Wage misperceptions and the sorting of early career workers to jobs

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Introduction

Research question

There is a growing literature on misinformation in the labor market. Literature

↪ Misperceptions in the differences between jobs could distort search and lead to mismatch.

↪ Mismatch might be particularly important for early career workers.

- Consider a young job seeker with relative misperceptions about job types.
- They search for job A instead of job B despite (unknowingly) preferring job B
- They are hired at A and possibly never learn true information about B.

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The focus of this project:

To what extent do early career workers have misperceptions about the difference between jobs?

Are these misperceptions relevant to their job search process?

Key results

- **New facts on early career workers' beliefs about entry wages between jobs:**
  - They perceive that there is heterogeneity between jobs.
  - But, they have large misperceptions about the actual wage gaps. (36% of wage rankings are wrong)
- **Receiving information on past cohorts' average wages for different jobs:**
  - Changes beliefs about own wages in the jobs. (30% learning rate)
  - Leaves unchanged beliefs about non-wage amenities in the jobs.
  - *Increases planned applications to higher-paying jobs.*
  - *Preliminary model calculations suggest that 1 in 10 applications are distorted.*
- **Early career workers care about wages, but not exclusively:**
  - Elasticity of planned application w.r.t. perceived wage just under 3.

Survey description

Challenge 1: Target sample

Objective: Sample early career workers searching for jobs

- Two samples:
  - New UI claimants in summer of 2023, age < 40
  - (Near-)Graduates from the University of Copenhagen in summer 23
- Survey distributed via official government email.
  Response rate just over 15%, after sampling restrictions the sample is 1,900 persons.

Successful targeting:

- 77% are currently studying or graduated at most 2 years ago.
- 65% are actively searching for a job.

Descriptive statistics | More details

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Challenge 2: Job types tailored to the education

Objective: ask respondents about 3 job types specific to their education

- There are 200 different education types
  - 6-digit code on level and field (Ex: BA Communications, Ms Physics).
- Which dimensions and levels of granularity of jobs best capture the different options?
  - Occupation code.
  - Industry code.
  - Public vs. private small (below 50 employees) vs. private large (above 50).
- Data-driven approach using transitions of past cohorts to jobs (2010-2018), to ensure:
  - Top 3 job types cover most transitions.
  - All 3 job types are non-negligible.
  - A good prediction of wage differences.

More details Example How well the respondents understood the job types Share getting joptype example correct

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Survey overview

1. **Beliefs about past cohorts:**
   Incentivized questions about the perceived average wages of job types in past cohorts, $\widetilde{V_{i,j}}$, with an anchor for the average across all education.
   Average monthly gross wages during the first year of work for persons that graduated with your education in the 2010s.
2. **Information treatment:**
   50 % of respondents are shown the actual averages in the register data, $V_{i,j}$. Examples
3. **Stated behavior:**
   Likelihood of applying for the three hypothetical job types $\Pi_{i,j}$.
4. **Perceived own outcomes**
   The outcomes they expect for themselves in the hypothetical jobs, including own wages $\widetilde{W_{i,j}}$

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Misperceptions

Understanding misperceptions about the difference between jobs

- We want to document misperceptions in the wage gaps between jobs of past cohort.
- For all respondents, i, and all pairs of jobs j, j', we compute the gap in actual average earnings between jobs minus the perceived gap, as a percent of the actual gap.
  The *Wage Gap Underestimation Rate*:

$$\text{WGUR}_{i,j} = \frac{(V_{i,j} - V_{i,j'}) - \left(\widetilde{V_{i,j}} - \widetilde{V_{i,j'}}\right)}{V_{i,j} - V_{i,j'}} \equiv \frac{\Delta V_{i,j,j'} - \Delta \widetilde{V_{i,j,j'}}}{\Delta V_{i,j,j'}} \tag{1}$$

  We include all pairwise job comparisons for each respondent.

