Pitfalls of pay transparency: Evidence from the lab and the field

EEA-ESEM Congress 2022

by

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Introduction

Motivation

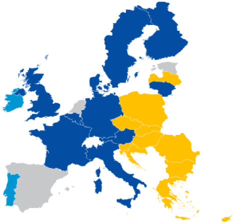
ARTICLE

Germany: Government Proposes Law to Reduce Gender Pay Gap

(Jan. 18, 2017) On January 11, 2017, the German government agreed on a draft act that aims to ensure equal pay for work of equal value for women and men in the same workplace. (Gesetzentwurf der Bundesregierung, Entwurf eines Gesetzes zur Förderung der Transparenz von Entgeltstrukturen [Draft Act of the Federal Government, Draft Act to Promote Transparency in Pay Structures] (Jan. 11, 2017), Federal Ministry for Family Affairs, Senior Citizens, Women, and Youth website.)

The New York Times

Britain Aims to Close Gender Pay Gap With Transparency and Shame



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Council of the EU Press release 6 December 2021 16:35

Council agrees on common position to tackle gender pay gap

The Council today agreed on its position on a draft law on pay transparency which will help to tackle the existing pay discrimination at work and contribute to closing the gender pay gap. The proposed law aims to empower workers to enforce their right to equal pay for equal work or work of equal value between men and women through a set of binding measures on pay transparency.

Bloomberg Equality

NYC Aims to Close Stubborn Gender Pay Gap With Salary Disclosure

States and cities are increasingly requiring companies to disclose how much they pay

ARTICLE Share Follow Question Print Translate

France: Gender Pay Gap Transparency: French Ministry Of Labour Will Publish Smaller Companies' Results In 2021

Motivation

- EU-wide gender pay gap amounted to 14.1% in 2019
- Heterogeneous wage transparency policy landscape to tackle wage gap

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- Heterogeneous wage transparency policy landscape to tackle wage gap
- Little evidence on what determines the effectiveness of wage transparency measures
- Wage transparency measures can have two purposes:
    1. Reveal discriminatory practices
    2. Correcting misspecified beliefs

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- Heterogeneous wage transparency policy landscape to tackle wage gap
- Little evidence on what determines the effectiveness of wage transparency measures
- Wage transparency measures can have two purposes:
    1. Reveal discriminatory practices
    2. Correcting misspecified beliefs
- Gender differences in beliefs:
  Females more pessimistic about others' wages (Briel et al., 2021), effectiveness might depend on confidence in own performance (Niederle and Vesterlund, 2007)

Research questions: Combining the lab and the field

Research question 1

Are ‘pay information rights’ effective in decreasing the gender wage gap?

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Field: Investigate introduction of pay transparency regulation in Germany

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Research question 2

How and when is wage transparency effective in decreasing wage inequality?

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Are 'pay information rights' effective in decreasing the gender wage gap?

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Research question 2

How and when is wage transparency effective in decreasing wage inequality?

Lab: Examine specific characteristics of transparency regulations

- Pay information rights vs. pay reporting duties: How is wage information provided?
- In which environments does wage transparency help?
- Closer look at mechanisms: How are beliefs corrected?

Literature

Gender differences in wage negotiations as a driver of the gender pay gap

- Women enter negotiations less often

  e.g. Babcock et al. (2003), Croson and Gneezy (2009), Greig (2008) & Leibbrandt and List (2015)

- Women ask for less in negotiations and are offered less

  e.g. Roussille (2020), Hernandez-Arenaz and Iriberri (2018) & Säve-Söderbergh (2019)

- Women face more backlash for negotiating

  e.g. Bowles et al. (2007) & Amanatullah and Tinsley (2013)

- Varying success of proposed policies for improvement that target negotiations

  e.g. Recalde and Vesterlund (2020), Exley et al. (2020), Gihleb et al. (2020), Werner (2019) & Rigdon (2012)

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Literature

Mixed evidence on the effectiveness of pay transparency:

