Gender Differences in Reservation Wages: New Evidence for Germany

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Motivation I

Despite political emphasis, substantial gender differences in pay persist (e.g., Blau and Kahn, 2017).

Previous research suggests that females – compared to males – have:

- lower wage expectations prior to entering the labor market (e.g., Reuben et al., 2017; Briel et al., 2021);
- lower reservation wages (e.g., Brown et al., 2011; Le Barbanchon et al., 2020).

Since aspirations and expectations about wages can be self-fulfilling, differences in reservation wages might transmit to actual pay differences.

Hence, a better understanding of the gender reservation wage differential may help to explain persistent gender gaps in realized wages.

Motivation II

Reservation Wage: lowest wage at which an individual is willing to work.

It plays an important role in labor supply and job search models.

In labor supply models, the reservation wage depends on the marginal rate of substitution between consumption and leisure and on the non-wage income (e.g., Blundell and Macurdy, 1999).

In job search models, the reservation wage depends on the distribution of wages and on the arrival rate of job offers (e.g., Mortensen, 1986).

Thus, measures of reservation wages might reflect both a consumption-leisure trade-off and job search concerns.

Previous Literature

Brown et al. (2011) find a substantial gender gap in reservation wages of non-employed individuals using British panel data.

Caliendo et al. (2017) show that a substantial part of the gender wage gap can be explained by reservation wages using a sample of newly unemployed individuals in Germany.

Humpert and Pfeifer (2013) study determinants of male and female reservation wages using German survey data.

Le Barbanchon et al. (2020) find that women have lower reservation wages and accept shorter commuting time than men using French administrative data of unemployed individuals.

Data

- In 1987, the SOEP first asked non-employed individuals about their monthly reservation wage.
- However, non-employed individuals were first asked about their desired weekly working hours in 2007.
- Since 2007, information about monthly reservation wages and desired working hours are available on a yearly basis.
- Thus, we base our analysis on an unbalanced panel from 2007 to 2019.

Hourly Reservation Wage

Individuals in the SOEP who are currently not employed and who do not rule out future employment are asked the following two questions:

1. "What would your net income have to be for you to accept a position?"
   (*"Wie hoch müsste der Nettoverdienst mindestens sein, damit Sie eine angebotene Stelle annehmen würden?"*)
2. "How many hours per week would you have to work to earn this net income?"
   (*"Und was meinen Sie, wie viele Stunden pro Woche müssten Sie für diesen Nettoverdienst arbeiten?"*)

Based on the answers to these two questions we construct the hourly reservation wage as

$$\text{Hourly Reservation Wage} = \left(\frac{\text{Monthly Reservation Wage}}{4.25 \cdot \text{Desired Weekly Working Hours}}\right) \cdot \frac{1}{CPI_{2015}}$$

Sample

- Our Sample includes non-employed individuals that report reservation wage and desired working hours.
- Years: 2007 - 2019
- Age: 25 - 65
- We drop observations with one percent smallest and one percent largest value of hourly reservation wage.
- We drop observations with missing covariates.

We use an unbalanced panel:

- 6,700 Observations
- 3,855 Individuals
- Average number of observations per individual is 1.74.

Descriptive Statistics

Table: Summary Statistics

	Males	Females	Difference
Reservation Wages			
Monthly Reservation Wage	1572.39 (687.57)	1156.22 (586.25)	416.17***
Desired Working Hours	38.01 (7.54)	28.75 (10.62)	9.26***
Hourly Reservation Wage	9.84 (3.93)	9.86 (4.14)	-0.02
Background Variables			
Age	42.98 (11.29)	40 (9.82)	2.98***
Married	0.5 (0.5)	0.61 (0.49)	-0.11***
Household Net Income	1949.12 (1321.77)	2513.87 (1792.13)	-564.75***
Childcare	0.36 (0.48)	0.66 (0.47)	-0.3***
Education			
Vocational Degree	0.71 (0.45)	0.69 (0.46)	0.02**
College Degree	0.14 (0.34)	0.21 (0.41)	-0.08***
Labor Market History			
Full-Time Experience	15.34 (11.86)	7.47 (7.78)	7.86***
Part-Time Experience	1.24 (2.36)	3.77 (4.62)	-2.53***
Unemployment Experience	4.31 (4.76)	2.95 (4.67)	1.37***
Last Net Hourly Wage	7.96 (5.87)	7.92 (5.53)	0.04
Observations	2,473	4,227	

Note: The first two columns show means and standard deviations (in parentheses). The last column shows the the difference in means between males and females. *, ** and *** indicate statistical significance of the difference at the 10%-, 5%-, and 1%-level, respectively. *Source:* SOEP, own calculations.