  Properties of this measure:

  < 0 $\Rightarrow$ Overestimates the wage gap
  $= 0$ $\Rightarrow$ Exact correct belief about the gap.
  $\in (0,1]$ $\Rightarrow$ Relative ranking correct, but underestimates the gap.
  1 $\Rightarrow$ Underestimate the ranking by more than 100%, meaning they get the ranking wrong

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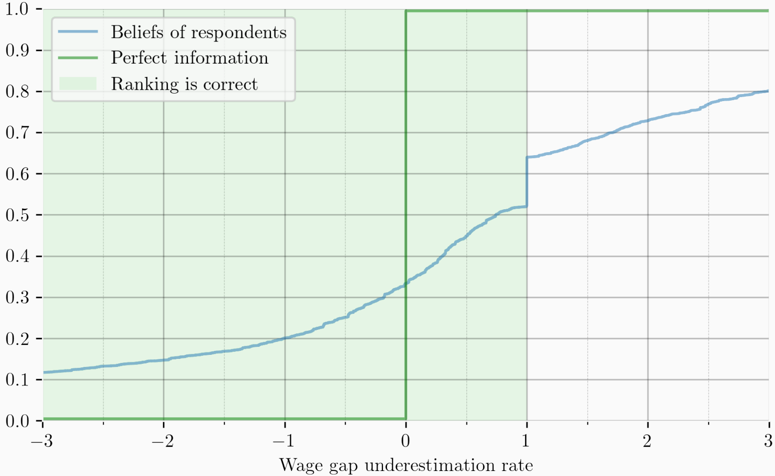
The wage gap underestimation rate, WGUR$_{i,j}$



36% gets the ranking wrong. Median belief gets the ranking correct but underestimates the wage premium by 75% Conditioning on actual gap Gap in logs Robustness exercises Absolute misperceptions Correlation

Information treatment

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Naive treatment effects

	Perceived gap in individual wages $\Delta\widetilde{w_{i,j,j'}}$		Gap in log likelihood of applying, $\Delta\pi_{i,j,j'}$	
	(1)	(2)	(3)	(4)
Treatment, T_i	0.043***	0.041***	0.219***	0.206***
	(0.005)	(0.005)	(0.073)	(0.071)
Controls		✓		✓
Persons	1902	1902	1902	1902
N	5706	5706	5706	5706

Only includes job comparisons that underestimated the wage gap, i.e. $\Delta v_{i,j,j'} - \Delta\widetilde{v_{i,j,j'}} > 0$. Controls are the same pre-treatment variables as in the balance checks, plus fixed effects on education level and field. The sample is the survey population from educations that were eligible for treatment. Std. errors are clustered at person. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

At the job level

How does the information treatment affect perceived own wage

Using the experiment, we can get at the degree of beliefs updating from treatment. Beliefs framework

$$\Delta \widetilde{w_{i,j,j'}} = \tau_1 T_i (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) + \tau_2 (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) + \Delta e_{i,j,j'} \tag{2}$$

- $\Delta \widetilde{w_{i,j,j'}}$ is the perceived log gap in own earnings between job j and j'.
- $\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}$ is the actual log gap relative to the perceived in the earnings of job j and j', for past cohorts.
  Or the underestimation of the past cohorts' earnings gaps in logs.

We expect the treatment effect to be:

- Positive for underestimation of the gap, $(\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) > 0$
- Negative for overestimation of the gap, $(\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) < 0$

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Effect of information on perceived gap in own wage $\Delta\widetilde{w_{i,j,j'}}$

	(1) Base	(2) Control for $\Delta v_{i,j,j'} - \Delta\widetilde{v_{i,j,j'}}$ squared and cubed	(3) Pre-experiment controls
$T_i \cdot (\Delta v_{i,j,j'} - \Delta\widetilde{v_{i,j,j'}})$	0.315***	0.314***	0.312***
	(0.037)	(0.036)	(0.036)
Educations	83	83	83
Persons	1902	1902	1902
N	11412	11412	11412

Amenities correlation Spill-over to other jobs

No spill-over to beliefs about non-pecuniary aspects of the job: Spill-over to job

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Effect on search behavior

The effect of perceived wages on stated behavior

The treatment regression functions as a first stage:

$$\widehat{\Delta \widetilde{w_{i,j,j'}}} = \tau_1 T_i (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) + \tau_2 (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) + \Delta e_{i,j,j'} \tag{3}$$

To the second stage regression:

$$\Delta \pi_{i,j,j'} = \beta_1 \widehat{\Delta \widetilde{w_{i,j,j'}}} + \beta_2 (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) + \Delta \epsilon_{i,j,j'} \tag{4}$$

