MELBOURNE INSTITUTE
Applied Economic & Social Research

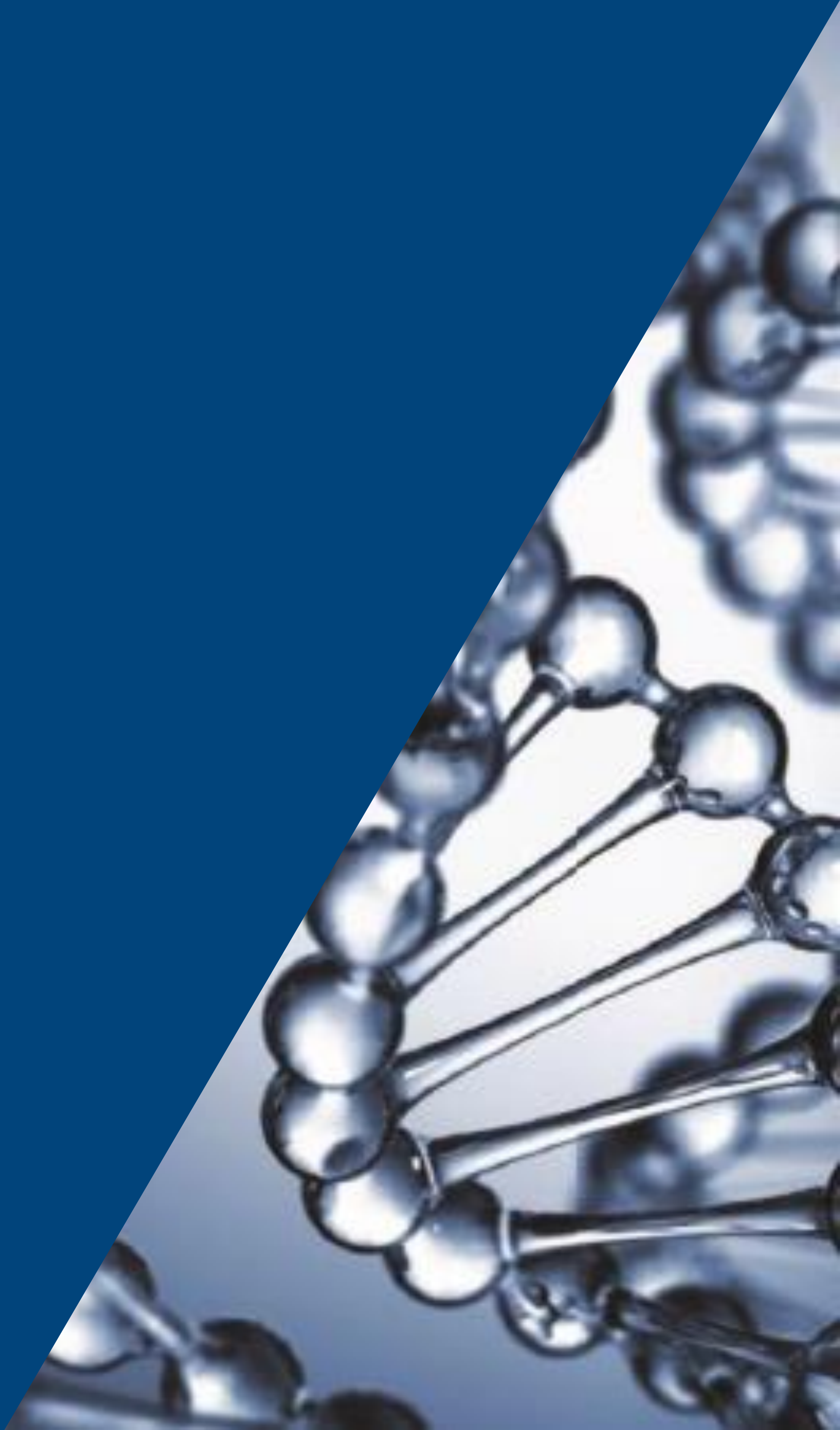
Gender Wage Differences in Indonesia: Does Education Mismatch Matter?

Armida Alisjahbana (University Padjadjaran)

Diana Contreras Suarez (University of Melbourne)

Pipit Pitriyan (University Padjadjaran)

12 July 2021



Empirical evidence on gender wage gap

- Differences in individual characteristics (productivity related ones: education, experience, cognitive and non-cognitive skills);
- Social beliefs, expectations, preferences, norms (e.g. Wang et al, 2013);
- Labour market dynamics (rigidities, market failures, segregation);
- Discriminatory hiring practices (Unconscious bias); or
- Other practices.
  - See Blau and Kahn (2017) JEL for a review

BLINDER-OAXACA DECOMPOSITION

- Differences in characteristics (*endowments*)
- Differences in the way they are rewarded (*Unexplained/discrimination*)
  - Unobserved productive characteristics

Blinder-Oaxaca Decomposition

Having a wage function

$$W_{i,g} = X'_{i,g}\beta_g + \varepsilon_{i,g}, \qquad E[\varepsilon_{i,g}] = 0, \qquad g = \boldsymbol{male}, \boldsymbol{female},$$

The Raw wage gap is defined as

$$R = E(W_m) - E(W_f) = E(X_m)'\hat{\beta}_m - E(X_f)'\hat{\beta}_f + E(X_f)'\hat{\beta}_m - E(X_f)'\hat{\beta}_m$$