More

Estimation of the Unexplained Gender Gap

The related literature generally uses Blinder-Oaxaca decompositions (Blinder, 1973; Oaxaca, 1973) to estimate the unexplained gender gap in reservation wages.

Recent studies suggest that the size of the estimated unexplained gender pay gap is very sensitive to methodological choices (Briel and Töpfer, 2020; Strittmatter and Wunsch, 2021).

We estimate the unexplained gender gap in reservation wages using a variety of estimators:

- Linear Regression (LRM)
- Blinder-Oaxaca Decomposition (BO)
- Inverse Probability Weighting (IPW)
- Augmented Inverse Probability Weighting (AIPW)

In addition, we allow for model flexibility using machine learning methods.

Linear Regression I

We estimate the linear regression model

$$y_i = \beta_0 + \delta_{LRM} \cdot df_i + \mathbf{x}_i \boldsymbol{\beta} + u_i \tag{1}$$

y_i: Log hourly reservation wage

df_i: Dummy variable that is equal to one if individual is female

$\mathbf{x}_i$: Vector of control variables that includes inter alia information on age, marital status, household income, children, education, labor market experience, last job, last wage, unemployment benefits, job search, and personality Overview

u_i: Error term

Linear Regression II

Table: Reservation Wage Regressions

	(1) Raw	(2) Controls	(3) Males	(4) Females
Female	-0.0040	-0.0629***		
	(0.0124)	(0.0136)		
Married		0.0120	0.0406**	-0.0040
		(0.0111)	(0.0168)	(0.0145)
Log HH Income		0.1005***	0.1047***	0.0911***
		(0.0113)	(0.0171)	(0.0150)
Partner Full-Time		-0.0874***	-0.0950***	-0.0716***
		(0.0118)	(0.0209)	(0.0147)
Youngest Child ≤ 3		0.0631**	0.0227	0.0765**
		(0.0278)	(0.0370)	(0.0388)
Childcare		0.0221*	0.0311*	0.0215
		(0.0117)	(0.0178)	(0.0149)
Vocational Degree		-0.0091	-0.0041	-0.0181
		(0.0126)	(0.0183)	(0.0162)
College Degree		0.1217***	0.1095***	0.1202***
		(0.0156)	(0.0266)	(0.0190)
Log Wage Last Job		0.0663***	0.0457***	0.0790***
		(0.0087)	(0.0134)	(0.0117)
Reg. as Unemployed		-0.0404***	-0.0208	-0.0561***
		(0.0132)	(0.0207)	(0.0168)
Controls		✓	✓	✓
Observations	6,700	6,700	2,473	4,227

Note: Dependent variable is the log of the hourly reservation wage. In Columns 2 to 4, we include our baseline control variables. Standard errors are clustered at the individual level and are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%-, 5%-, and 1%-level, respectively. *Source:* German Socio-Economic Panel v36, own calculations.

Blinder-Oaxaca Decomposition I

$$y_{ig} = \beta_{0g} + \mathbf{x}_i \boldsymbol{\beta}_g + u_{ig} \quad \text{for} \quad g = M, F \tag{2}$$

Decomposition of the mean difference (Oaxaca, 1973; Blinder, 1973):

$$\begin{aligned} \hat{\Delta}_O &= \overline{y_F} - \overline{y_M} \\ &= \underbrace{(\hat{\beta}_{0F} - \hat{\beta}_{0M}) + \overline{\mathbf{x}}_F(\hat{\boldsymbol{\beta}}_F - \hat{\boldsymbol{\beta}}_M)}_{\hat{\Delta}_U} + \underbrace{(\overline{\mathbf{x}}_F - \overline{\mathbf{x}}_M)\hat{\boldsymbol{\beta}}_M}_{\hat{\Delta}_E} \end{aligned} \tag{3}$$

