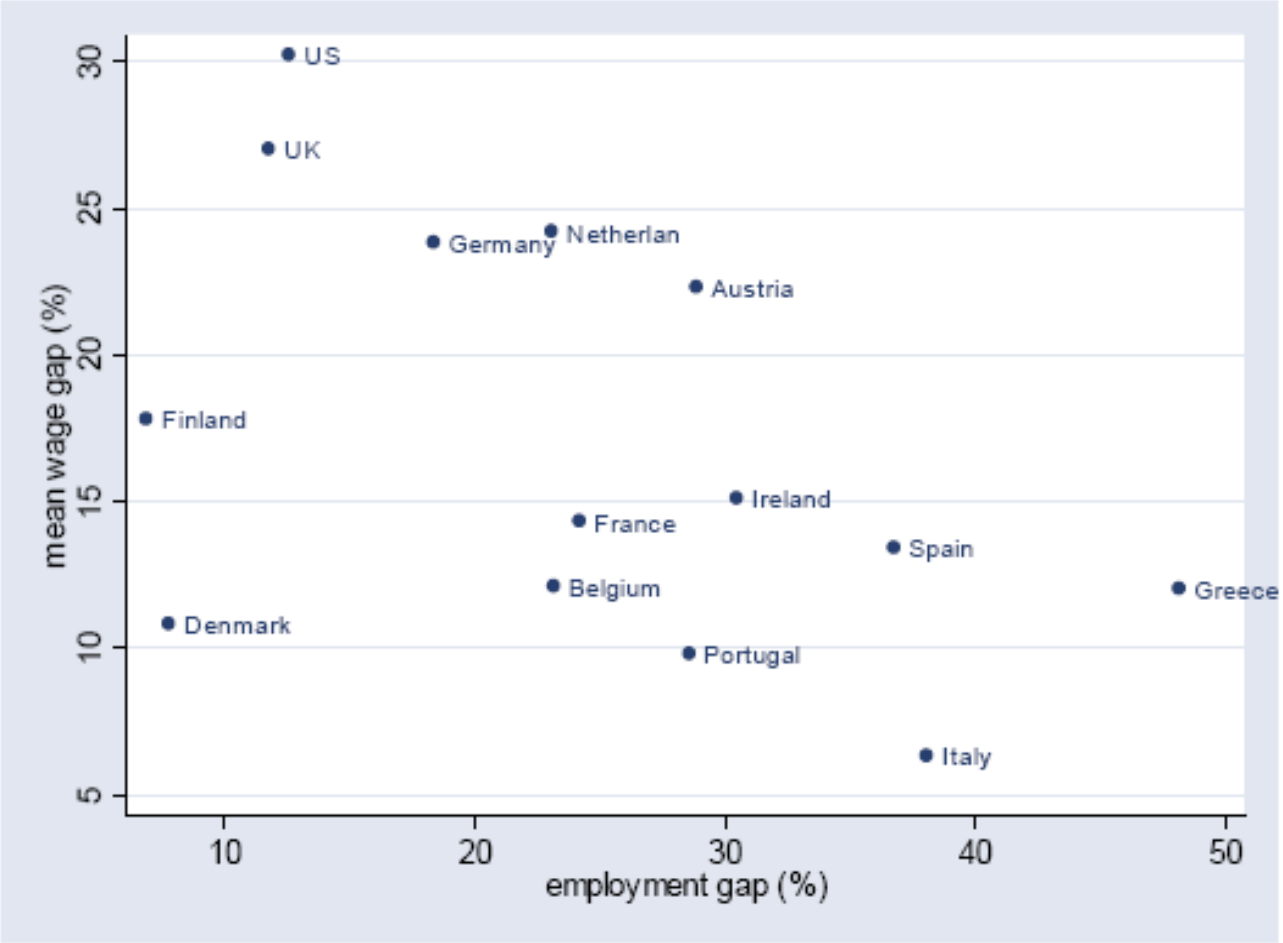


Figure 1: Gender gaps in median hourly wages and in employment, 1994-2001

Figure 3: Gender Gaps in Median Wages and Employment

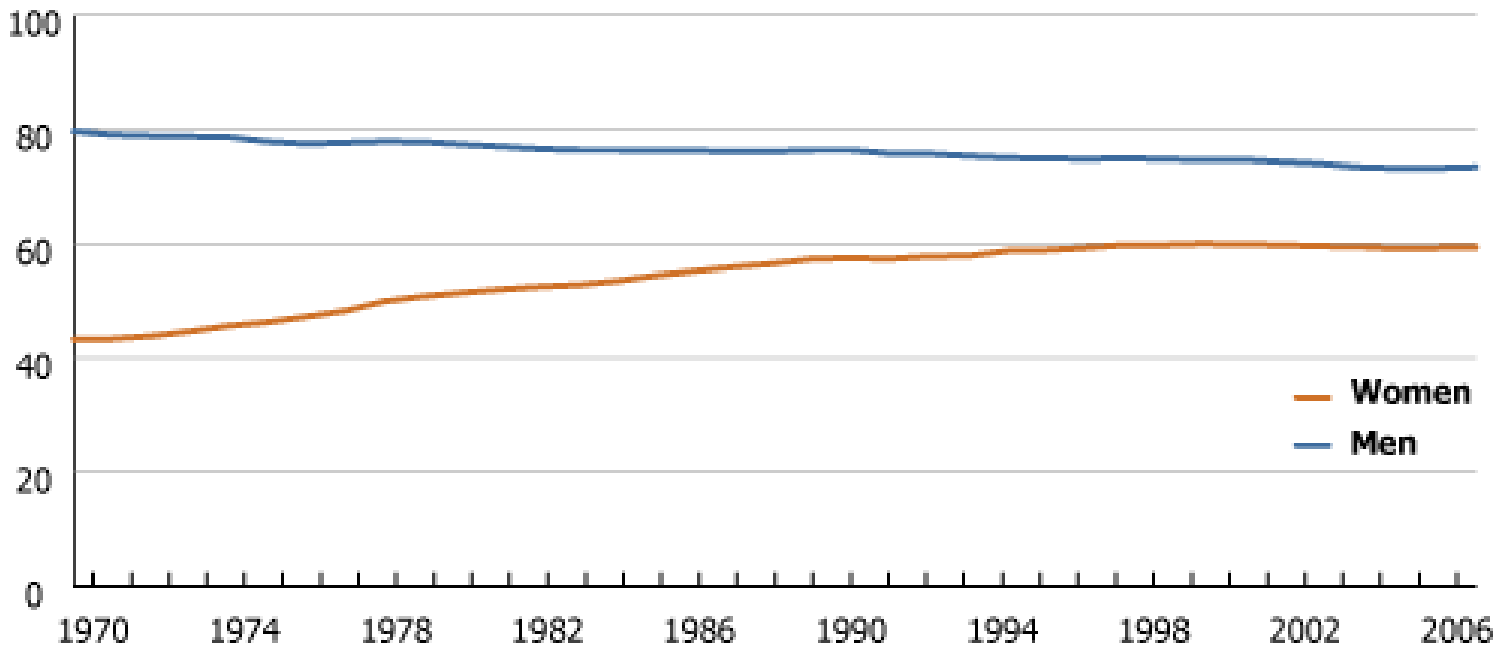


Figure 4: US LFP by Gender

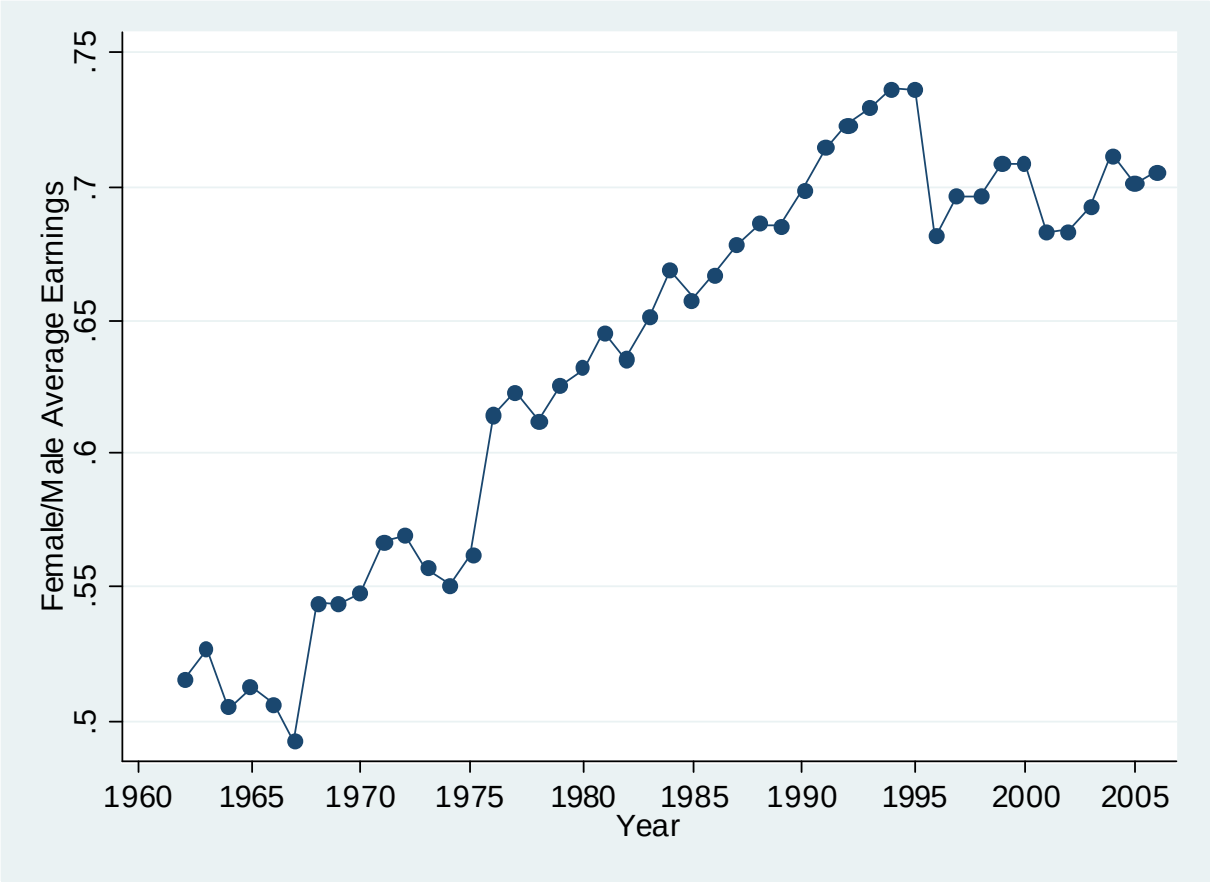


Figure 5: US Gender Wage Gap

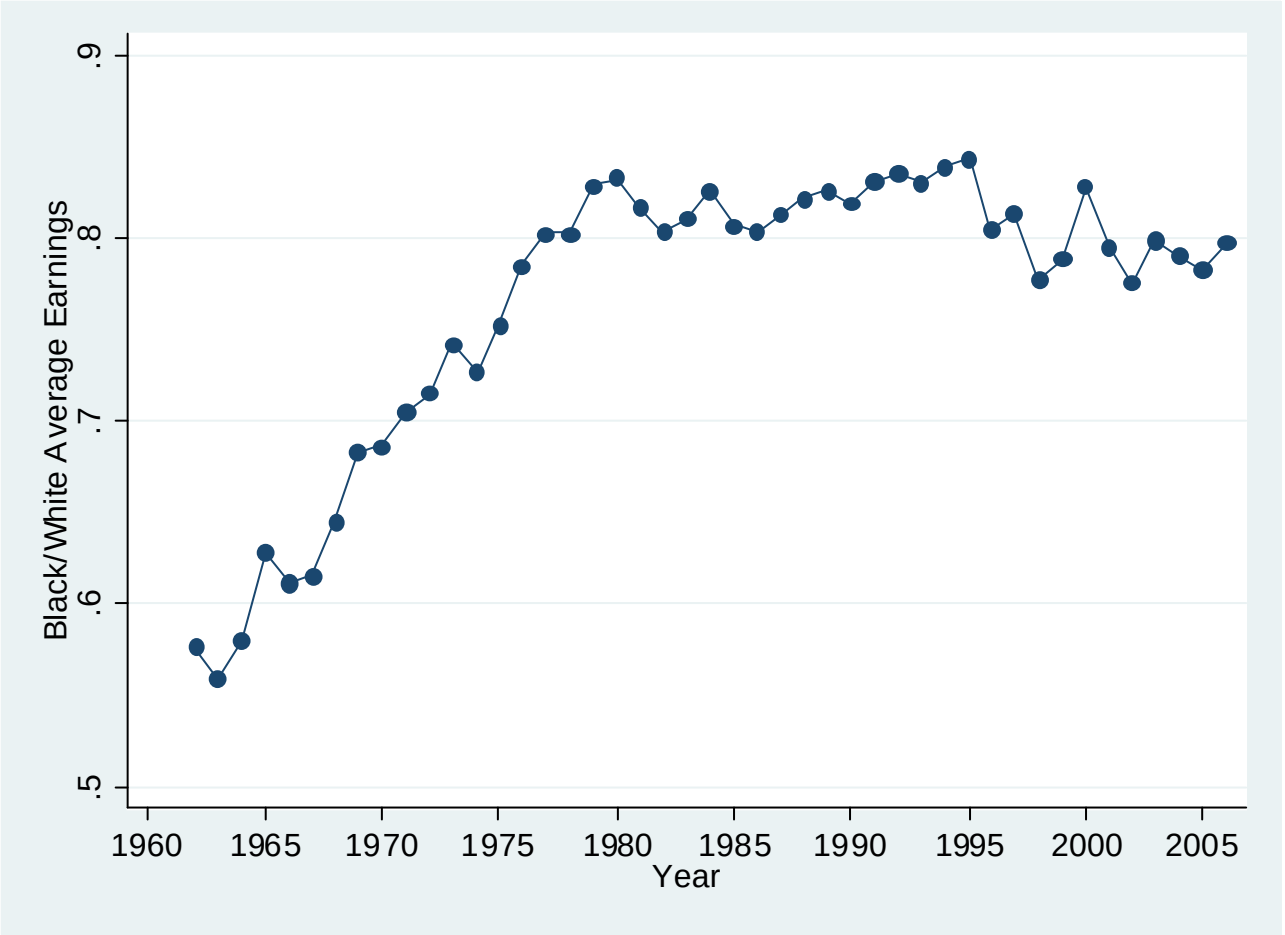


Figure 6: US Black-White Earnings Gap

But: Mulligan and Rubinstein (2008) argue that