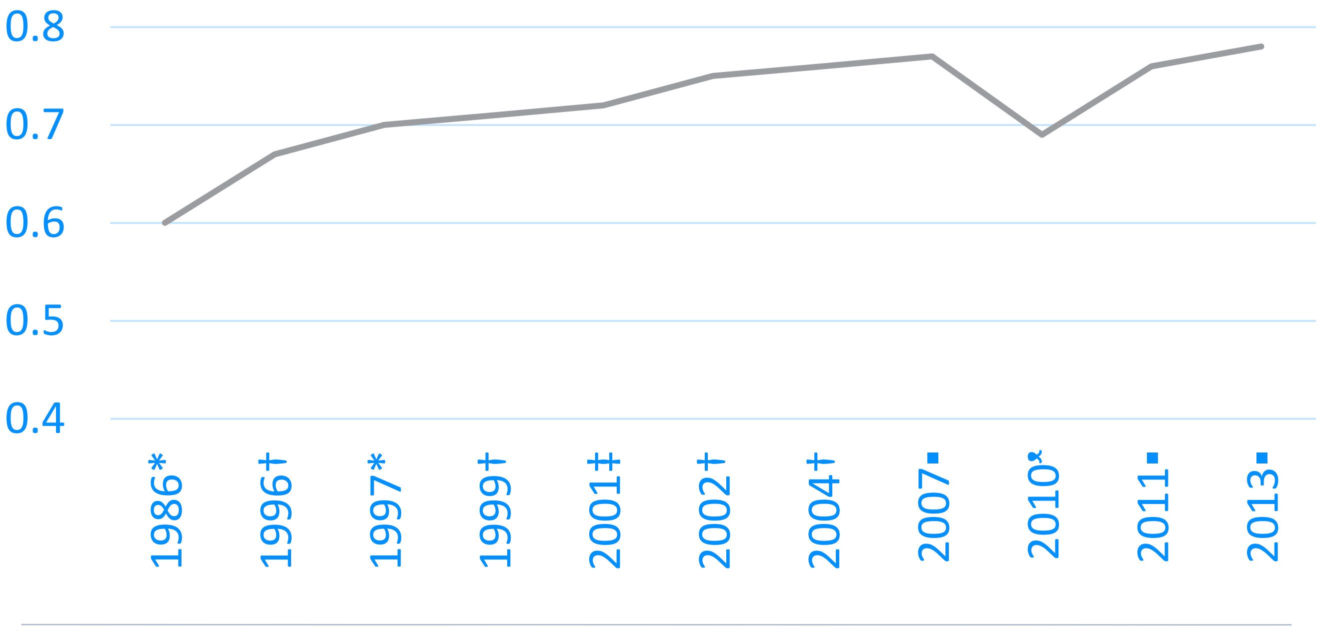
$$= [E(X_m) - E(X_f)]'\hat{\beta}_m \quad + \quad E(X_f)'[\hat{\beta}_m - \hat{\beta}_f]$$

$$= \quad [\overline{X_m} - \overline{X_f}]'\hat{\beta}_m \quad + \quad \overline{X_f}'[\hat{\beta}_m - \hat{\beta}_f]$$

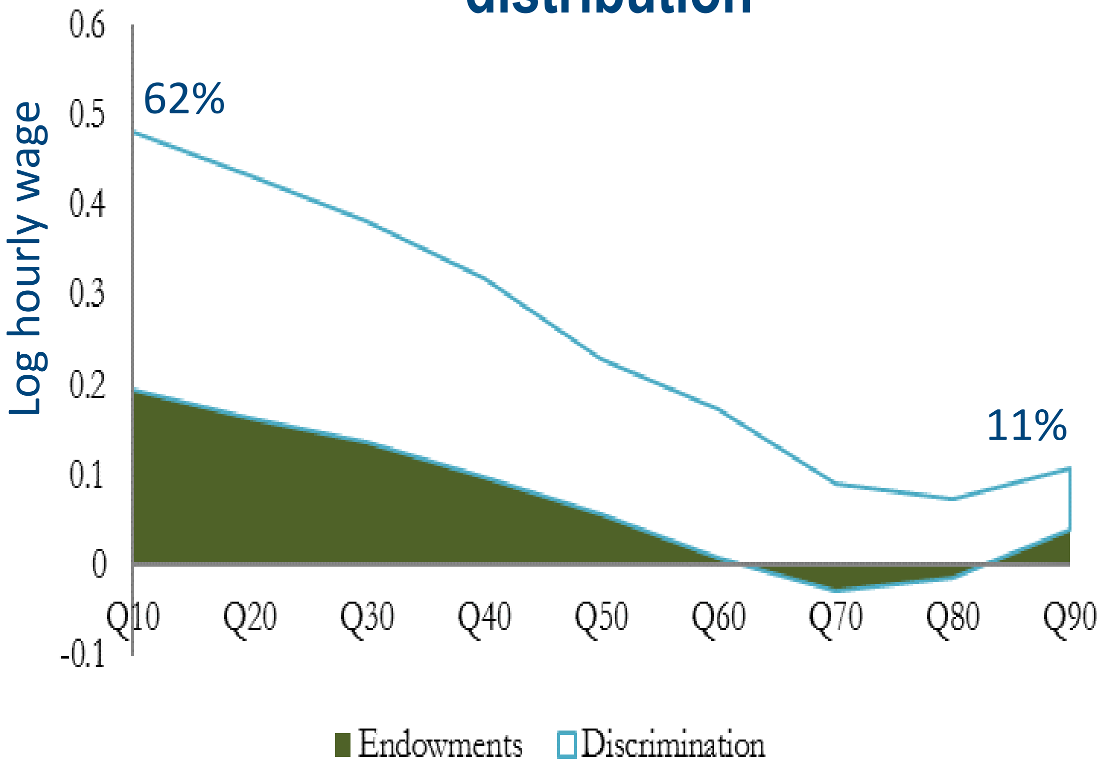
$$= \underbrace{\quad \widehat{\Delta}_X^{\mu} \quad}_{\text{Explained}} + \underbrace{\quad \widehat{\Delta}_S^{\mu} \quad}_{\text{Unexplained}}$$

Gender wage gap Indonesia – Previous research

Female/Male Ratio for Wage workers



Gender wage gap across the distribution



Source: Cameron and Contreras-Suarez (2017)

THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE

What do we know about the effect of mismatch on wages?

- Mismatches affect wages strongly
  - Education mismatch have a large negative effect on wages in the long run (Allen et al., 2001; Baert et al., 2013)
  - There is a wage premium but with diminishing returns to over-education (Johansson et al., 2007).
  - Undereducated workers earn less than workers in similar jobs with the required level of education.

What about differences by gender?

- Females are mismatched more than males
  - College females are more likely to be over-qualified then their male counterparts (Addison et al., 2017).
  - The wage penalty for all mismatched women while only for over-educated men (Mavromas et el., 2013)
  - The wage penalty for mismatch on the field of study and the current job is larger for men (Robst 2007)

What do we know about the effect of mismatch on wages?

What about differences by gender? (Cont.)

- The effect of mismatch on wage gap by gender is still mixed
  - In the US about 7% of the GWG comes from quality matches differential among college graduates (Addison et al., 2017)
  - In Sweden vertical mismatch explains about 2% of the GWG (Johansson et al., 2007).
  - In Austria mismatch reduces the proportion of unexplained GWG by 6% (Cristl et al., 2020)
  - In Spain also vertical mismatch reduces the unexplained GWG to almost zero (Salinas-Jimenez el at., 2013)
  - In Turkey horizontal mismatch does not have any significant effects on wages (Orbay et al., 2021)

Contribution of the paper

- Calculate the incidence of vertical and horizontal mismatch in the tertiary educated Indonesians working in the formal sector
- Estimate the effect of mismatch on wages
- Estimate the contribution of mismatch on explaining gender wage gap

Mismatch definitions (Normative approach)

- Vertical: Level of skill required at job relative to level of study (Using ISCO classification)
  - Adequate, over or under - education
- Horizontal: Field of study relative to the job industry
  - Highly related, partially related or unrelated - job

Data

SAKERNAS 2016 (Industry and Occupation of employment at 3 digits)

Sample:

- Tertiary educated adults aged between 25 and 55;
- Working in formal employment;

We obtained a sample of 7,000 adults (47% men).