$\hat{\Delta}_U^{\mu}$: Unexplained part that captures differences in male and female coefficient vector and intercepts

$\hat{\Delta}_E^{\mu}$: Explained part that captures gender differences in observed characteristics

The unexplained part can alternatively be expressed as

$$\hat{\Delta}_U^{\mu} = \hat{\delta}_{BO} = \frac{1}{N_F} \sum_{i=1}^{N} df_i (y_i - \hat{\mu}_M(\mathbf{x}_i)), \tag{4}$$

where $N_F = \sum_{i=1}^{N} df_i$ and $\hat{\mu}_M(\mathbf{x}_i) \equiv \hat{\beta}_{0M} + \mathbf{x}_i \hat{\boldsymbol{\beta}}_M$.

Blinder-Oaxaca Decomposition II

Table: Reservation Wage Decomposition

	Aggregate Decomposition	
Raw Gender Gap	-0.0040	
	(0.0124)	
Explained Part	0.0660***	
	(0.0180)	
Unexplained Part	-0.0700***	
	(0.0188)	
	Contr. Expl. Part	Contr. Unexpl. Part
Partner	-0.0200***	-0.0111
	(0.0066)	(0.0167)
Household	0.0270***	-0.0494*
	(0.0046)	(0.0282)
Children	0.0100*	0.0003
	(0.0052)	(0.0156)
Education	0.0086***	-0.0073
	(0.0025)	(0.0198)
Labor Market History	0.0194	0.0841
	(0.0169)	(0.0666)
Unemployment	0.0026	0.0000
	(0.0058)	(0.0108)
Job Search	0.0094	0.0185
	(0.0087)	(0.0201)
Personality	-0.0002	0.0152
	(0.0040)	(0.0487)
Remainder	0.0093	0.0470
	(0.0071)	(0.2273)
Observations	6,700	

Note: The dependent variable is the log of the hourly reservation wage. The male coefficient vector is used as the reference vector. The standard errors are calculated as described by Jann (2008), are clustered at the individual level, and are shown in parenthesis. *, ** and *** indicate statistical significance at the 10%-, 5%-, and 1%-level, respectively.
Source: German Socio-Economic Panel v36, own calculations.

Inverse Probability Weighting

We estimate the conditional probability of being female based on the model

$$p(\mathbf{x}_i) = \Pr(df_i = 1|\mathbf{x}_i) = G(\mathbf{x}_i\boldsymbol{\gamma}), \tag{5}$$

where we use the logistic distribution function as the binary link function $G(\cdot)$.

Next, we predict $\hat{p}(\mathbf{x}_i)$ for all observations and estimate the unexplained gender gap as

$$\hat{\delta}_{IPW} = \frac{1}{N_F}\sum_{i=1}^{N} df_i \cdot y_i - \sum_{i=1}^{N} \hat{w}_i^M \cdot y_i, \tag{6}$$

where

$$\hat{w}_i^M = \frac{(1-df_i)\hat{p}(\mathbf{x}_i)}{1-\hat{p}(\mathbf{x}_i)} \Bigg/ \sum_{i=1}^{N} \frac{(1-df_i)\hat{p}(\mathbf{x}_i)}{1-\hat{p}(\mathbf{x}_i)} \tag{7}$$

are the IPW weights.

Augmented Inverse Probability Weighting

Additionally, we estimate the unexplained gender gap using AIPW.

AIPW is doubly robust, i.e. it requires only either the propensity score or the reservation wage model to be correctly specified.

The AIPW estimator is given by

$$\hat{\delta}_{AIPW} = \frac{1}{N_F} \sum_{i=1}^{N} df_i(y_i - \hat{\mu}_M(\mathbf{x}_i)) - \sum_{i=1}^{N} \hat{w}_i^M (y_i - \hat{\mu}_M(\mathbf{x}_i)). \tag{8}$$

While the first right hand term in (8) is identical to the BO estimator, the second right hand term has an expected value of zero but makes a finite sample adjustment by re-weighting the observable bias in $\hat{\mu}_M(\mathbf{x}_i)$.