- the majority of the apparent narrowing of the gender wage gap reflects increased attachment of the most able women to the labor force,

- demographic groups with high and stable female employment rates have little measured relative wage growth for women in the US, and

- growing wage equality between genders coincided with growing inequality within gender.

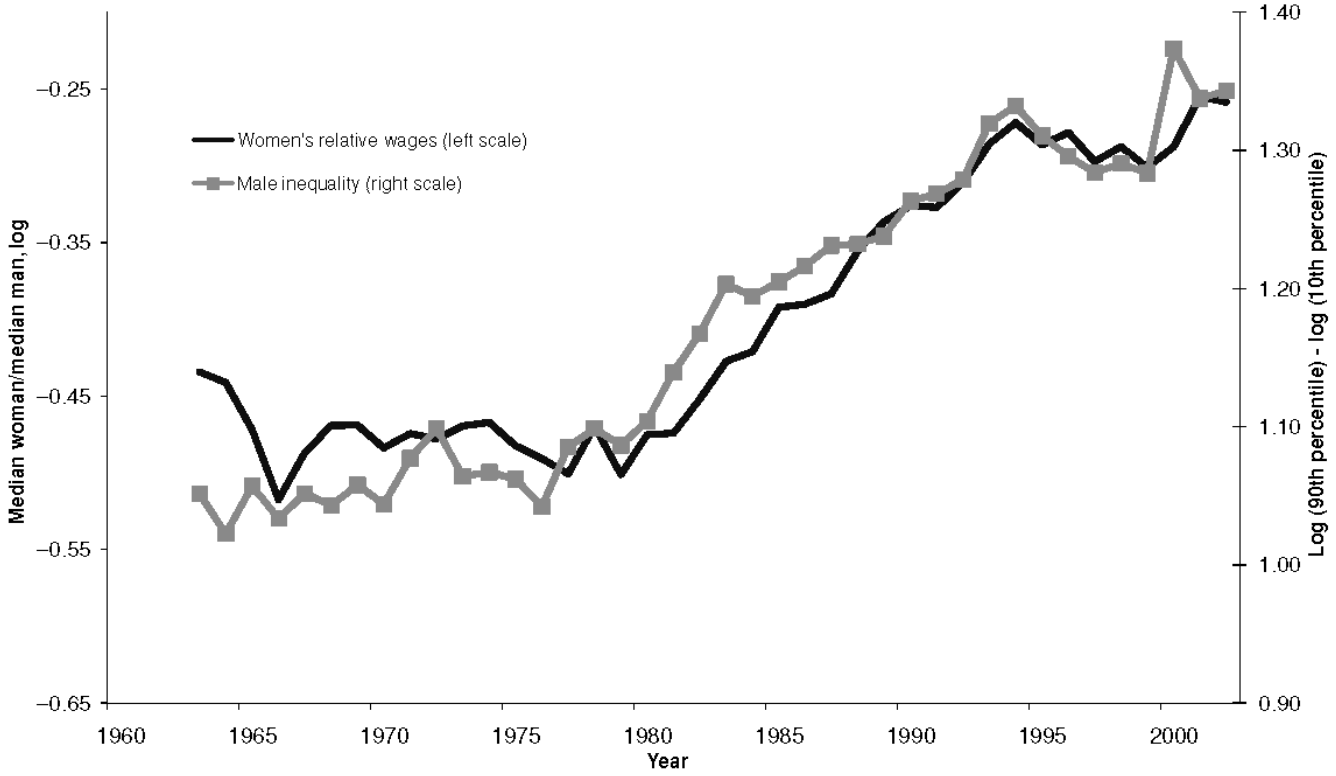


FIGURE I

Wage Inequality within and between Genders

The figure graphs time series of (a) the log of the ratio of the wage of the median working woman to that of the median working man (left scale, no markers), and (b) the log of the ratio of the wage of a man at the 90th percentile of the male wage distribution to that of a man at the 10th percentile (right scale, square markers). The calculations use our CPS wage sample of white persons aged 25–54, without trimming of outliers or adjusting topcodes.