- Wage information can reduce the gender pay gap

  Wage information reduces pay inequality at Canadian universities (Baker et al., 2019; Gamage et al., 2020), reduces the gender pay gap in Denmark (Bennedsen et al., 2019) and the UK (Duchini et al., 2020; Blundell, 2021)

- Wage information is not always effective and has downsides

  Pay statistics in Austria have no effect (Gulyas et al., 2020; Böheim and Gust, 2021), wage transparency may reduce job satisfaction (Card et al., 2012) and results in lower overall wages in the US (Cullen and Pakzad-Hurson, 2021)

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Our contribution: Combining field with lab evidence

- Investigate a popular policy tool and explore mechanisms that determine its effectiveness
- Varying type of information: Wage information of comparable others
- Provision of information: By default or only on request

Field evidence

German wage transparency policy

Transparent Remuneration Law introduced in 2017:

- Information on request: Firms with more than 200 employees have to offer employees information about the wage of ‘comparable workers’
- Low take-up: Only 13% of employers with 200-500 employees have received a request for wage comparison by 2019 (Baumann et al., 2019)

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Linked-Employer-Employee-Data of the IAB (LIAB):

- Administrative data of entire employment histories of all employees at a representative sample of nearly 15,500 German establishments

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Linked-Employer-Employee-Data of the IAB (LIAB):

- Administrative data of entire employment histories of all employees at a representative sample of nearly 15,500 German establishments

Identification strategy:

- Triple-difference analysis with exogenous variation induced by cutoff in firm size

LIAB

Regression equation

$$Y_{ijt} = \beta_1(Female_i \times Large_j \times Post_t) + \beta_2(Female_i \times Post_t) + \beta_3(Large_j \times Post_t) + \beta_4(Female_i \times Large_j) + \alpha_i + \alpha_j + \alpha_t + \delta X_{ijt} + u_{ijt}$$

- Y_{ijt}: Log daily wage of individual i at firm j in year t
- $Female_i$: Indicator for an employee being female
- $Large_j$: Indicator for firms with more than 200 employees in 2018
- $Post_t$: Indicator for post-intervention years
- $\alpha_i, \alpha_j, \alpha_t$: Individual-, firm- and year-fixed effects
- X_{ijt}: Time-varying controls (educational attainment, part-time employment & age squared)
- β_1 is the coefficient of interest

Results

The wage transparency regulation does not impact the wages of males.

	Log of daily wage					
	Both gender	Men	Women	Both genders	Men	Women
Large × Post	0.0022	0.0009	0.0027	0.0051	0.0044	0.002
	(0.46)	(0.17)	(0.42)	(0.82)	(0.71)	(0.31)
Female × Large × Post	-0.0001			-0.0028		
	(-0.01)			(-0.36)		
Female × Large	-0.0249			0.0037		
	(-0.83)			(0.17)		
Female × Post	0.0146***			0.0045		
	(3.30)			(0.91)		
Individual time-varying controls	✓	✓	✓			
Firm-, individual- & time- FE	✓	✓	✓	✓	✓	✓
Firm size	150-250	150-250	150-250	150-250	150-250	150-250
Observations	584,026	325,869	257,544	778,441	435,591	342,066

Standard errors clustered at the firm level. T-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results

The wage transparency regulation does not impact the wages of females.

	Log of daily wage					
	Both gender	Men	Women	Both genders	Men	Women
Large × Post	0.0022	0.0009	0.0027	0.0051	0.0044	0.0022
	(0.46)	(0.17)	(0.42)	(0.82)	(0.71)	(0.31)
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Results

The gender pay gap closes.

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Large × Post	0.0022	0.0009	0.0027	0.0051	0.0044	0.002
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Results

This is not driven by the introduction of the wage transparency regulation.