Variables:

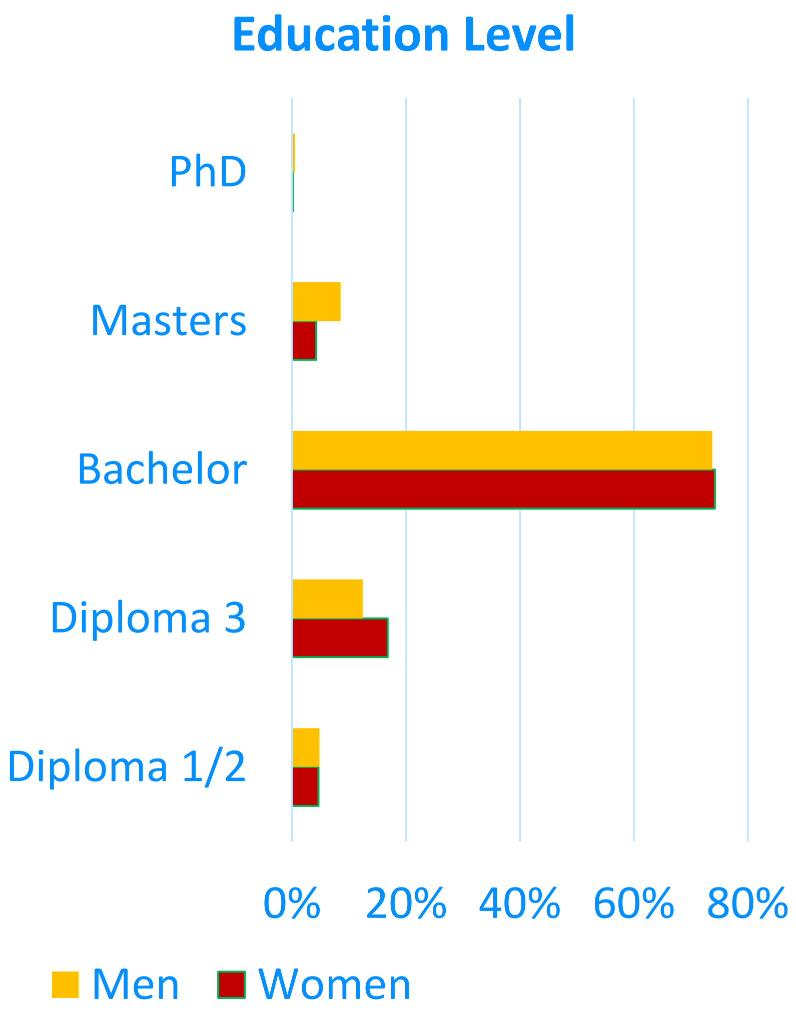
- Wage per hour (in log)
- Education (level of education and major of study)
- Socio-economic characteristics (gender, age, marital status, geography)
- Job characteristics (Occupation, sector, training, tenure)

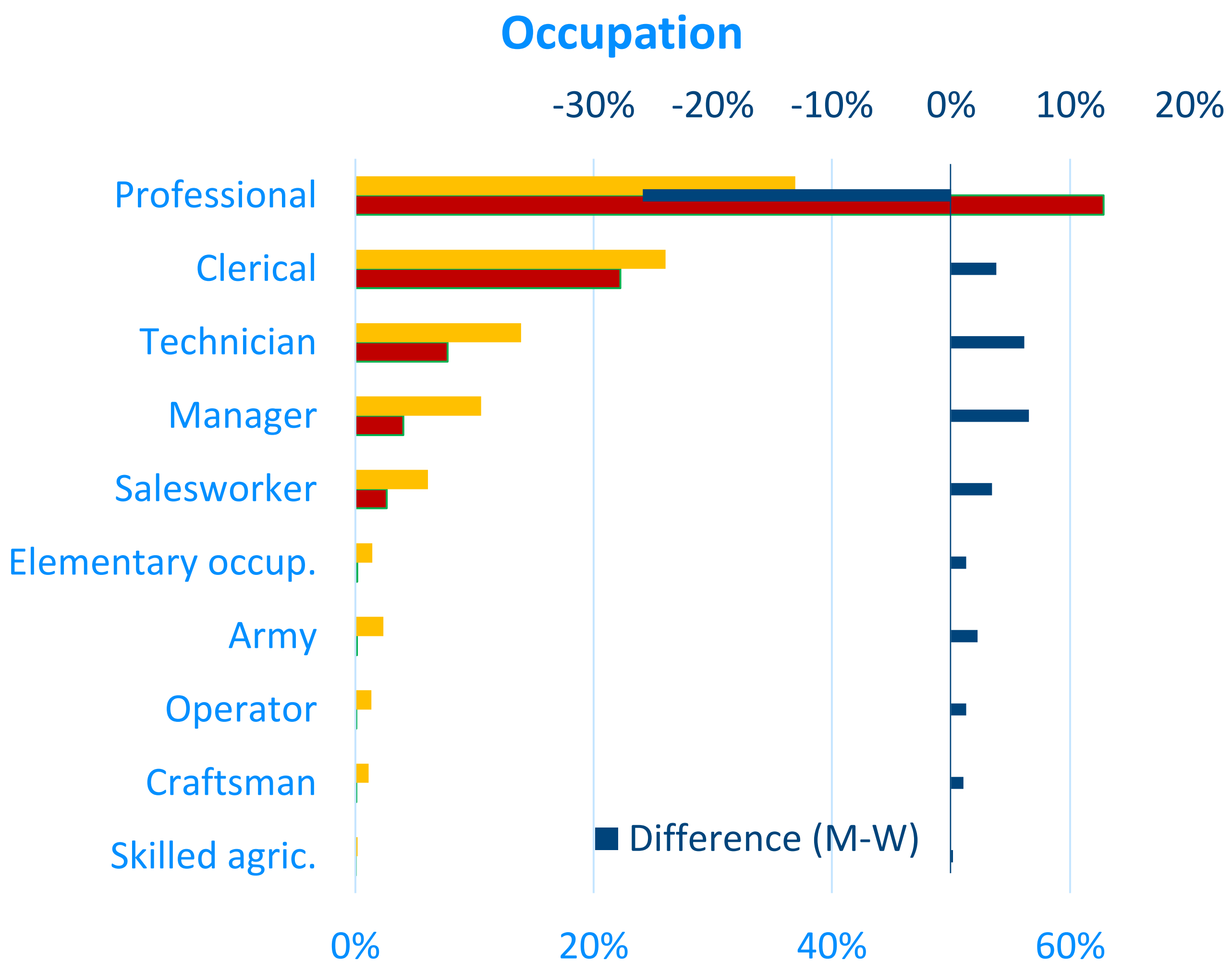
Descriptive Statistics – Socio demographic characteristics