Figure 7: Women's relative wages and Male wage inequality, 1963-2005

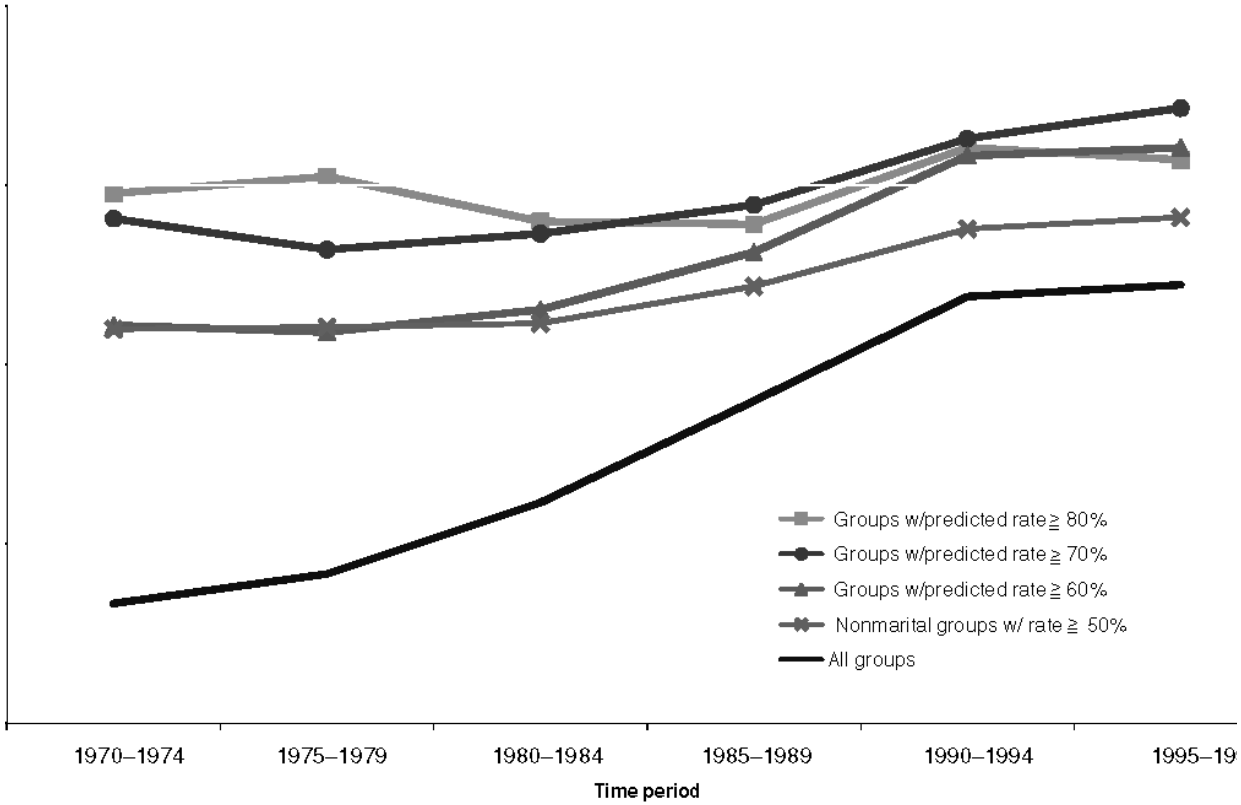


FIGURE V
Gender Wage Gaps Among Strongly Attached Groups, Various Thresholds

Figure 8: Gender Wage Gaps for Strongly Attached Groups and All (no mark)

1.3.3 Studies of Wage Gap and Segregation

Again, not very useful. Women tend to concentrate in low-paying occupations and industries (and firms). (Hence, part of the wage gap.) Why?

1. discriminating employers prevent women from entering high-wage occupations

2. 'female' occupations offer costly non-wage characteristics preferred by women

Measures of occupational segregation do not distinguish 1. from 2.

Wage indirect research on US data: the 'penalty' to working in 'female' occupations shrinks when controlling for occupational attributes and/or unmeasured worker preferences and quality (switchers).

Jurajda and Harmgart (2007) follow Hunt (2002) to suggest that even the 'penalty' depends on the extent of participation by low-wage women.

What about role-model managers? In the US, the share of female executives is increasing (close to 10%) and the managerial gender pay gap is narrowing.*

*There is a growing literature asking whether female directors or executives help or harm firm performance. Wolfers (2006, JEEA) finds no systematic differences in returns to holding stock in female-headed firms, consistent with no prejudice against female CEOs among investors. Adams and Ferreira (2009, JFE) show the effects of female directors on board inputs. Ahern and Dittmar (2009) suggest that the 40% female quota imposed on Norwegian boards of directors leads to a negative effect on firm value, caused by their lower experience. IZA Discussion Paper no. 4526 consistent with strong effects of 'femaleness' on survival chances of Austrian startups.

1.4 Testing for Discrimination

Competition and Discrimination Becker (1957): preference-based discrimination should be competed away. Firms in more concentrated (less competitive) product markets should have higher gender wage gaps since rents are available for indulging such tastes.

Ashenfelter and Hannan (1986) show that US banks facing more competition hire more women and have lower gender wage gaps.

There is also a positive relationship across manufacturing firms in the share of women and performance, but only in industries facing low competition (Hellerstein, Neumark, and Troske, 2002).

Similarly, the firm-level gender wage gap has gone down faster in those Hungarian industries that became more open to international trade and less concentrated (Lovasz, 2007).

Black-White Wage Gaps and Pre-Market Characteristics Neal and Johnson (1996): 'pre-market' skills (AFQT) appear to explain a large part of racial earnings gap for currently employed workers.

Low scoring blacks are less likely to participate in labor market. To deal with selection, use median regressions: if nonparticipants have wage offers lower than the median wage, use 0. Table 4: much less of the gap is explained now.

What explains AFQT scores? Huge racial gaps are reduced by controlling for family background and school quality. Still, some gap remains. But it may be that minority members invest less in skills because of pessimistic expectations about fair rewards, so it is all about discrimination after all, not about traits.

Carneiro, Heckman and Masterov (2003): racial gaps in ability open up at very early ages => importance of early (preschool) family factors => policies that foster early development better than additional civil rights and affirmative action policies targeted at the workplace.

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.