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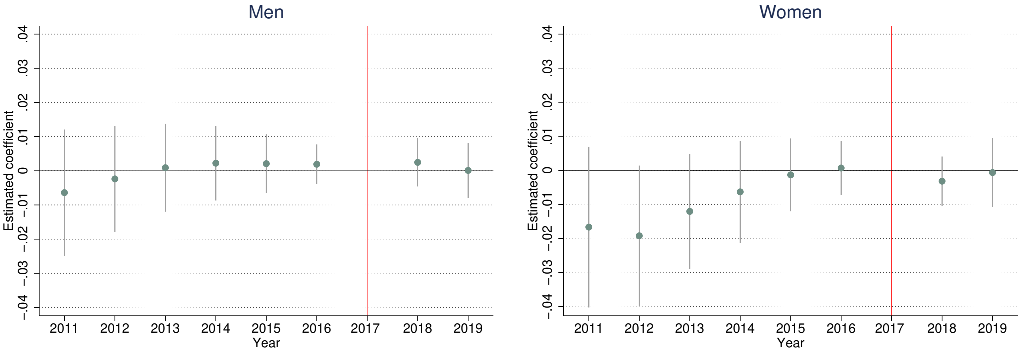
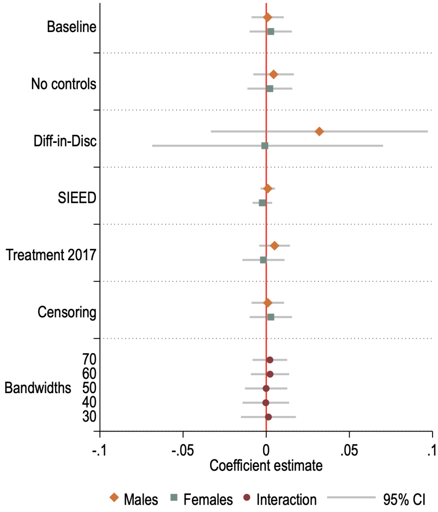
Event study specification



Joint plot

Major robustness checks

- Difference-in-discontinuities estimation link
  Addressing any potential pre-existing discontinuity
- SIEED data set link
  Larger data set without 2019 data
- Manipulation of the running variable
  - McCrary test link
  - Treatment assignment based on 2017 link
- Addressing censoring link
  Removing top-coded employment spells
- Different bandwidths link



Laboratory evidence

Experimental setup

- Subjects are assigned to be either a worker or a firm
- Randomly matched workers and firm negotiate over the split of a previously produced pie
- Period 1 used for information generation:
  Comparable worker is the worker that was paired with a worker's current firm in Period 1
- No information on gender: Shut down potential discrimination channel

Experimental design

- Production stage determines the negotiation budget, which is a sum of:
  - Worker's output from production task
    Maze task (Gneezy et al., 2003) and matrix task (Weber and Schram, 2017)
  - Unknown firm-specific constant
- Only firm knows the size of the budget

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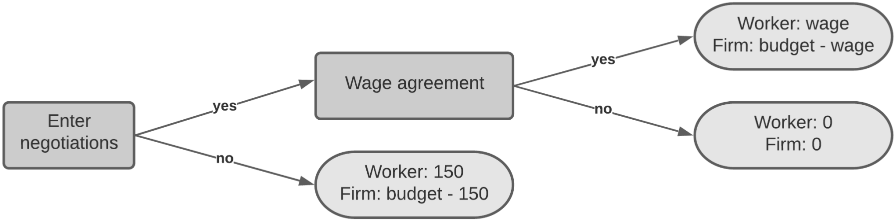
  - Unknown firm-specific constant
- Only firm knows the size of the budget
- Negotiation stage determines the payoff:



Treatments

Six treatments:

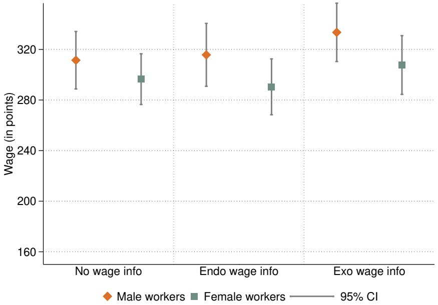
- Between-subject variation of wage information about comparable worker

  1. No wage information
  2. Endogenous wage information
  3. Exogenous wage information

- Within-subject variation of relative performance information (part 1 or part 2)