- $\Delta \pi_{i,j,j'}$ is the log gap in the stated likelihood of applying for job j relative to job j'.
- This formulation is motivated by a discrete choice logit model. Framework

Elasticity Log odds approach FD version Exogeneity

2stage, gap in log application likelihood, $\Delta\pi_{i,j,j'}$

	(1) Base	(2) Control for $\Delta v_{i,j,j'} - \Delta\widetilde{v_{i,j,j'}}$ squared and cubed	(3) Pre-experiment controls
$\Delta\widetilde{w_{i,j,j'}}$	4.175***	4.141***	3.917***
	(1.441)	(1.417)	(1.405)
First stage F-stat	73.69	74.83	71.80
Average elasticity $\widehat{\mathcal{E}}^a$	2.91	2.89	2.73
Educations	83	83	83
Persons	1902	1902	1902
N	11412	11412	11412

Spill-over to job | Spill-over to wages | Reduced form | OLS | Log odds | Full table | Controlling for spill-overs

If perceived own wage increases by 1%, the stated likelihood of applying increases by around 3%.

Conclusion

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- Early career workers are misinformed about wages, including the relative wages of jobs.
- They expect wage differences between job types, but tend to underestimate them.
- Wage expectations about different types of jobs matter for the direction of job search.
  - Find an elasticity of wage on the likelihood of a job application around 3.

Ongoing work:

- Our treatment increases planned applications to higher-paying jobs.
- Model calculations suggest that 1 in 10 applications are distorted.

Future work:

- Relative misperceptions in likelihood of a successful application. Misperception figure
- Ongoing: Link survey to Danish register data with actual search behavior and outcomes.
- Compare our elasticity to firm-specific labor supply curve. Elasticity literature

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Appendix

Appendix

Get back

Literature - misperceptions i

Growing evidence that workers may have *misperceptions* about jobs that are relevant to them.

- Workers anchor their beliefs about wages in other jobs towards their own wage (Jäger et al., 2024).
- Workers have large misperceptions about specific potential firms they could work at Caldwell et al. (2025).
- Job seekers tend to anchor their reservation wage at their previous wage (Krueger and Mueller, 2016).
- Spinnewijn (2015) Mueller et al. (2021) document misperceptions about the expected duration of unemployment.
- A strand of the literature focuses on *within-firm pay transparency* (Cullen and Perez-Truglia, 2022, 2023; Baker et al., 2023), which seems to matter for negotiation and be important for the *gender pay gap* (Roussille, 2024; Cortés et al., 2024). Bennedsen et al. (2023) document that studies consistently find that pay transparency decreases the gender pay gap.

Literature - misperceptions ii

- Cullen and Pakzad-Hurson (2023) model pay transparency and find that while pay transparency increases wage compression, it also reduces the bargaining power of the individual worker, as the firm now take into account the second-order effect of increasing the wages of one worker, during wage negations, thus lowering average wages.
- *Employers* are also meaningfully unaware of what other employers pay (Cullen et al., 2022).
- Altmann et al. (2024), document that a group of job seekers who search for jobs in occupations they do not have prior experience in, observe worse labor market outcomes.
- Job seekers not choosing job types optimally suggests positive effects from information provision (Belot et al., 2019, 2022a; Behaghel et al., 2024; Altmann et al., 2018; Ben Dhia et al., 2022; Altmann et al., 2022).
- Sockin and Sojourner (2023) discuss the relevance of information on job search platforms given by the platform reviews, this allows dissemination of less tangible information.

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Literature - choice model

- Underlying model: McFadden (1977), McFadden (1980), and Train (2009)
- Relating to elicited choice probabilities: Manski (1999) and Blass et al. (2010)
- Examples: Giustinelli and Shapiro (2024), Gong et al. (2024), Wiswall and Zafar (2015), and Wiswall and Zafar (2018)

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Literature - information updating i

- Theoretically motivated updating rules: Haaland et al. (2023), Roth and Wohlfart (2020), Jäger et al. (2024) Cullen and Perez-Truglia (2022), and Fuster et al. (2022)
- Difference between prior and posterior (e.g. Haaland and Roth (2023))
- Predicting changes in log level of posterior (Cullen and Perez-Truglia (2022) and Haaland and Roth (2023))

Overview:

- Jäger et al. (2024) Information experiment on german workers on outside option wages
- Haaland et al. (2023) Literature review.
- Roth et al. (2022) Information experiment about macroeconomic beliefs and personal expectations.
- Cullen and Perez-Truglia (2022) Information experiment about how information about boss and peer wages affect effort.