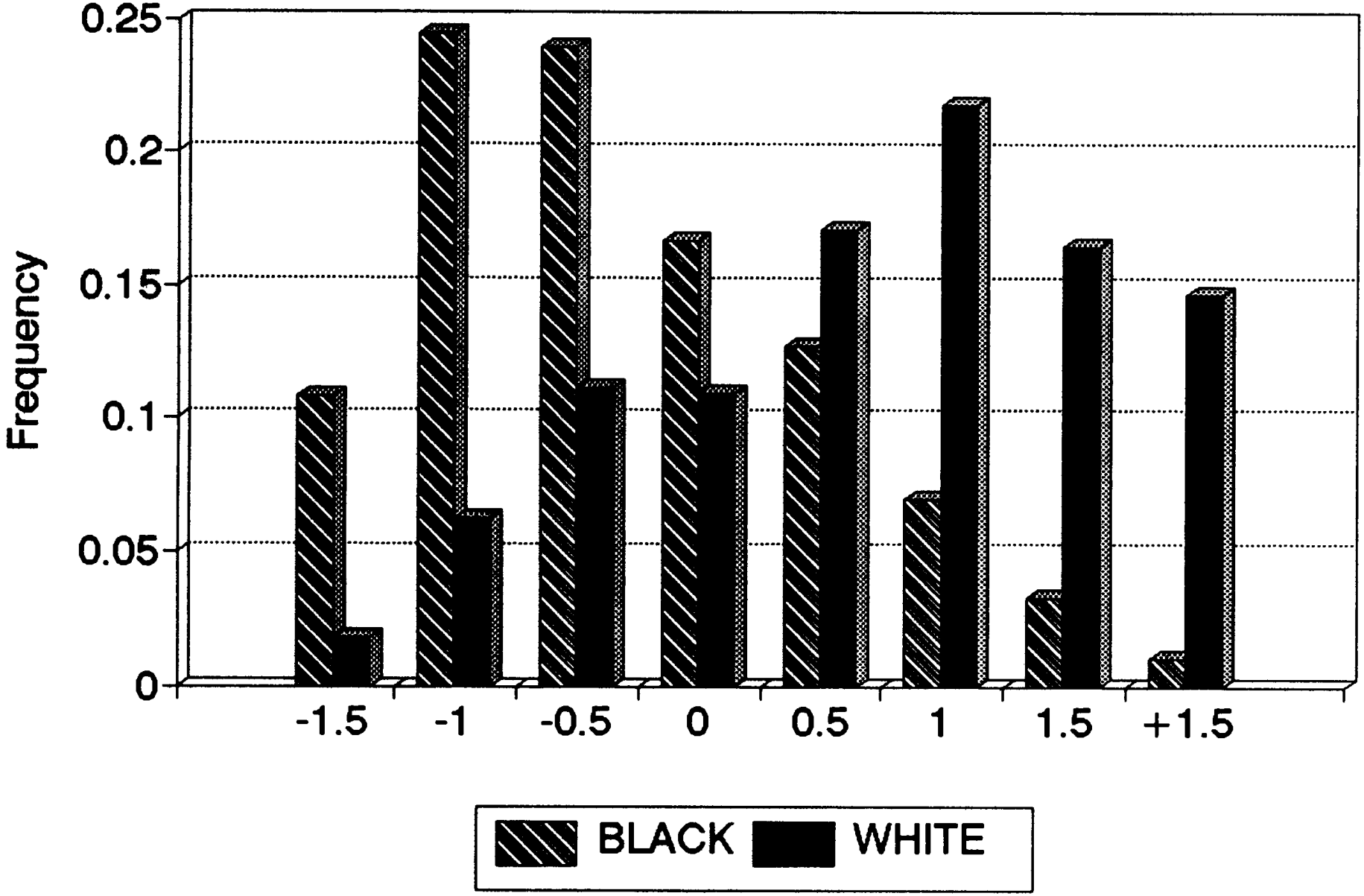


FIG. 2.—Age-adjusted AFQT scores: men

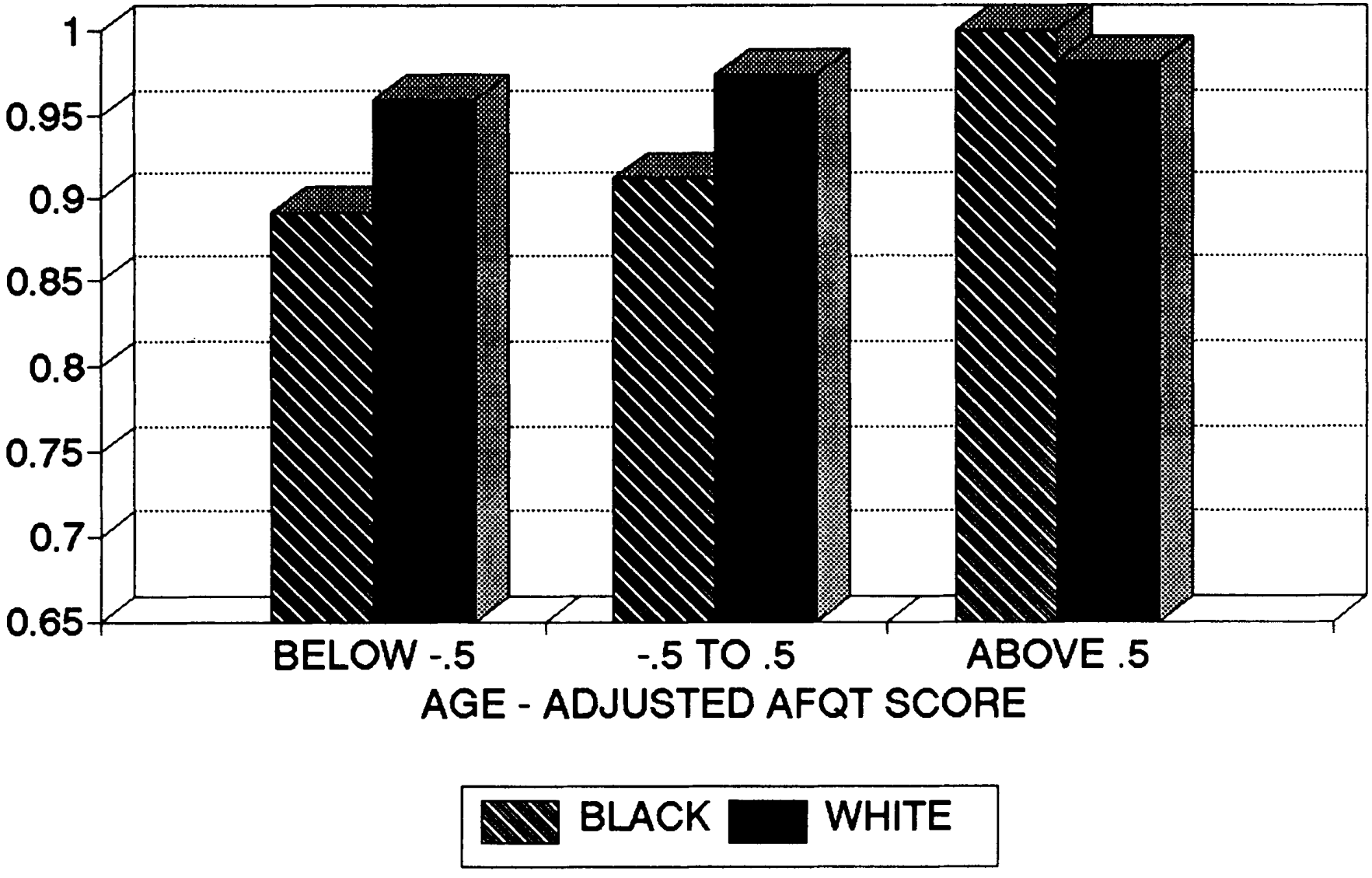


FIG. 1.—Male participation rates, 1990–91

TABLE 4

MEDIAN LOG WAGE REGRESSIONS: MEN (N = 1,674)

	(1)	(2)
Black	−.352	−.134
	(.029)	(.035)
Hispanic	−.180	−.007
	(.034)	(.038)
Age	.067	.055
	(.015)	(.017)
AFQT	...	.206
		(.015)
$AFQT^2$	...	−.010
		(.014)

NOTE.—The dependent variable is log hourly wages. The sample is the sample described in table 1 plus the sample of nonparticipants. Nonparticipants include workers who report not working between their 1989 and 1991 interviews. Nonparticipants also include workers who did not work between their 1989 and 1990 interviews and were not interviewed in 1991. Some respondents are excluded from the previous regression analyses solely because their wage observations are invalid. These respondents are also excluded from this analysis. All respondents were born after 1961. Standard errors are in parentheses.