Details Theory Beliefs

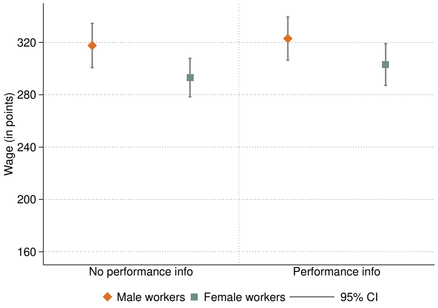
The effects of wage information



- *Endogenously* provided wage information has no effect on wages ($p = 0.643$)
- *Exogenously* provided wage information increases wages ($p = 0.076$)
- Neither wage transparency policy affects the gender wage gap

Regressions

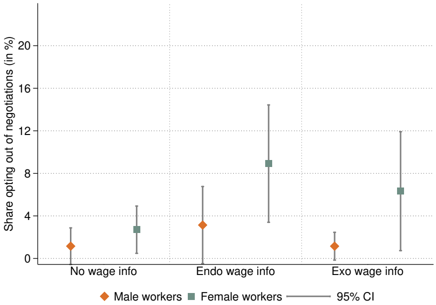
The effects of performance information



- Performance information increases wages ($p = 0.039$)
- No differential impact for males or females ($p = 0.593$)
- Joint vs. separate provision of performance and wage information does not affect wages

Regressions

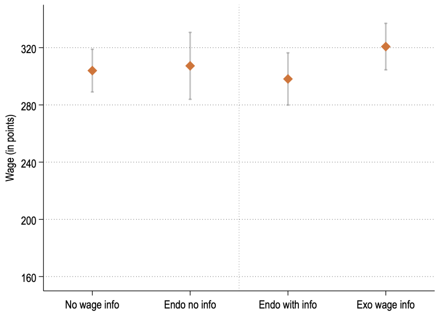
Entry decisions



- Women generally enter negotiations less often ($p = 0.003$)
- Wage transparency reduces entry by women ($p = 0.024$)
- Women who opt out of negotiations lose on average more than 110 points

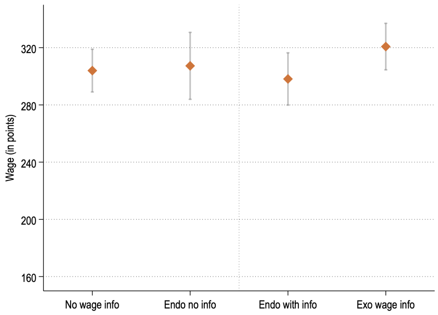
Regressions

Information use



- Wage information is chosen in 48% of cases
- Endogenously compared to exogenously acquired wage information reduces wages ($p = 0.031$)

Information use



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Selection:

- Requesting wage information is less useful the higher the worker's performance ($p = 0.005$)
- The likelihood of requesting information increases in the worker's performance ($p = 0.044$)

Regressions Beliefs

Conclusion

Conclusion

Results from the field

- The German ‘pay information rights’ legislation has no effect on wages for either gender

Conclusion

Results from the field

- The German ‘pay information rights’ legislation has no effect on wages for either gender

Results from the lab

- Exogenously, but not endogenously, provided wage information can increase wages
- Wage transparency may backfire:
  - Women enter negotiations less often
  - Requesting wage information decreases wages due to selection
  - The environment matters: High wages partially attributed to high performance if no performance information provided

Thank you!

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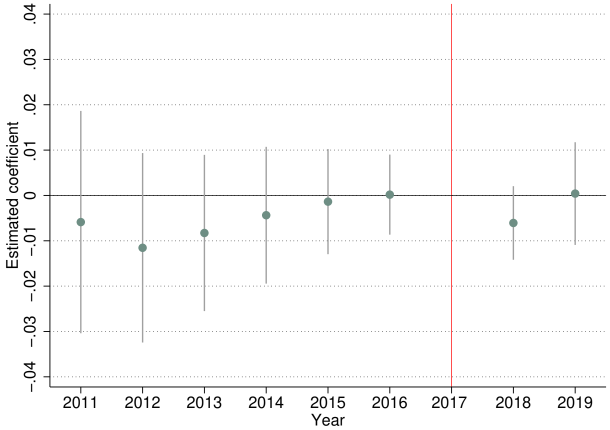
Appendix