Data-Driven Model Specifications

Apart from varying the estimation method, we also use data-driven model specifications.

We expand the set of potential controls by including more variables (e.g., parental education, religion) and by constructing various higher-order polynomials and interaction terms.

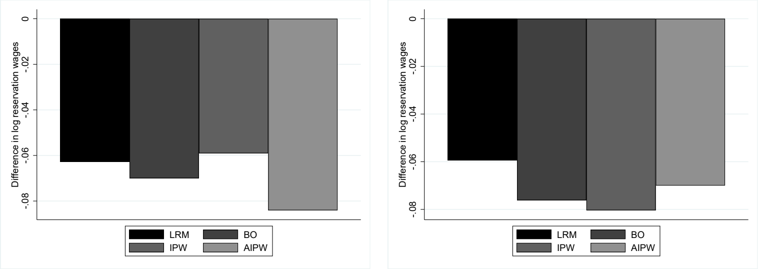
We use the Least Absolute Shrinkage and Selection Operator (LASSO) to specify our data-driven models.

In particular:

- in case of LRM, we apply the post-double-selection procedure proposed by Belloni et al. (2014a,b).
- in case of BO, we estimate the conditional male reservation wage, $\hat{\mu}_M(\mathbf{x})$, using the LASSO.
- in case of IPW, we estimate the propensity score, $\hat{p}(\mathbf{x})$, using the logit-LASSO (Hastie et al., 2015).
- in case of AIPW, we estimate $\hat{\mu}_M(\mathbf{x})$ and $\hat{p}(\mathbf{x})$ using the LASSO and the logit-LASSO, respectively.

Comparison of Unexplained Gender Gap Estimates

Figure: **Unexplained Gender Gap in Reservation Wages, Various Estimators**



(a) Baseline Model (b) Data-Driven Model

Notes: Figure displays estimates of the unexplained gender gap in reservation wages using linear regressions (LRM), Blinder-Oaxaca decompositions (BO), inverse probability weighting (IPW), and augmented inverse probability weighting (AIPW). Subfigure (a) shows estimates based on our baseline model, while Subfigure (b) shows estimates based on our data-driven model. *Source:* German Socio-Economic Panel v36, own calculations.

Table

Conclusion

- We find no statistically significant raw gender gap in log hourly reservation wages in our sample.
- However, once we control for various characteristics of individuals, we find a statistically significant unexplained gender gap in reservation wages ranging from 6 to 8 percent.
- Overall, we do not see large differences in the size of the estimated unexplained gender gap depending on the estimator and the model specification.
- Our findings provide robust empirical evidence that German non-employed women set considerably lower reservation wages than comparable men.

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Overview Control Variables

Baseline:

- Background variables: age, married, log household net income, household size, employment status partner (full-time, part-time, unemployed), age of youngest child (under 3, 6, 18), childcare, migration background, federal state fixed effects, year fixed effects, log unemployment rate at federal state level
- Education: vocational degree, college degree
- Labor Market History: full-time experience, part-time experience, unemployment experience, log hourly wage last job, ISCO88 (1-digit) last job, NACE (1-digit) last job
- Unemployment: registered as unemployed, ALG 1, ALG 2, amount of ALG 1
- Job Search: looking for full-time employment, difficulty of finding job, could accept job immediately, active job search in last four weeks, intended time of employment, likelihood of future employment
- Personality: risk tolerance, big five personality traits