Literature - information updating ii

- Fuster et al. (2022) Using a survey to estimate the value of information.
- Haaland and Roth (2023) Information experiment about beliefs about discrimination and preferences for policy.
- Cavallo et al. (2017) Inflation expectations.

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Literature - elasticity

- Manning (2011) Few cleanly identified estimates. Staiger et al. (2010) (≈ 0.1) and Falch (2010) ($\approx 1 - 1.9$) are likely biased downwards as the are estimated using policy changes.
- Mueller et al. (2024) ≈ 0 on vacancy duration. The probability of filling a vacancy, θ, is the inverse of its expected duration, $d = \frac{1}{\theta}$. So in a world of constant elasticities, the elasticity of d with respect to the wage is equal to minus 1 times the elasticity of θ with respect to the wage, $\frac{\partial \ln d}{\partial w_{i,j}} = -\frac{\partial \ln \theta}{\partial w_{i,j}}$.
- Belot et al. (2022b) look at the applicants' side of view using an experiment and find elasticities between 0.7 and 0.9, they argue that the elasticity could be dampened by the belief that high-wage posting vacancies are more competitive.
- Marinescu and Wolthoff (2020) finds an elasticity of around 0.7 between posted wages and applications on an online job search platform, for jobs with the same job title.
- Bassier et al. (2023) challenge these low estimates and find estimates closer to this paper around 3 to 5. Combines an external measure, changes in pay settlements or bargaining agreements, and an internal measure, large firm-level changes in the posted wage in the data.

Examples of job categories

Ms. Economics.

- Private sector, in the industry of banking, financial, and insurance activities
- Public sector, in the industry of public administration, defense, and social security
- Private sector, in the industry of professional, scientific and technical activities

Ms. Physics

- Public sector, teaching and research at a university.
- Public sector, teaching at the level of high school
- Private sector workplace with than 50 workers, doing development and analysis of software and applications.

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Job types tailored to the education -extended

Objective: ask respondents about 3 job categories specific to their education

- There are 200 different education types
  - 6-digit code on level and field (Ex: BA Communication, Ms Physics).
- Which dimensions of jobs best capture the different options?
  - Occupation code: 3- or 4- or 6- digits.
  - Industry code: 1- or 2-digits.
  - Public vs. private small (below 50 employees) vs. private large (above 50).
- Data-driven approach: using transitions of graduates in 2010-2018:
  1. Construct all possible categorizations
  2. Select those that satisfy the criteria
     - 3 biggest categories cover $]40;100[$ % of transitions
     - 3rd biggest category cover $>$ 5% of transitions
  3. If several categorizations: keep the one minimizing MSE(wage) (cross-validation)
  4. Hand check (virtually no change)

Appendix TOC | Example | How well the respondents understood the job types | Share getting joptype example correct | Get back to slides

Survey sampling and logistics

Institutional background:

- Danish graduates can receive UI when entering the labor market: $\approx 50\%$ do
- Most graduate in the summer months. $\approx 60\%$ of those accepted to receive unemployment insurance in June-August 2019, graduated within 3 months prior.

Logistics:

- Respondents contacted via Eboks, 15% answered, 9% completed. Attrition

Samples:

1. UCPH: (near-)graduates from the University of Copenhagen in summer 23 ($\sim$ 3,000) (invited in early June, typically graduate in late June)
2. STAR: New UI recipients in summer 23, age < 40 ($\sim$ 43,000) (invited at most 3 weeks after UI signup)

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Survey overview i

A. **Welcome:**
The survey begins with an introduction thanking participants for their involvement in the study on job search and career choices. As a token of appreciation, participants are informed about the chance to win one of twenty gift cards, each worth 1,000 DKK. Half of these gift cards will be distributed randomly among those who complete the entire questionnaire. The other half will be awarded to participants who perform particularly well in specific tasks throughout the survey, to incentives focus on these questions.