Linked-Employer-Employee-Data of the IAB (LIAB)

- Employer-employee matched data set combines administrative data and an annual establishment survey
- Entire employment histories of all employees at a representative sample of nearly 15,500 German establishments
- 861,673 employee-establishment-year observations between 2011 and 2019 for firms with 150 - 250 employees
- *Administrative* data on daily wages (top-censored), age, education, gender as well as establishment characteristics
- SIEED data set: more observations, but data only until 2018

back

Event study for the differential effects on males vs. females



back

Difference-in-Discontinuities: Regression equation

$$Y_{ijt} = \beta_1 Size_j + Large_j \times (\gamma_1 + \gamma_2 Size_j) + Post_t[\delta_1 Size_j + Large_j \times (\lambda_1 + \lambda_2 Size_j)] + \alpha_t + u_{ijt}$$

- $Size_j$: Number of employees of firm j in year 2018
- λ_1 is the coefficient of interest
- Identifying assumption: Continuity in potential outcomes at the cutoff
- Following recent literature on RDD, we use a local linear regression, instead of a higher order/global approach.

back

Difference-in-Discontinuities: Results

	Log of daily wage					
	Both gender	Men	Women	Both gender	Men	Women
Diff-in-disc	0.0307	0.0320	0.0008	0.0024	0.0025	-0.0578
	(0.88)	(0.96)	(0.02)	(0.04)	(0.04)	(-1.11)
Female $\times$ Diff-in-disc	-0.0251			-0.0603		
	(-0.70)			(-1.02)		
Individual time-varying controls	✓	✓	✓			
Time FE	✓	✓	✓	✓	✓	✓
Firm size	150-250	150-250	150-250	150-250	150-250	150-250
Observations	639,395	357,630	281,765	852,465	478,000	374,465

Standard errors clustered at the firm level. T-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

back

Sample of Integrated Employer-Employee Data (SIEED)

- Administrative panel data set capturing a representative sample of 1.5% of all establishments in Germany
- Employer-employee matched data: Entire employment histories of all employees at panel establishments
- 1.8 million employee-establishment-year observations between 2011 and 2018 for firms with 150 - 250 employees
- Information on daily wages (top-censored), age, education, gender as well as establishment characteristics

back

Diff-in-Diff results using SIEED data

	Log of daily wage					
	Both gender	Men	Women	Both gender	Men	Women
Large × Post	0.0006	0.0009	-0.0024	0.0023	0.0023	0.0018
	(0.0022)	(0.0022)	(0.0030)	(0.0027)	(0.0026)	(0.0030)
Female × Large × Post	-0.0032			-0.0004		
	(0.0034)			(0.0036)		
Female × Large	0.0134			0.021		
	(0.0158)			(0.0014)		
Female × Post	0.0213***			0.0139***		
	(0.0021)			(0.0022)		
Individual time-varying controls	✓	✓	✓			
Firm FE	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Firm size	150-250	150-250	150-250	150-250	150-250	150-250
Observations	1,137,638	632,974	504,269	1,652,424	909,136	742,997

Standard errors clustered at the firm level. T-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