TABLE 5

DETERMINANTS OF AFQT: MEN

	FULL SAMPLE (N = 1,873)			VALID RESPONSE TO SCHOOL SURVEY (N = 954)
	(1)	(2)	(3)	(4)
Black	−1.03	−.70	−.57	−.42
	(.05)	(.05)	(.05)	(.07)
Hispanic	−.70	−.31	−.22	−.02
	(.06)	(.05)	(.05)	(.08)
Mother high school graduate	...	.36	.26	.18
		(.04)	(.04)	(.06)
Mother college graduate	...	.21	.16	.09
		(.08)	(.08)	(.11)
Father high school graduate	...	.32	.25	.22
		(.05)	(.05)	(.06)
Father college graduate	...	.32	.30	.31
		(.07)	(.07)	(.09)
Mother professional	...	.20	.17	.08
		(.07)	(.07)	(.10)
Father professional	...	.26	.23	.21
		(.06)	(.06)	(.08)
Number of siblings	...	...	−.05	−.05
			(.01)	(.01)
No reading materials	...	...	−.19	−.31
			(.06)	(.09)
Numerous reading materials	...	...	.25	.27
			(.04)	(.06)
Student/teacher ratio	...	...	...	−.017
				(.006)
Disadvantaged student ratio	...	...	...	−.002
				(.001)
Dropout rate	...	...	...	−.004
				(.001)
Teacher turnover rate	...	...	...	−.005
				(.003)
R^2	.219	.382	.415	.392

Statistical Discrimination Return to Altonji and Pierret (2001): their test of the signalling hypothesis is a test of 'statistical discrimination' on education. Are employers initially using education as a proxy for unobserved (noisy) ability? Yes.

Do employers statistically discriminate on race as a proxy for AFQT? If so, race ought to be negative absent the AFQT x time measure. Once the time interaction is added, this should make the race main effect more negative, while the time interaction with race should be more positive. If race is taken as a (negative) productivity signal early in the career, it should become less important over time as actual productivity is revealed.

In fact, the opposite occurs. So, there appears to be little statistical discrimination on race, employers may be obeying the legal prohibition of statistical discrimination.

TABLE I

THE EFFECTS OF STANDARDIZED AFQT AND SCHOOLING ON WAGES

Dependent Variable: Log Wage; OLS estimates (standard errors).

Panel 1—Experience measure: potential experience				
Model:	(1)	(2)	(3)	(4)
(a) Education	0.0586	0.0829	0.0638	0.0785
	(0.0118)	(0.0150)	(0.0120)	(0.0153)
(b) Black	−0.1565	−0.1553	0.0001	−0.0565
	(0.0256)	(0.0256)	(0.0621)	(0.0723)
(c) Standardized AFQT	0.0834	−0.0060	0.0831	0.0221
	(0.0144)	(0.0360)	(0.0144)	(0.0421)
(d) Education *	−0.0032	−0.0234	−0.0068	−0.0193
experience/10	(0.0094)	(0.0123)	(0.0095)	(0.0127)
(e) Standardized AFQT *		0.0752		0.0515
experience/10		(0.0286)		(0.0343)
(f) Black * experience/10			−0.1315	−0.0834
			(0.0482)	(0.0581)
R^2	0.2861	0.2870	0.2870	0.2873

Figure 9: Altonji and Pierret (2001)

1.4.1 Direct Tests in Specific Settings

Discrimination in Sports Price and Wolfers (2007) study NBA referees. They find – even conditioning on player and referee fixed effects – that more personal fouls are called against players when they are officiated by an opposite-race refereeing crew. This affects who wins.

Discrimination in Arts Goldin and Rouse (2001, AER): Some symphony orchestras started using screens during solo auditions to hide the identity of auditioners. Women were historically viewed as unsuitable for orchestras.

On average, women do worse on blind rounds. But this could be due to changing composition of female pool: it is possible that only the very best women competed when the game was lopsided. Indeed, estimation limited to musicians (male and female) who auditioned both blind and non-blind suggest that women did relatively better in blind rounds.

Discrimination in Hiring Bertrand and Mullainathan (2003): audit field-experiment study. Apply for jobs by sending resume (CV) by mail or fax. Use distinctively ethnic names, but keep the same resume. Are 'callback' rates lower for distinctively black-named applicants? Yes. Also, black names benefit less from having better resume. Is this evidence against statistical discrimination? Consider expectations of unobserved Xs conditional on observed data. Bigger problem: Differences in variance and statistical discrimination: Suppose observed X is low and firms hire anyone above a threshold productivity estimate. If white applicants have higher variance of unobserved productivity X, they will be hired more likely. (For a solution see Neumark (2012, JHR).

Hiring/promotion committees at universities: IZA DP No. 5537: random assignment of an extra woman on a committee in Spain in 2002-2006 really helps female applicants to full professor positions; PNAS 2012 field experiment with CVs for a lab manager: "Female professors were just as biased against women students as their male colleagues".

Discrimination Misc. Body height and BMI predict wage differences (in a predictable way). A beauty premium (Hammermesh, 2006). Is there a consumption value basis for the beauty premium?

Oster and Jensen (2007): access to cable and satellite TV in rural India is associated with improvements in women's status.

Jurajda and Munich (2007) look at alphabet sorting in school admission.

Cavalcanti and Tavares (2008): a decrease in the relative price of home appliances increases female labour force participation.

Science? Randomly assigned female professor has little impact on male students, but powerful effect on female students' performance in math and science classes and on high-performing female students' likelihood of taking future math and science courses (Carell et al. QJE 2010).

Psychological Explanations for Lack of Female Managers, Scientists In experiments, women are less effective than men in competitive environments, even if they perform as well in non-competitive settings (Gneezy, et al., 2003). Örs et al. (2008) and Jurajda&Munich (2008): similar evidence from university admissions. Niederle and Vesterlund (2007): men (of equal ability) select into competitive environments (a tournament) more. Innate gaps or gender stereotyping?

Gneezy et al. (2008): men prefer competition more in a patriarchal society (the Maasai in Tanzania) while women do so in a matrilineal society (the Khasi in India). Booth and Nolen (2008): girls from single-sex schools are as likely to choose a gamble as boys from either coed or single sex schools.

Babcock and Laschever (2003) report that women do not negotiate as toughly as men on salaries. But this is natural if their access to these jobs is harder.