Survey overview ii

B-C. **Demography and Background and Labor Information:**
In this section, participants are asked about their educational labor market status. They are asked about their highest completed education, which determines their educational group and the job type examples they are shown. If they are still studying their educational group is their current study. They choose their education through a detailed drop-down, first choosing a level, then a broad topic, and then a specific education. They are also asked whether they are currently employed and whether they are searching for a job.

D. **Perception of Job Types:**
Given their stated education, we can now provide the three relevant job types. They are introduced in this section, and the respondents are asked if they feel they understand the job types, and whether they know persons who work in them.

Survey overview iii

E. **Priors:**
These are the incentivized questions in which the respondents answer what they think the average starting wage, wage growth, and likelihood of getting a job in each job type is. In this paper I focus on the starting wage, to limit the scope and because this relation to the information treatment.
The question ask specifically about the monthly gross salary gross salary (i.e. before tax and including contribution to pension savings) of people who graduated in 2010-2018 and began working full-time in each job type after. Their answer will be referenced as respondent i's perceived average wage for job j, $\widetilde{V_{i,j}}$.
Because we are primarily interested in the relative beliefs, the respondents are given the anchor that the overall average in this period was 31,000 DKK. It is also stated that full-time employment refers to contracts of employment of at least 37 hours of work a week.

Survey overview iv

F. **Treatment:**
Half of the respondents with eligible educations are randomly chosen for treatment. These respondents are shown the actual average monthly wage for the three jobs in comparison with their stated answers. The control group is reminded of their previous answers in a scatter plot with three jobs on the x-axis and the stated average wage on the y-axis. The treatment group are shown the same plot but with bars indicating the average calculated from the register data.
The actual average calculated with the register data will be denoted $v_{i,j}$. It was calculated as the average monthly wage of persons who graduated in 2010-2018, and worked full-time in the job type within one year of graduation.

G. **Behavior and Posteriors:**

In this section, participants are asked to imagine three different jobs, one from each job type, that are representative of what they think a job of that job type would offer them. They are then asked specific questions on what they think about the job and what they would expect to experience in the job if they were hired.

They are asked to imagine a hypothetical scenario, where they are given offers from all three jobs at the same time, and then answer the likelihood they would accept each job, including the likelihood that they would reject all three offers. This variable will be referred to as $\pi_{i,j}$. The answers were recorded using three sliders that were adjusted to make sure the probabilities always summed to 100% by automatically adjusting the other sliders. They are all bounded between 1 and 97%. This likelihood will be referred to as $\pi_{i,j}$ for person i in job j, with $j = 0$ being the likelihood of accepting all three jobs.

They are also asked to imagine the monthly gross wage they think they would make themselves if they worked at the job. This variable will be referred to as $\widetilde{W}_{i,j}$

Survey overview vi

E. **Additional Background Information:**
This section gathers more personal information about the participants.

F. **Reminder:**
In the concluding section, participants in the treatment group are reminded of the actual wage data they were shown earlier, with the same graph being presented again. They are also given the opportunity to provide any additional thoughts or feedback about the survey or job search in general. The survey concludes with a thank you message for their participation.

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Descriptive statistics

	UCPH only	UCPH and STAR	STAR only	All	Eligible
Total invited	2,609	366	43,256	46,231	
Total answers	482	72	6,609	7,163	2,928
Completed answers	296	45	4,019	4,360	1,941
Has custom jobtypes	243	33	2,485	2,761	1,941
Eligible for treatment	173	30	1,738	1,941	1,941
Age	27.89	27.73	28.65	28.59	28.10
Female	0.65	0.71	0.63	0.63	0.63
Higher education	1.00	1.00	0.81	0.83	1.00
Masters	1.00	1.00	0.43	0.48	0.64
Graduated at most 2 years ago	0.61	0.87	0.60	0.60	0.70
Currently studying	0.39	0.11	0.05	0.07	0.07
Expect to graduate in 2 months	0.24	0.11	0.01	0.03	0.04
Expect to graduate in 1 year	0.38	0.11	0.02	0.05	0.05
Employed	0.53	0.09	0.18	0.20	0.19
Active job searcher	0.36	0.62	0.70	0.68	0.65
Active job searcher and neither employed nor studying	0.15	0.58	0.60	0.57	0.56
Studying and employed	0.25	0.07	0.01	0.03	0.03
Not studying and not employed	0.33	0.87	0.79	0.76	0.77
Studying and active job searcher	0.13	0.04	0.02	0.03	0.03

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Data cleaning

- 39 people answered zero to one of the wage questions. One person was able to break the question with the slider and enter an invalid value. These are dropped for the analysis.
- All numeric variables entered in free fields where winsorized at the 2.5th and 97.5th percentile on the eligible for treatment sample who finished the survey. Following e.g. Epper et al. (2020); Hvidberg et al. (2023); Roth et al. (2022).
- Wiswall and Zafar (2018) instead uses LAD estimates.