back

Event study with SIEED data

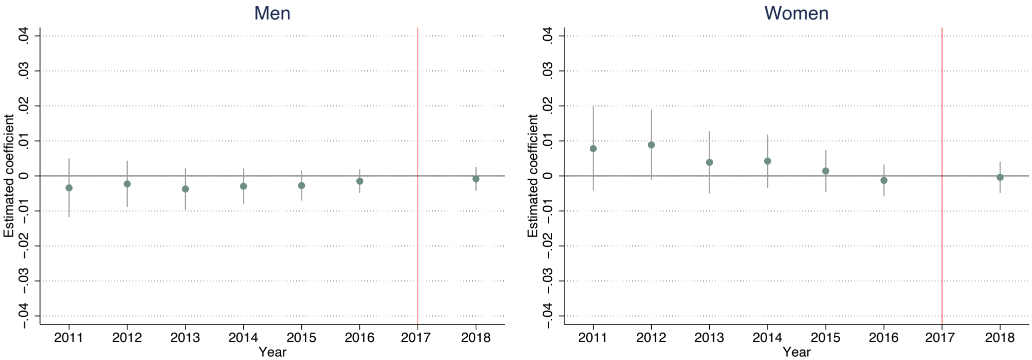


Figure: Gender-specific effects of the German transparency law – SIEED

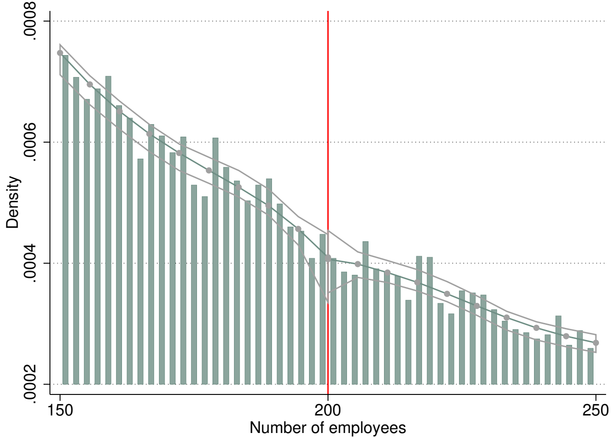
back

McCrary Test

- Firms face an incentive to manipulate their size to not fall under the wage transparency regulation
- If there is manipulation, we would expect the density of the variable $Size_j$ around the cutoff of 200 employees not to be continuous
- McCrary tests for the continuity of the running variable around the cutoff
  - McCrary test for 2017: $p = 0.8360$
  - McCrary test for 2018: $p = 0.7118$
- No evidence of manipulation

back

Density plot



back

Treatment based on number of employees in 2017

	Log of daily wage					
	Both gender	Men	Women	Both gender	Men	Women
Large × Post	0.0055	0.0050	-0.0017	0.0040	0.0112*	0.0011
	(1.18)	(1.07)	(-0.26)	(0.64)	(1.79)	(0.16)
Female × Large × Post	-0.0073			-0.0064		
	(-1.12)			(-0.82)		
Female × Large	-0.136***			-0.0481**		
	(-3.88)			(-2.10)		
Female × Post	0.0187***			0.0060		
	(4.24)			(1.25)		
Individual time-varying controls	✓	✓	✓			
Firm-, individual- & time- FE	✓	✓	✓	✓	✓	✓
Firm size	150-250	150-250	150-250	150-250	150-250	150-250
Observations	585,822	333,183	252,051	778,441	446,733	340,632

Standard errors clustered at the firm level. T-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

back

Removing top-coded employment spells

- Daily wage is top censored: Wages above the upper earnings limit for statutory pension insurance are top-coded
- 1.29% of observations are affected
- As a robustness check, we remove all top-coded observations

back

Removing top-coded employment spells: Results

	Log of daily wage					
	Both gender	Men	Women	Both gender	Men	Women
Large × Post	0.0023	0.0009	0.0028	0.0050	0.0043	0.0022
	(0.47)	(0.19)	(0.42)	(0.79)	(0.69)	(0.32)
Female × Large × Post	-0.0001			-0.0026		
	(-0.01)			(-0.34)		
Female × Large	-0.0231			0.0045		
	(-0.76)			(0.20)		
Female × Post	0.0145***			0.0041		
	(3.25)			(0.80)		
Individual time-varying controls	✓	✓	✓			
Firm-, individual- & time- FE	✓	✓	✓	✓	✓	✓
Firm size	150-250	150-250	150-250	150-250	150-250	150-250
Observations	576,495	319,700	256,186	770,238	428,867	340,589