	All	Women	Men
Wage per hour	$ 9,797.42	$ 8,557.03	$ 11,384.43
Age	37.97	37.10	38.94
Age 25 – 39	0.42	0.37	0.47
Age 40 – 54	0.58	0.63	0.53
Married	0.80	0.79	0.82
University	0.81	0.79	0.83
Training in job	0.61	0.60	0.62
Tenure (years)	10.32	10.18	10.47
Urban	0.66	0.64	0.68

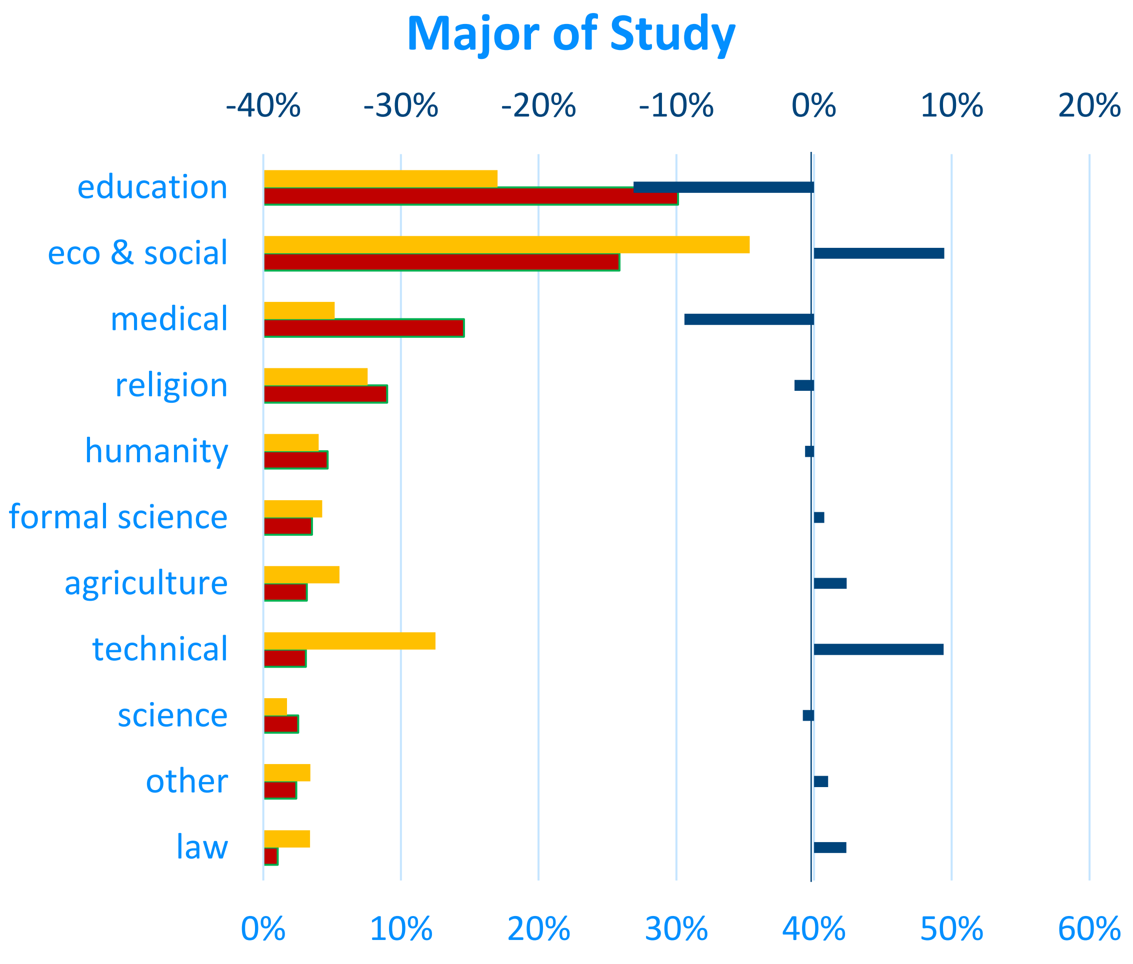
$\Rightarrow$ This is a raw wage gap of 25%