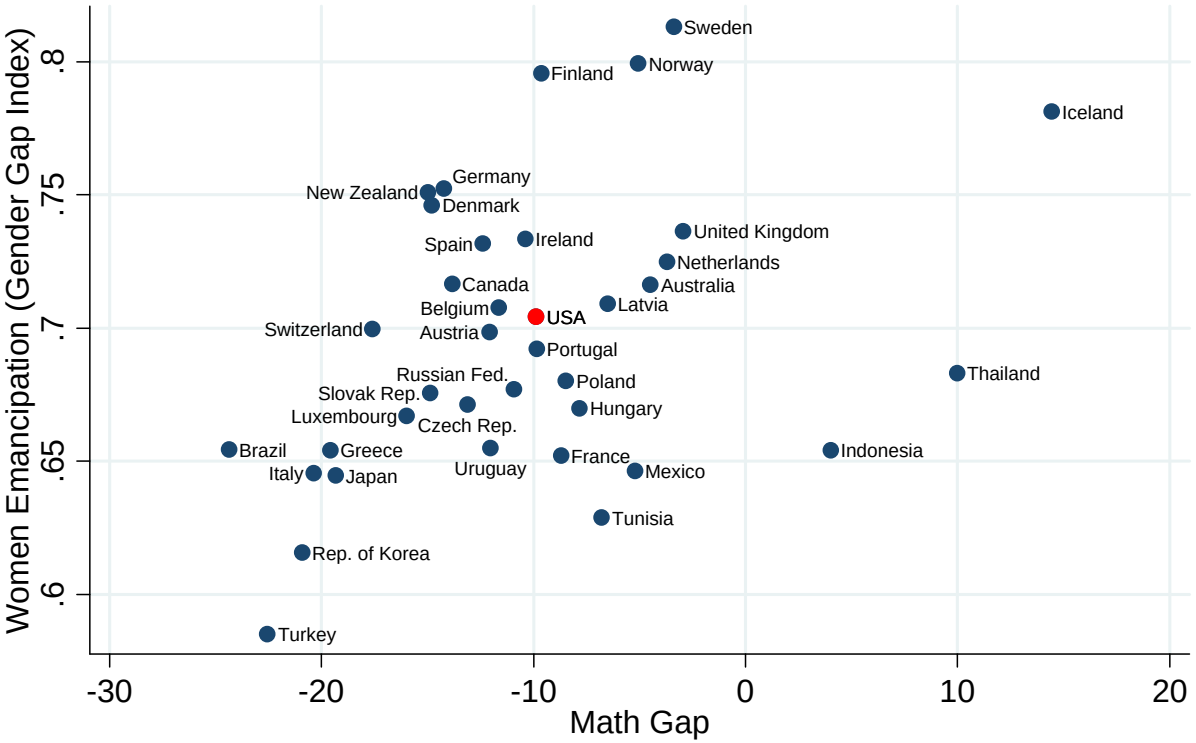


Figure 10: Guiso et al. (2008, *Science*): PISA math gap disappears (but girls' comparative advantage in humanities remains - few women in hard sciences).

1.5 Czech Labor-Market Gender Facts

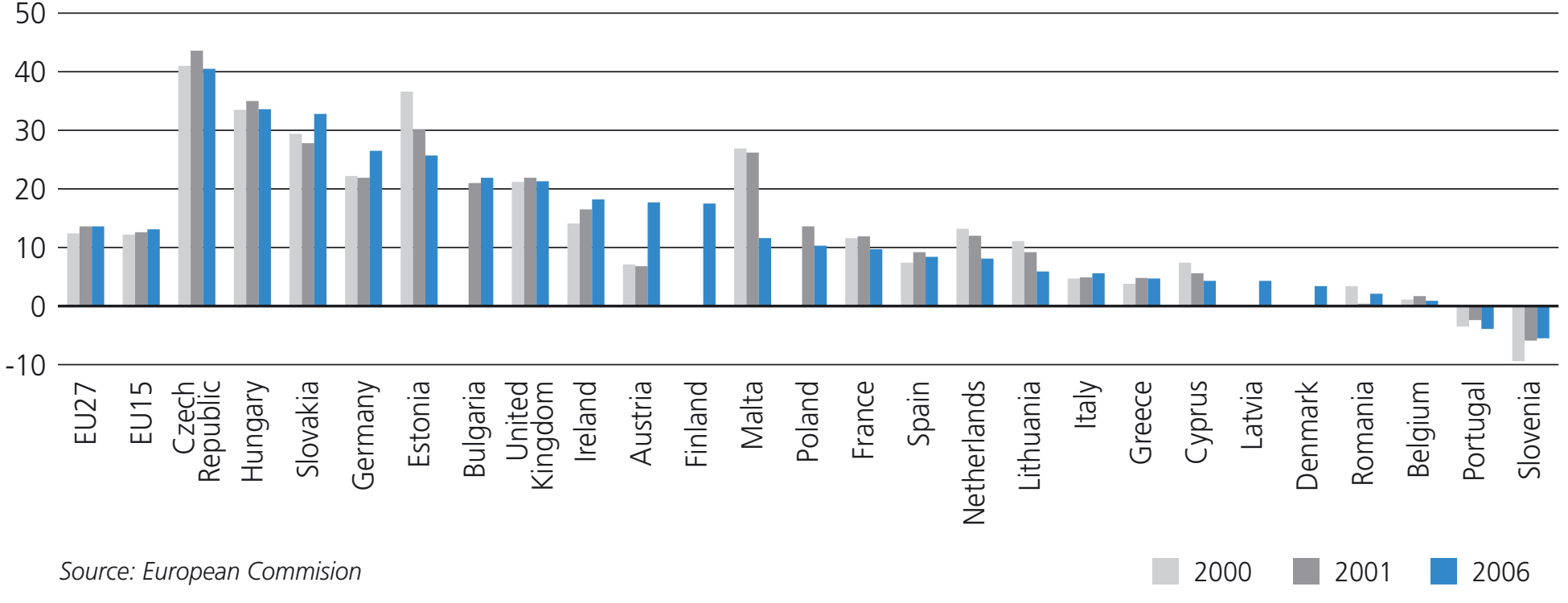
CZ used to have unusually high employment rate of women aged 25-54 with less than tertiary level of education $=>$ expect higher (raw) gender wage gap.

CZ part-time female employment is low ($5\% < 26\%$ in EU27.), while female employment is high $=$ unusually high full-time employment rates of younger Czech women (and their low fertility).

CZ employment rate gap between women with and without young children is the highest in the EU, thanks probably to incentives and lack of child care.

CZ occupational gender segregation is similar to EU-15, thanks to a recent decline in occupational segregation for younger workers.

Figure V.2.4 Employment Impact of Parenthood for Women (difference in percentage points in employment rates without a presence of any children and with presence of a child aged 0–6)