Standard errors clustered at the firm level. T-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

back

Different bandwidths

	Log of daily wage				
	(1)	(2)	(3)	(4)	(5)
Large × Post	0.0009	-0.0008	0.0022	0.0031	0.0015
	(0.22)	(-0.19)	(0.46)	(0.56)	(0.22)
Female × Large × Post	0.0022	0.0023	-0.0001	-0.0003	0.0013
	(0.41)	(0.39)	(-0.01)	(-0.04)	(0.16)
Female × Large	-0.0425*	-0.0442	-0.0249	-0.0283	-0.0208
	(-1.87)	(-1.42)	(-0.83)	(-0.71)	(-0.38)
Female × Post	0.0152***	0.0164***	0.0146***	0.0123**	0.0144**
	(4.38)	(4.21)	(3.30)	(2.45)	(2.28)
Individual time-varying controls	✓	✓	✓	✓	✓
Firm-, individual- & time- FE	✓	✓	✓	✓	✓
Firm size	130-270	140-260	150-250	160-240	170-230
Observations	852,267	707,938	584,026	464,504	333,935

Standard errors clustered at the firm level. T-statistics in parentheses. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

back

Theoretical model

- Nash bargaining over wage w_i to the worker who contributes c_i
- Workers are averse to receiving a piece rate $\frac{w_i}{\hat{c}_i}$ that they believe to be different from the comparable worker's piece rate $\frac{\hat{\hat{w}}_i}{\hat{\hat{c}}_i}$
- Firms maximize profits

$$U_i^W(\mathbf{w}, \mathbf{c}) = w_i - \alpha_i \left(\frac{w_i}{\hat{c}_i} - \frac{\hat{\hat{w}}_i}{\hat{\hat{c}}_i} \right)^2$$

$$U_j^F(w_i) = \pi - w_i$$

back

Tasks

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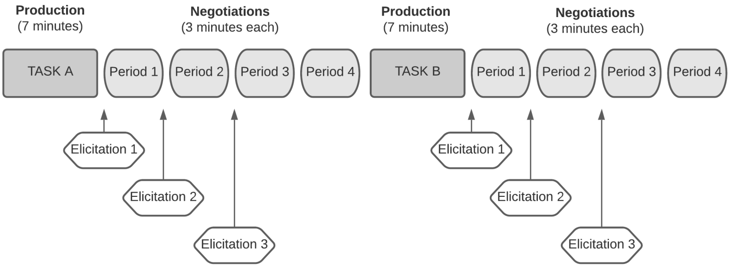
Belief elicitations



Worker's beliefs elicited using binarized scoring rule (Hossain and Okui, 2013):

E 1 Beliefs about own and the comparable worker's performance

E 2 Beliefs about the comparable worker's wage

E 3 *Treatment specific*: Re-elicit belief about the comparable worker's wage and performance

Experimental details

- Experiment run at the CREED (Amsterdam) and MELESSA (Munich) laboratories
- 528 subjects, across 22 sessions
- Participants earned 26.59 Euros on average, including show-up fee of 6 Euros
- Online experiment lasted approx. 88 minutes
- 2.22% of observations discarded due to technical difficulties on the subject's side

back

The effects of wage information

	Worker's wage		
Endo wage	-4.92		-5.44
	(10.57)		(14.05)
Exo wage	12.18	14.65*	14.55
	(9.13)	(8.13)	(12.48)
Female			3.38
			(12.34)
Endo wage × Female			0.95
			(14.52)
Exo wage × Female			-4.80
			(15.67)
Controls & FE	✓	✓	✓
Observations	1548	1548	1548
Clusters	66	66	66
R-squared	0.265	0.265	0.262