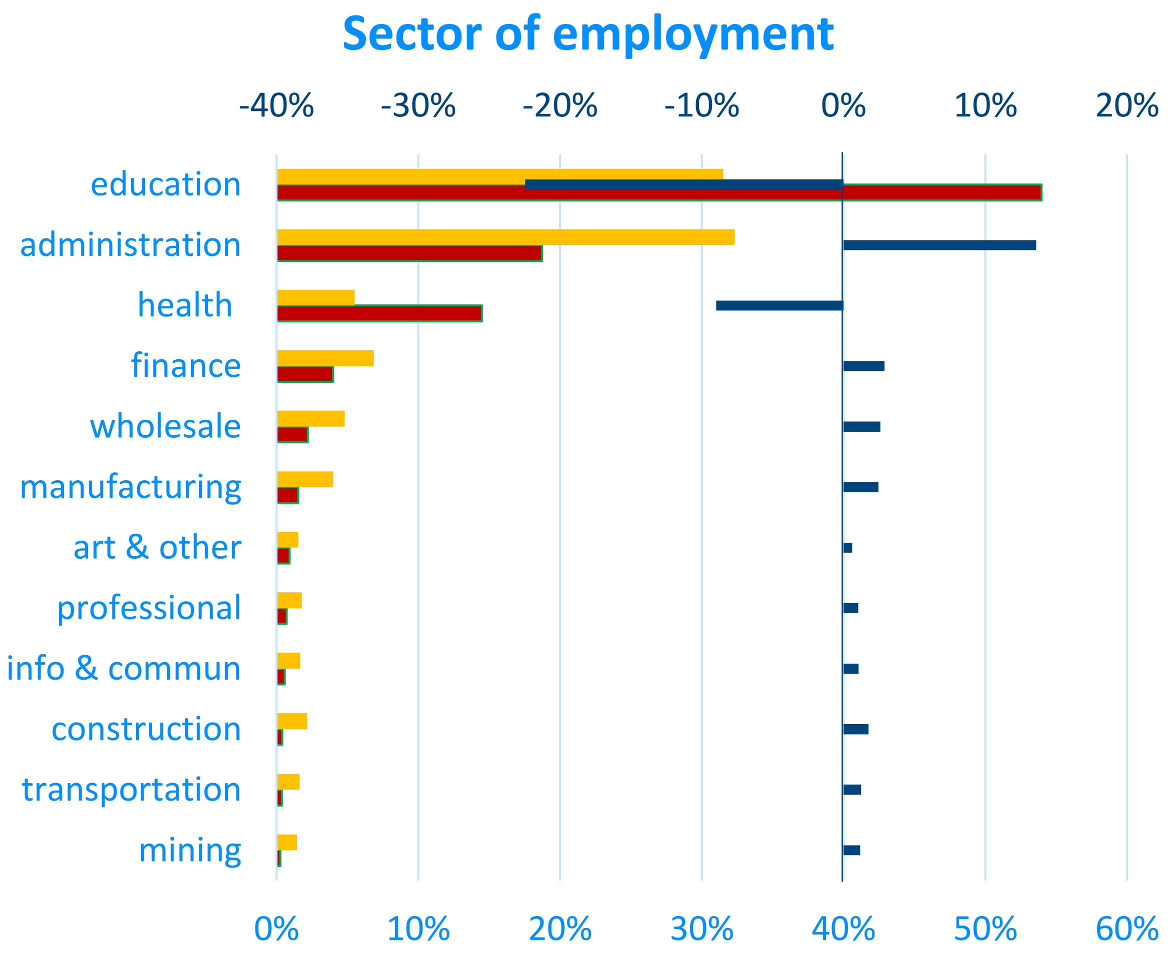
Descriptive Statistics – Vertical Mismatch related variables





Descriptive Statistics – Horizontal Mismatch related variables





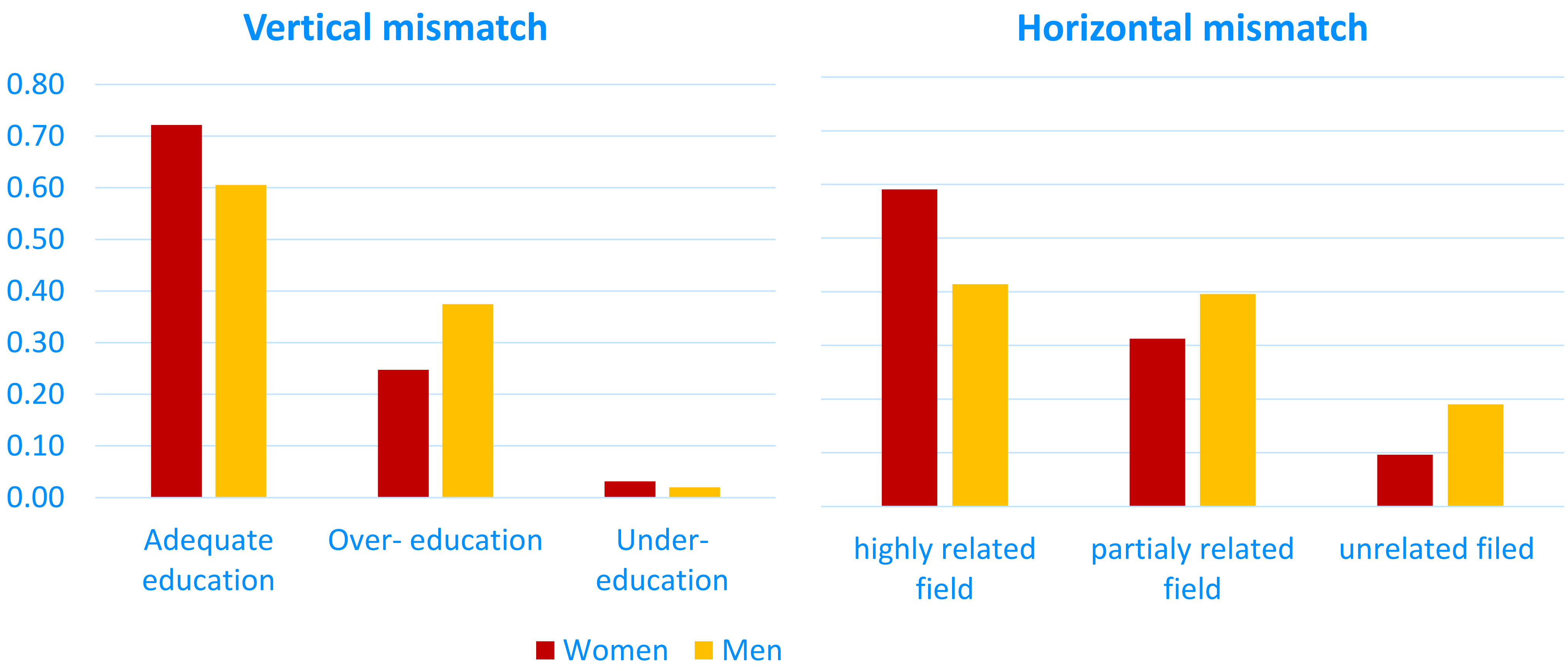
Women Men Difference (M-W)

Elec & gas, water, rent, agriculture, real estate and accommodation not plotted

THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE

Descriptive Statistics –Mismatch Status



THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE

Wage equation

Returns to productive characteristics (OLS)

$$W_{i,g} = X'_{i,g}\beta_g + M'_{i,g}\alpha_g + \delta_p + \varepsilon_{i,g} \qquad g = male, female$$

$W_{i,g}$ is the log of the hourly wage for individual i of gender g

$X_{i,g}$ are productive characteristics (Socio-economic, education, job characteristics)

$M_{i,g}$ are the mismatch indicators

δ_p are province fixed effects

$\mathrm{E}[\varepsilon_{i,g}] = 0.$

To account for lower women's labour supply we correct with a Heckman selection model (25%)

Results – Wage Equation

	Women	Men		Women	Men
Household characteristics			***Major(ref: humanities)***		
Age	0.1103***	0.1010***	Law	0.2439	-0.0215
Age squared	-0.0009**	-0.0010***	Technical	0.2107	0.0769
Married	-0.0982	0.1786***	Medical	0.2072	0.2015**
Living in urban	0.1227**	0.1203***	Science	0.2044	0.1117
University graduate	0.4012***	0.2278***	Formal science	0.1389	0.1204
Training in the job	0.2971***	0.2084***	Agriculture	0.1023	0.068
Tenure	0.0248***	0.0186***	Education	0.0918	0.0333
***Occupation** (ref: clerical)*			Economics & social	0.0826	0.0666
Manager	0.3832*	0.5423***	Religion	0.0737	-0.009
Professional	0.2980	0.2997***	Other	0.0267	0.1783**

Results – Wage Equation (Cont.)