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Treatment page, shown to treated group

Tidligere spurgte vi dig om den **gennemsnitlige bruttomånedsløn for fuldtidsansatte nyuddannede** i forskellige typer af job.

Vi har undersøgt den **faktiske** bruttomånedsløn for personer med din uddannelse ("Økonomi, Lange videregående uddannelser"), som færdiggjorde deres uddannelse og arbejdede fuldtid (mindst 37 timer) i forskellige jobkategorier i 2010'erne. Den følgende graf viser den **faktiske gennemsnitlige bruttomånedsløn for fuldtidsansatte i det første år på jobbet efter dimissionen (de 3 søjler) og sammenligner dem med dit gæt (de 3 prikker)**:

FIGUR: FAKTISK DATA OMKRING LØNNINGER VS. DINE GÆT

Bemærk: Når du går videre kan du ikke klikke tilbage til denne graf. Du kan fortsætte ved at klikke på "næste" knappen efter 15 sekunder på denne side.

næste

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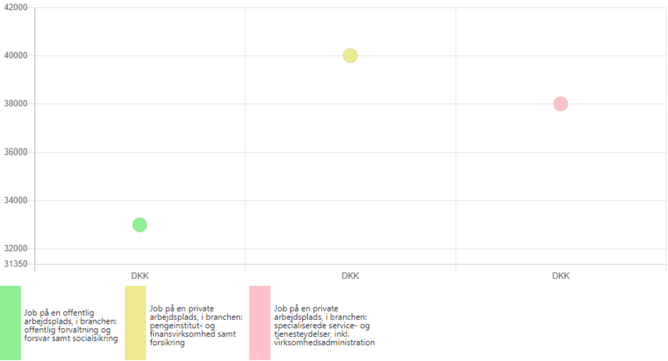
Treatment page, shown to control

På en tidligere side spurgte vi dig om **fuldtidslønninger for nyuddannede** i forskellige jobtyper.

Helt præcist handlede spørgsmålet om, hvad bruttomånedslønnen var for personer med din uddannelse ("Økonomi, Lange videregående uddannelser"), som færdiggjorde deres uddannelse og arbejdede fuldtid (mindst 37 timer) i forskellige jobkategorier i 2010'erne. Den følgende graf viser **dine gæt** om den **gennemsnitlige bruttomånedsløn for fuldtidsansatte i det første år på jobbet efter dimissionen**.

FIGUR: DINE GÆT ANGÅENDE LØNNINGER



Bemærk:. Du kan fortsætte ved at klikke på "næste" knappen efter 15 sekunder på denne side.

næste

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Basic statics

	UCPH only	UCPH and STAR	STAR only wave 1	STAR only wave 2	STAR only wave 3	All	Eligible
Total invited	2,609	366	16,471	21,773	5,012	46,231	
Total answers	482	72	2,193	3,598	818	7,163	2,928
Completed answers	296	45	1,308	2,226	485	4,360	1,941
Has custom jobtypes	243	33	773	1,459	253	2,761	1,941
Eligible for treatment	173	30	549	1,008	181	1,941	1,941
Age	27.89	27.73	29.26	28.56	27.44	28.59	28.10
Female	0.65	0.71	0.65	0.63	0.58	0.63	0.63
Higher education	1.00	1.00	0.79	0.84	0.75	0.83	1.00
Masters	1.00	1.00	0.41	0.46	0.39	0.48	0.64
Graduated at most 2 years ago	0.61	0.87	0.52	0.67	0.46	0.60	0.70
Currently studying	0.39	0.11	0.05	0.04	0.07	0.07	0.07
Expect to graduate in 2 months	0.24	0.11	0.02	0.01	0.00	0.03	0.04
Expect to graduate in 1 year	0.38	0.11	0.03	0.02	0.02	0.05	0.05
Employed	0.53	0.09	0.16	0.18	0.18	0.20	0.19
Active job searcher	0.36	0.62	0.71	0.68	0.75	0.68	0.65
Active job searcher and neither employed or studying	0.15	0.58	0.61	0.59	0.63	0.57	0.56
Studying and employed	0.25	0.07	0.01	0.01	0.02	0.03	0.03
Not studying and not employed	0.33	0.87	0.81	0.79	0.76	0.76	0.77
Studying and active job searcher	0.13	0.04	0.03	0.02	0.05	0.03	0.03