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

back

The effects of performance information

	Worker's wage				
Endo wage	-5.44			-1.40	-5.02
	(14.05)			(13.08)	(17.74)
Exo wage	14.55			15.33	22.13
	(12.48)			(11.96)	(16.09)
Female	3.38		4.74		7.09
	(12.34)		(8.98)		(18.05)
Endo wage × Female	0.95				7.00
	(14.52)				(22.17)
Exo wage × Female	-4.80				-13.88
	(15.67)				(22.49)
Performance		10.73**	13.45*	15.25*	19.05
		(5.08)	(7.57)	(8.63)	(13.25)
Performance × Female			-5.43		-7.67
			(10.13)		(20.44)
Performance × Endo wage				-7.14	-1.19
				(12.34)	(18.45)
Performance × Exo wage				-6.32	-15.39
				(12.58)	(18.59)
Performance × Endo wage × Female					-11.70
					(25.31)
Performance × Exo wage × Female					18.53
					(25.94)
Controls & FE	✓	✓	✓	✓	✓
Observations	1548	1548	1548	1548	1548
Clusters	66	66	66	66	66
R-squared	0.265	0.264	0.264	0.267	0.268

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Entry decisions

	Worker's decision to opt-out of negotiations					
Endo wage	1.20***		1.40			
	(0.41)		(0.88)			
Exo wage	0.64		0.10			
	(0.46)		(0.89)			
Female		0.87**	0.81	0.76	0.44	1.73**
		(0.44)	(0.86)	(0.83)	(0.61)	(0.84)
Endo wage × Female			-0.38			
			(1.04)			
Exo wage × Female			0.63			
			(1.15)			
Controls & FE	✓	✓	✓	✓	✓	✓
Sample	*Full*	*Full*	*Full*	*NoWage*	*EndoWage*	*ExoWage*
Observations	1546	1546	1546	519	513	514
Clusters	66	66	66	22	22	22
Pseudo R-squared	0.235	0.229	0.251	0.200	0.237	0.323

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

back

Information use

	Worker's wage				
Info choice	-17.77	76.86**			
	(11.72)	(30.23)			
Info choice × Worker contribution		-0.25***			
		(0.08)			
Endo wage			4.79		
			(11.80)		
Exo wage				26.14**	23.32
				(11.69)	(19.38)
Exo Wage × Worker contribution					-0.03
					(0.06)
Constant	67.34	19.77	-17.90	4.63	-41.58
	(66.20)	(69.78)	(48.85)	(42.52)	(39.47)
Controls & FE	✓	✓	✓	✓	✓
Sample	*EndoWage*	*EndoWage*	*No wage info*	*Wage info*	*NoWage & ExoWage*
Observations	515	515	789	759	1033
Clusters	22	22	44	44	44
R-squared	0.272	0.284	0.303	0.240	0.272

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

back

The role of beliefs

- Wage information induces changes in beliefs about performance ($p = 0.022$)
- Performance information induces changes in beliefs about wages ($p = 0.015$)

The role of beliefs

- Wage information induces changes in beliefs about performance ($p = 0.022$)
- Performance information induces changes in beliefs about wages ($p = 0.015$)
- Underconfident individuals gain from performance information ($p = 0.017$)
- Adding wage information offsets the benefit of performance information for underconfident compared to overconfident individuals ($p = 0.069$)

back

The role of beliefs

	Worker's wage					
Wage	1.32		-4.37	-8.69		6.25
	(9.53)		(12.35)	(12.75)		(15.71)
Wage +	-33.81***	-31.86***	-55.03***			
	(12.27)	(10.17)	(18.41)			
Wage × Wage +	6.54		33.31			
	(14.43)		(21.86)			
Performance		8.94	1.76		21.00**	41.55***
		(5.95)	(11.62)		(8.61)	(14.61)
Performance × Wage +		4.69	38.55			
		(12.80)	(23.85)			
Wage × Performance			10.91			-30.98*
			(13.42)			(17.67)
Wage × Performance × Wage +			-49.28*			
			(28.08)			
Own Perf +				-11.45	9.75	9.17
				(13.91)	(9.62)	(17.66)
Wage × Own Perf +				20.56		1.42
				(15.10)		(19.63)
Performance × Own Perf +					-17.43	-43.45**
					(10.60)	(17.10)
Wage × Performance × Own Perf +						39.11*
						(21.18)
Controls & FEs	✓	✓	✓	✓	✓	✓
Observations	1548	1548	1548	1548	1548	1548
Clusters	66	66	66	66	66	66
R-squared	0.274	0.276	0.279	0.264	0.265	0.268

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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