	Women	Men	Pooled
Vertical Mismatch *(ref: adequate education)*			
Overeducated	0.1667	0.1422**	0.1510***
Undereducated	-0.1600	-0.0027	-0.1881**
Horizontal Mismatch *(ref. highly related job)*			
Partially related job	0.0131	-0.0263	-0.0211
Unrelated job	0.0230	-0.0656*	-0.0311
Constant	7.6261***	8.7016***	8.195***
Observations	4,595	3,301	6962
R-squared		0.4005	0.3889

Method: Blinder-Oaxaca Decomposition (Cont.)

- We will follow Oaxaca and Ransom (1994) to select the comparison group
  - The reference group are the coefficients from a pooled regression $\hat{\beta}_*$

$$R = [E(X_m) - E(X_f)]'\hat{\beta}_* \quad + \quad E(X_m)'[\hat{\beta}_m - \hat{\beta}_*] + E(X_f)'[\hat{\beta}_* - \hat{\beta}_f]$$

  - In a robustness test we assume that the non-discriminatory scenario is using men wages. Results are similar.

- We follow Yun (2005) to correct for the base category bias when performing the detailed decomposition.

Results – Oaxaca decomposition: No mismatch

Raw wage ratio	**75%**
Difference in log (adj.)	0.8389***
	(0.1111)
Explained	0.1962***
	23%
Unexplained	0.6427***
	77%

	Explained	Unexplained.
Sector	15% ***	8%
Occupation	-3% ***	-10%
Vertical		
Horizontal		
Age	6% ***	5% ***
Married	1% ***	25% ***
Urban	1% ***	0%
University	1% ***	-18% ***
Training	1% **	-6% **
Tenure	1%	-8% *
Mayor	-1%	2%
Province FE	2% ***	2% *
Constant		76% ***

THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE

Results – Oaxaca decomposition: Mismatch

Raw wage ratio	**75%**
Difference in log (adj.)	0.8921*** (0.1128)
Explained	0.1958*** **22%**
Unexplained	0.6962*** 78%

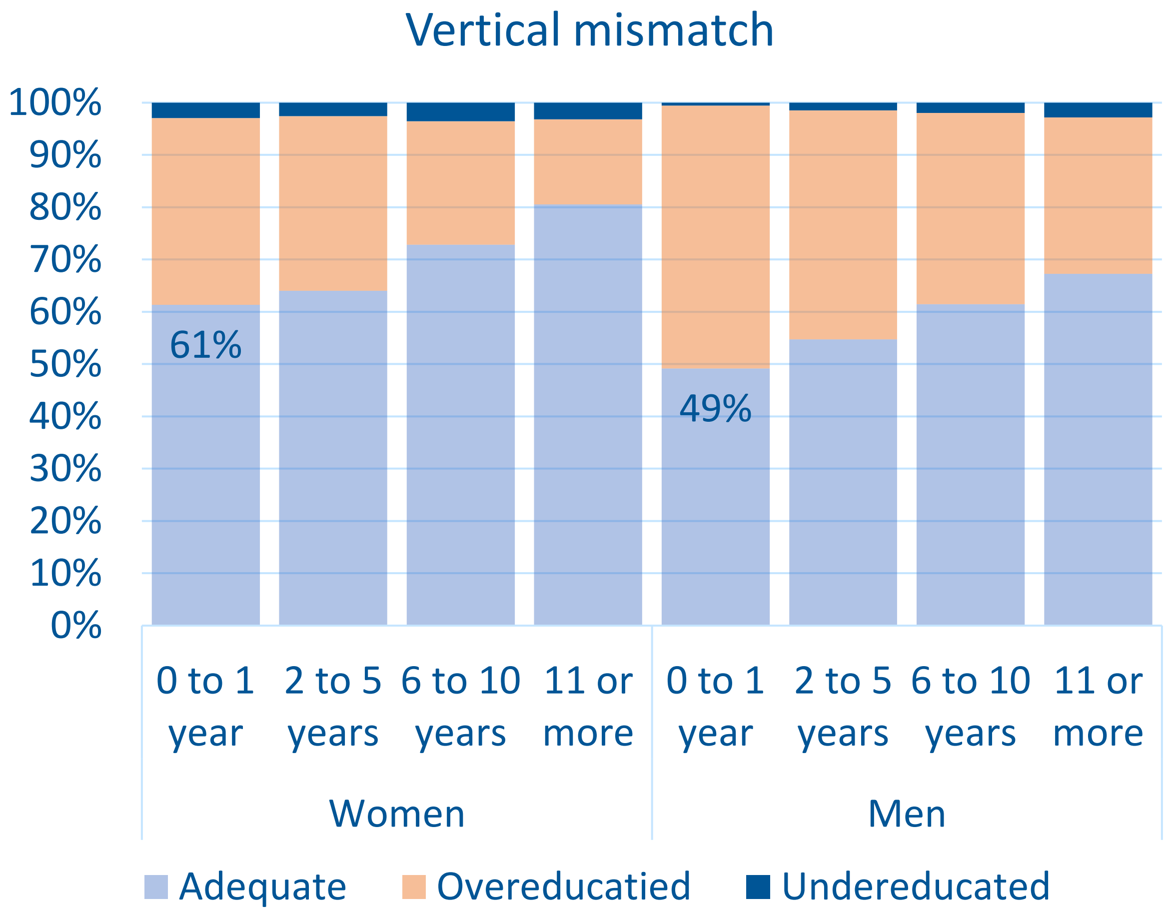
	Explained	Unexplained.
Sector	14% ***	7%
Occupation	-4% ***	-13%
Vertical	2% ***	-5%
Horizontal	0%	2% *
Age	5% ***	5% ***
Married	1% ***	25% ***
Urban	1% ***	0%
University	1% ***	-15% ***
Training	1% **	-6% **
Tenure	1%	-7% *
Mayor	0%	1%
Province FE	2% ***	2% *
Constant		83% ***