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Descriptive Statistics I

Table: Summary Statistics

	Males	Females	Difference
Background Variables			
Household Size	2.84 (1.53)	3.25 (1.36)	-0.41***
Partner Full-Time	0.16 (0.37)	0.49 (0.5)	-0.33***
Partner Part-Time	0.14 (0.34)	0.02 (0.14)	0.12***
Partner Unemployed	0.15 (0.35)	0.07 (0.25)	0.08***
Youngest Child $\leq$ 3	0.02 (0.16)	0.02 (0.14)	0
Youngest Child $\leq$ 6	0.1 (0.3)	0.12 (0.33)	-0.02***
Youngest Child $\leq$ 18	0.29 (0.45)	0.39 (0.49)	-0.1***
Migration Background	0.26 (0.44)	0.24 (0.43)	0.02*
Unemployment			
Registered as Unemployed	0.75 (0.43)	0.44 (0.5)	0.31***
Receiving ALG 1	0.28 (0.45)	0.14 (0.35)	0.14***
Receiving ALG 2	0.39 (0.49)	0.26 (0.44)	0.13***
Amount of ALG 1	295.35 (537.46)	107.62 (308.2)	187.72***
Observations	2,473	4,227	

Note: The first two columns show means and standard deviations (in parentheses). The last column shows the the difference in means between males and females. *, ** and *** indicate statistical significance of the difference at the 10%-, 5%-, and 1%-level, respectively.
Source: SOEP, own calculations.

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Descriptive Statistics II

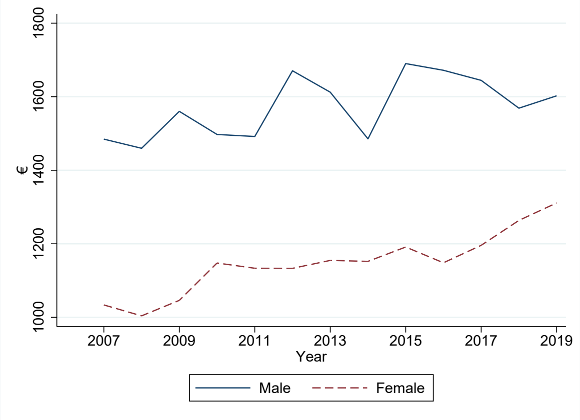
Table: Summary Statistics

	Males	Females	Difference
Job Search			
Looking for Full-Time Job	0.71 (0.46)	0.24 (0.43)	0.47***
Finding Vacancy: Difficult	0.59 (0.49)	0.57 (0.5)	0.02
Finding Vacancy: Impossible	0.22 (0.42)	0.18 (0.39)	0.04***
Could Accept Job Immediately	0.8 (0.4)	0.53 (0.5)	0.28***
Active Job Search	0.6 (0.49)	0.38 (0.48)	0.22***
Employment Intended Immediately	0.7 (0.46)	0.4 (0.49)	0.31***
Future Employment Unlikely	0.09 (0.29)	0.08 (0.27)	0.01
Personality			
Openness	4.49 (1.23)	4.71 (1.17)	-0.22***
Conscientiousness	3.01 (0.99)	3.22 (0.89)	-0.21***
Extraversion	2.14 (1.15)	2.42 (1.11)	-0.28***
Neuroticism	1.2 (1.22)	1.55 (1.23)	-0.35***
Agreeableness	2.6 (1.02)	2.86 (0.93)	-0.27***
Risk Tolerance	5.32 (2.38)	4.52 (2.35)	0.8***
Observations	2,473	4,227	

Note: The first two columns show means and standard deviations (in parentheses). The last column shows the the difference in means between males and females. *, ** and *** indicate statistical significance of the difference at the 10%-, 5%-, and 1%-level, respectively. *Source:* SOEP, own calculations.