Source: European Commision

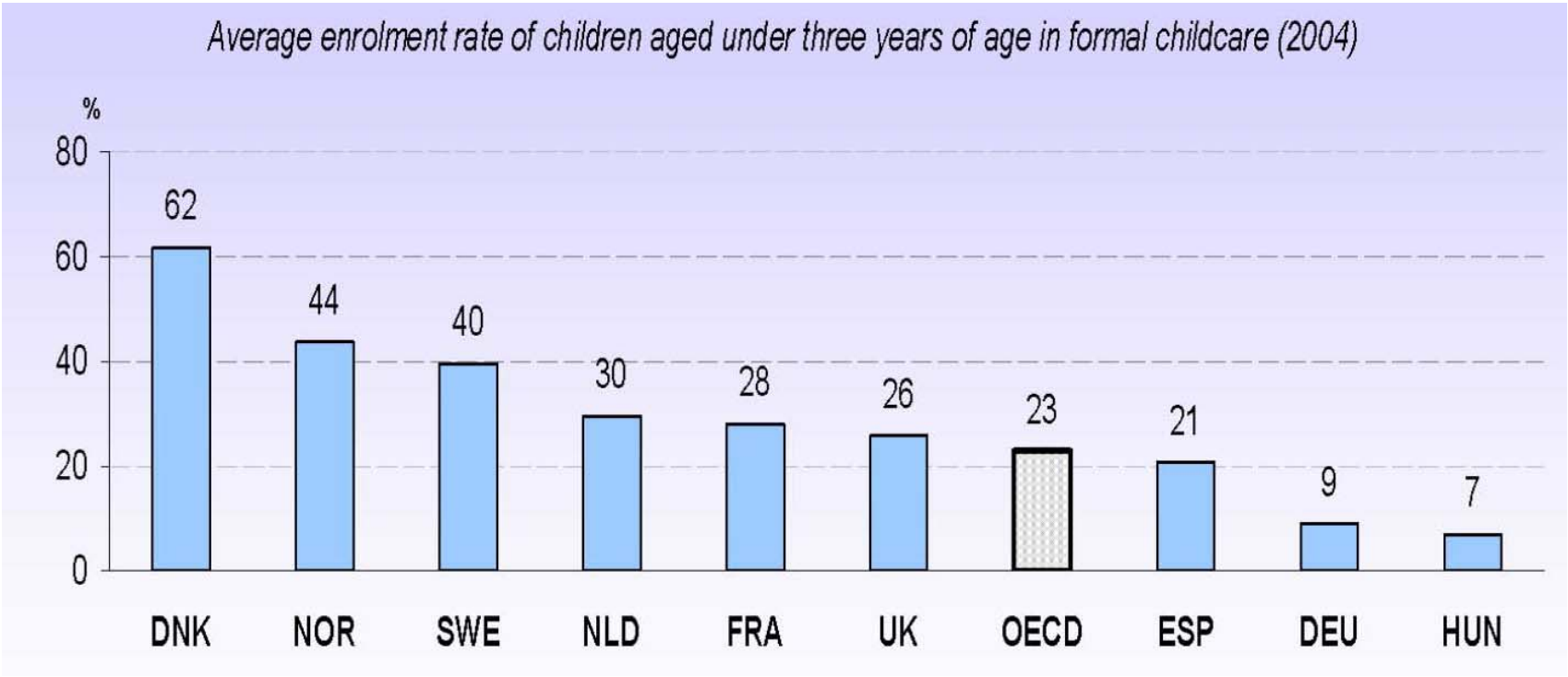


Figure 11: Enrolment in Childcare

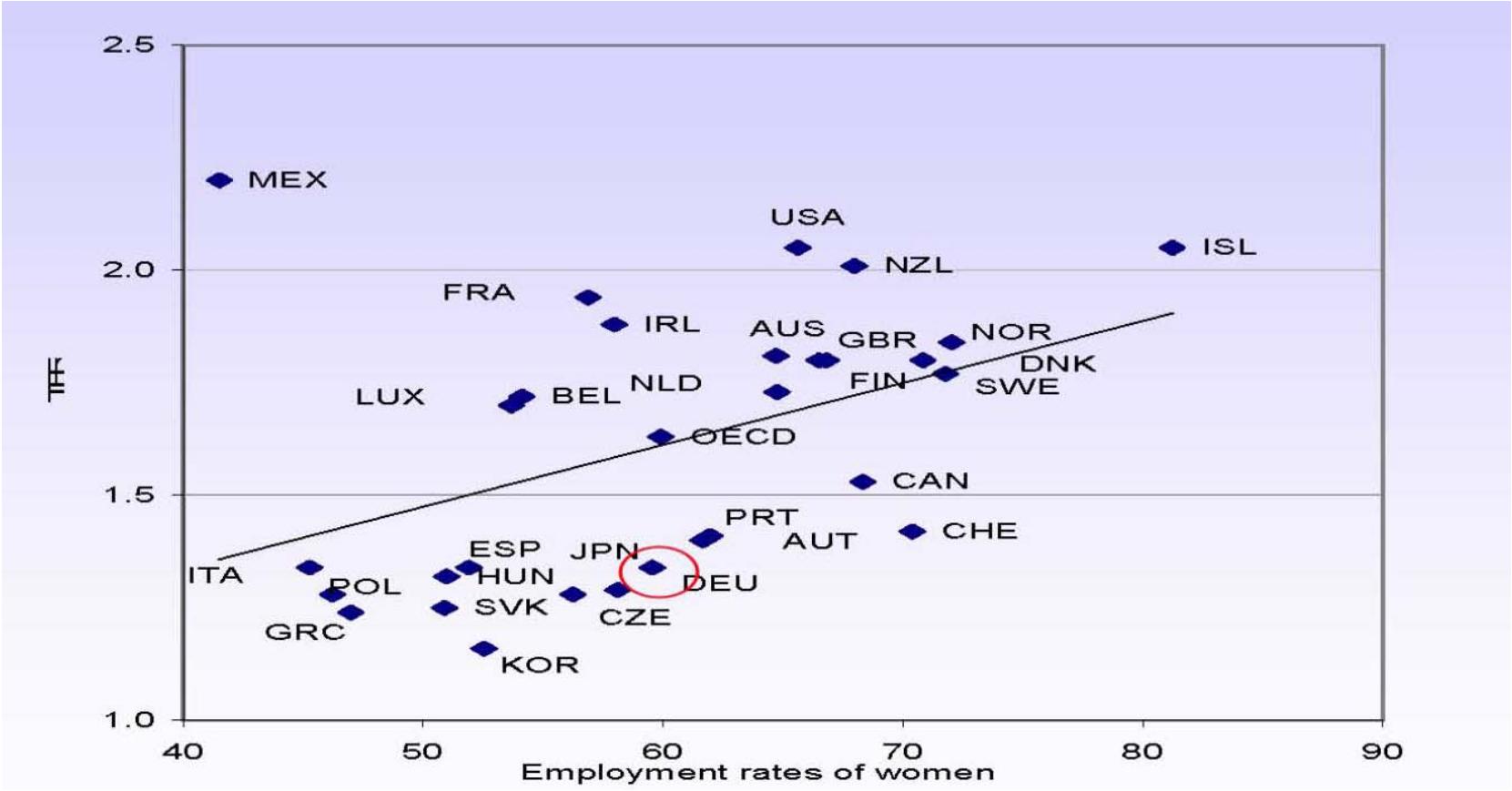


Figure 12: Female Employment Rates and Fertility Rates (2005)

2/3 of CZ gender wage gap in the enterprise sector are 'unexplained' (control for education, age, type of employer and the extent of gender segregation.) The 1/3 that is explained is related to segregation (at firm and occupation level). 10% gap exists even among men and women working in the same firm in the same detailed occupation. Not clear to what extent maternity leaves are at fault here.

CZ women are well represented in lower-managerial ranks, but only 7% of top-level CZ managers are women. This is quite comparable to US figures. The overall pay gap is higher for top managers - due to the highest paying firms having fewer female top managers.

Overall, not much useful evidence on discrimination. The overall situation appears similar to the EU average.