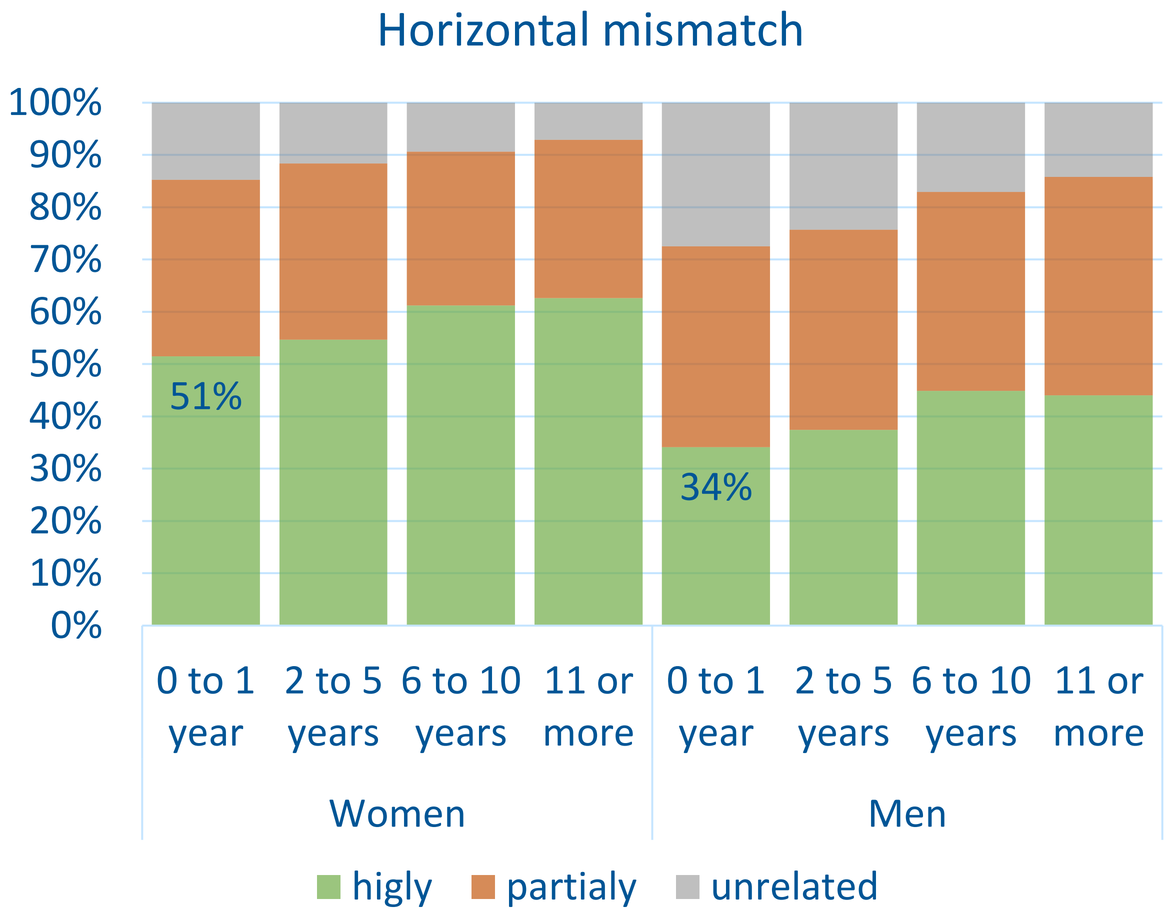
THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE

Results – Heterogeneity Analysis

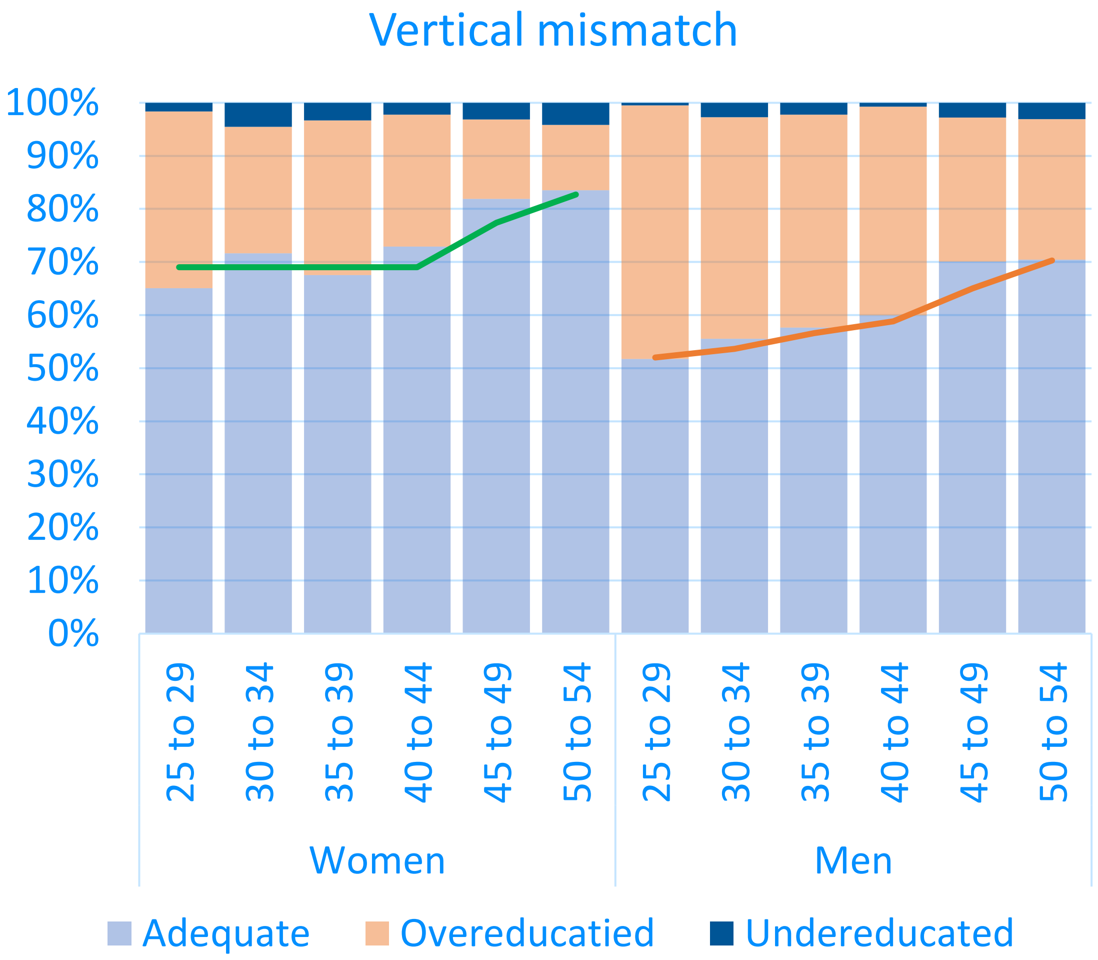
Tenure at the current job

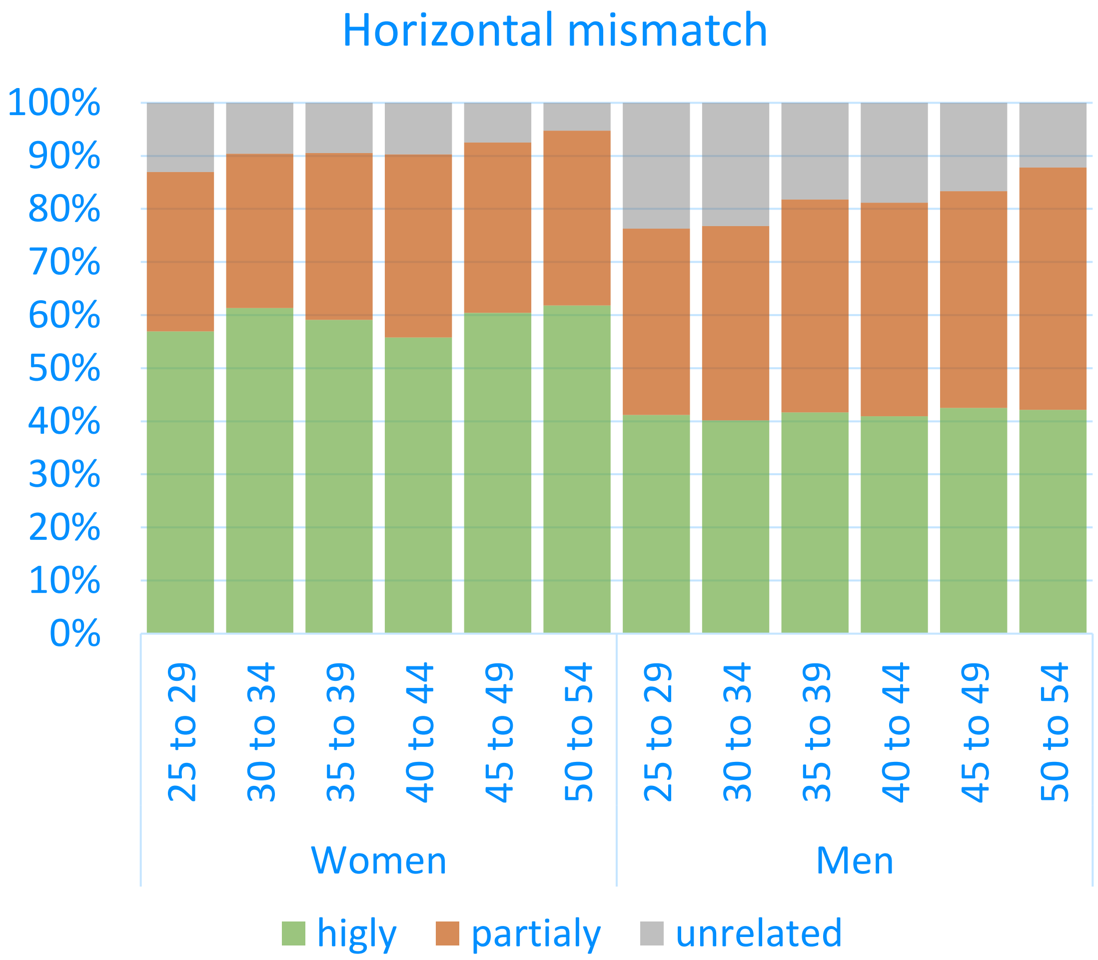




Results – Heterogeneity Analysis

Age cohorts





Results – Heterogeneity analysis: Oaxaca decomposition

In the job less than 2 years (69%)

	Explained 33%	Unexplained. 67%
Sector	18% ***	13%
Occupation	1%	-3%
Vertical	0%	3%
Horizontal	-4% **	-1%
Age	8% ***	9%
Married	0%	18%
Urban	-1%	-2%
University	-1%	-43% **
Training	1%	-6%
Tenure	-1%	7%
Mayor	8% ***	11% *

Age cohort 25 – 39 (75%)

	Explained 23%	Unexplained. 77%
Sector	22% ***	18% **
Occupation	-8% ***	-11%
Vertical	4% **	-7%
Horizontal	0%	3% *
Age	2% ***	-21% ***
Married	0%	22% ***
Urban	1% **	-3%
University	1% ***	-11%
Training	1%	-10% ***
Tenure	-1% ***	4%
Mayor	-1%	2%

THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE

Conclusions

- We find tertiary educated men to be more mismatch than tertiary educated women.
- There is a wage premium for over-education and the premium is larger for men while there is a wage penalty for undereducation (larger for women).
- We find vertical mismatch increases the proportion explained of the gap by 2% and if looking at younger cohorts it explains 4%.
- We do not find that the field-of-study mismatch increases the explained proportion of the gap (except for new workers), but suggest that if women were rewarded like the men the unexplained proportion would increase by 2%.
  - Disconnection between the education sector and the labour market
  - Inefficient as the country skills are not fully utilized (credentialism, discrimination, cultural bias)
  - Higher skills jobs are not growing fast enough relative to the skills of workers
- Consistent to previous lit, sector of employment is the main contributor to the explained gap, while marriage (↑) and education(↓) contribute to the unexplained proportion.

Thank you!

Diana.Contreras@unimelb.edu.au

THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE

Heckman selection model

VARIABLES	select	/mills	select	/mills
Age	0.0185***		0.0393***	
	(0.0029)		(0.0067)	
Years of schooling	0.1298***		0.1102***	
	(0.0188)		(0.0233)	
Married	-0.3243***		-0.3200***	
	(0.0634)		(0.0773)	
Children under 6 =1	0.0020		-0.1277*	
	(0.0494)		(0.0683)	
lambda		1.7801***		1.2698*
		(0.6789)		(0.6506)
Constant	-1.8210***		-2.0189***	
	(0.3436)		(0.4549)	
Observations	4,595	4,595	2,953	2,953
Selected	3661		2304	
Non-selected	934		649	
Sample	all women		women 25 to 39	

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Selection equation calculated on the wage equation including 6 categories of horizontal and vertical mismatch