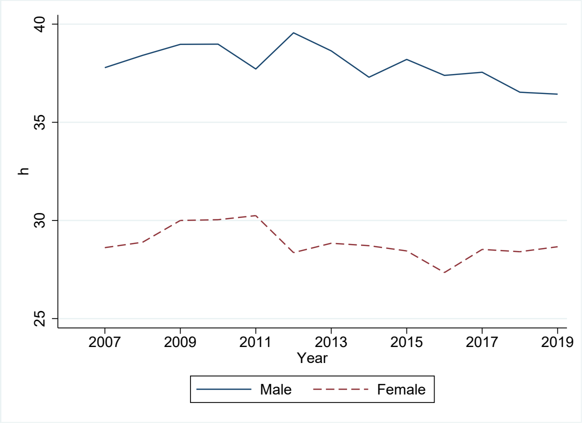
Reservation Wage across Years I

Figure: Monthly Reservation Wage by Gender



Reservation Wage across Years II

Figure: Desired Working Hours by Gender



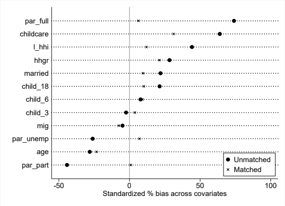
Reservation Wage across Years III

Figure: Hourly Reservation Wage by Gender

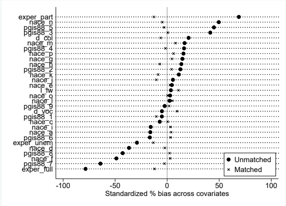
Covariate Balancing with Baseline Model

Figure: Balancing with IPW (Baseline Model)

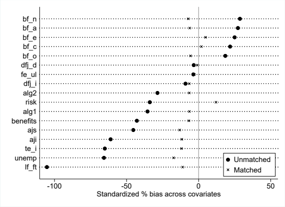
(a) Demographics



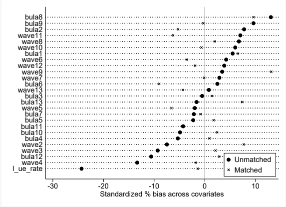
(b) Education and Labor Market History



(c) Unemployment, Job Search, and Personality



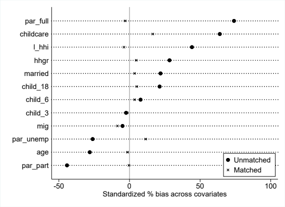
(d) Year, Federal State, and Unem. Rate



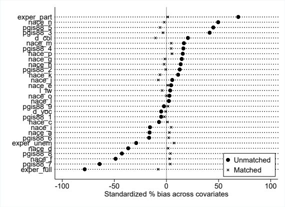
Covariate Balancing with Data-Driven Model

Figure: Balancing with IPW (Data-Driven Model)

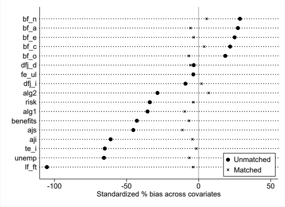
(a) Demographics



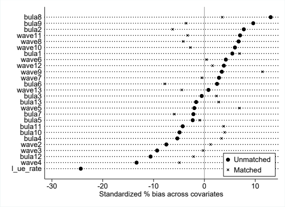
(b) Education and Labor Market History



(c) Unemployment, Job Search, and Personality



(d) Year, Federal State, and Unem. Rate



Comparison of Unexplained Gender Gap Estimates I

Table: Estimates of Unexplained Gender Gap in Reservation Wages (Baseline Model)

	(1) LRM	(2) OB	(3) IPW	(4) AIPW
Unexplained Gender Gap	-0.0629	-0.0700	-0.0591	-0.0841
	(0.0136)	(0.0188)	(0.0222)	(0.0204)
Observations	6700	6700	5204	5204

Note: Table shows different estimates of the unexplained gender difference in log hourly reservation wage. Column (1) Linear regression. Column (2) Blinder-Oaxaca decomposition. Column (3) Inverse Probability Weighting. Column (4) Augmented Inverse Probability Weighting. *Source:* German Socio-Economic Panel v36, own calculations.

Comparison of Unexplained Gender Gap Estimates II

Table: Estimates of Unexplained Gender Gap in Reservation Wages (Data-Driven Model)

	(1) LRM	(2) OB	(3) IPW	(4) AIPW
Unexplained Gender Gap	-0.0595	-0.0762	-0.0804	-0.0700
	(0.0126)		(0.0202)	
Observations	6700	6700	4494	4494

Note: Table shows different estimates of the unexplained gender difference in log hourly reservation wage. Column (1) Linear regression. Column (2) Blinder-Oaxaca decomposition. Column (3) Inverse Probability Weighting. Column (4) Augmented Inverse Probability Weighting. *Source:* German Socio-Economic Panel v36, own calculations.

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