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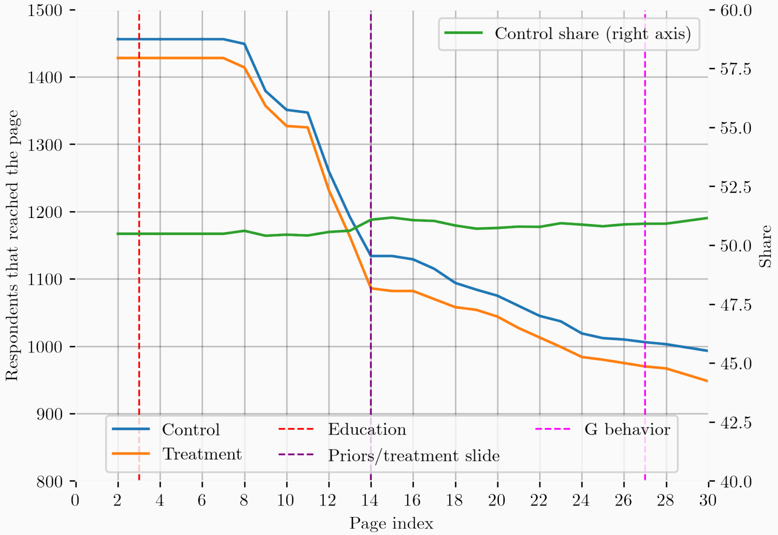
Sample size



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Balance table

	(1) Fully completed answers	(2) Not-completed answers	(3) Eligible for Treatment	(4) Not eligible	(5) Control group	(6) Treatment group	(7) p-value $(1)=(2)$	(8) p-value $(3)=(4)$	(9) p-value $(5)=(6)$
Age	28.59	28.44	28.10	28.99	28.17	28.02	0.156	0.000	0.385
Female	0.63	0.70	0.63	0.63	0.61	0.64	0.000	0.741	0.321
Higher education	0.83	0.72	1.00	0.69	1.00	1.00	0.000	0.000	
Masters	0.48	0.37	0.64	0.35	0.63	0.65	0.000	0.000	0.403
Graduated at most 1 year ago	0.54	0.52	0.64	0.45	0.64	0.65	0.188	0.000	0.528
Graduated at most 2 years ago	0.60	0.59	0.70	0.52	0.68	0.72	0.631	0.000	0.067
Currently studying	0.07	0.09	0.07	0.07	0.07	0.07	0.007	0.874	0.916
Expect to graduate in 2 months	0.03	0.03	0.04	0.02	0.04	0.04	0.537	0.001	0.857
Expect to graduate in 1 year	0.05	0.04	0.05	0.04	0.05	0.06	0.370	0.016	0.746
Employed	0.20	0.23	0.19	0.20	0.21	0.17	0.000	0.379	0.017
Studying and is employed	0.03	0.03	0.04	0.03	0.04	0.03	0.402	0.121	0.857
Neither studying or employed	0.76	0.72	0.77	0.75	0.75	0.79	0.000	0.177	0.037
Active jobbsearcher	0.68	0.65	0.65	0.70	0.63	0.67	0.041	0.002	0.113
Willingness to take a risk (1-10)	6.34	.	6.20	6.44	6.27	6.14		0.000	0.162
Job offers last 2 years	3.16	.	2.27	3.87	2.41	2.13		0.000	0.151
Wanted children	2.02	.	2.02	2.03	2.04	2.00		0.755	0.333
Likelihood of child next 4 years	45.50	.	46.56	44.66	47.48	45.58		0.108	0.273
Sum of abs. relative diff. btw. earnings belief and actual	0.59	0.74	0.58	0.63	0.55	0.60	0.067	0.448	0.598
Sum of abs. relative diff. btw. earnings growth belief and actual	0.61	0.54	0.58	0.68	0.55	0.61	0.777	0.605	0.428
Sum of abs. diff. btw. application success belief and actual	382.27	461.92	365.85	416.73	370.61	360.87	0.002	0.025	0.697
Observations	4360	2803	1941	2419	993	948			

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Balance table only control and treatment

	(1) Control group	(2) Treatment group	(3) p-value $(1)=(2)$
Age	28.15	27.98	0.326
Female	0.61	0.63	0.420
Months between survey and expected/actual graduation	17.44	15.53	0.210
Employed long term	0.12	0.11	0.270
Employed short term	0.06	0.04	0.117
Employed short term with next job	0.04	0.02	0.122
Unemployed with future job	0.25	0.25	0.972
Unemployed	0.53	0.58	0.060*
Currently studying	0.07	0.07	0.957
Active searching for a job	0.63	0.67	0.130
Months between survey and time of job search	2.99	3.01	0.952
Good understanding of:			
Most common job	0.81	0.82	0.564
Second most common job	0.73	0.73	0.940
Least common job	0.73	0.71	0.388
Close to someone:			
In most common job	0.60	0.58	0.394
In second most common job	0.48	0.49	0.666
In least common job	0.53	0.49	0.092*
Log avg. wage of prior cohort:			
In most common job	10.33	10.33	0.490
In second most common job	10.32	10.33	0.381
In least common job	10.36	10.36	0.825
Log avg. wage of prior cohort 5 years after:			
Starting at most common job	10.60	10.61	0.471
At second most common job	10.59	10.60	0.382
At least common job	10.60	10.57	0.346
Log chance of a succesful application:			
In most common job	1.24	1.24	0.895
In second most common job	1.07	1.11	0.407
In least common job	0.79	0.83	0.265
Part of STAR sample	0.91	0.91	0.971
Part of wave 1	0.39	0.39	0.762
Part of wave 2	0.52	0.51	0.644
Observations	976	926	

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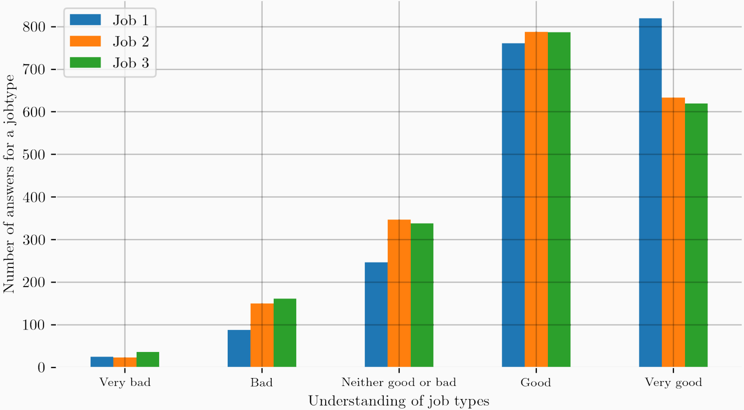
'How good is your understanding of what each of these job types mean?'



An additional test question at the end, asked respondents to place a particular example job in the right category: 77 percent answered correctly ⇒ Our job categories look to work in practice.

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Validation question

	Has custom jobtypes			Eligible for treatment		
	Job 1	Job 2	Job 3	Job 1	Job 2	Job 3
Eligible answers	755	817	680	494	558	442
Share of correct answers	0.81	0.75	0.80	0.80	0.72	0.79

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Validation question, by education

	Has custom jobtypes			Eligible for treatment		
	Job 1	Job 2	Job 3	Job 1	Job 2	Job 3
Total answers	632	688	553	451	510	395
Unique educations	49	48	47	34	33	33
Average correct answer weighted by educations	0.81	0.76	0.78	0.79	0.73	0.72
std	0.23	0.23	0.25	0.25	0.25	0.27
min	0.00	0.00	0.00	0.00	0.00	0.00
10%	0.50	0.50	0.42	0.51	0.44	0.40
25%	0.71	0.59	0.68	0.69	0.55	0.60
50%	0.87	0.83	0.83	0.85	0.81	0.78
75%	1.00	0.93	1.00	1.00	0.92	0.93
max	1.00	1.00	1.00	1.00	1.00	1.00

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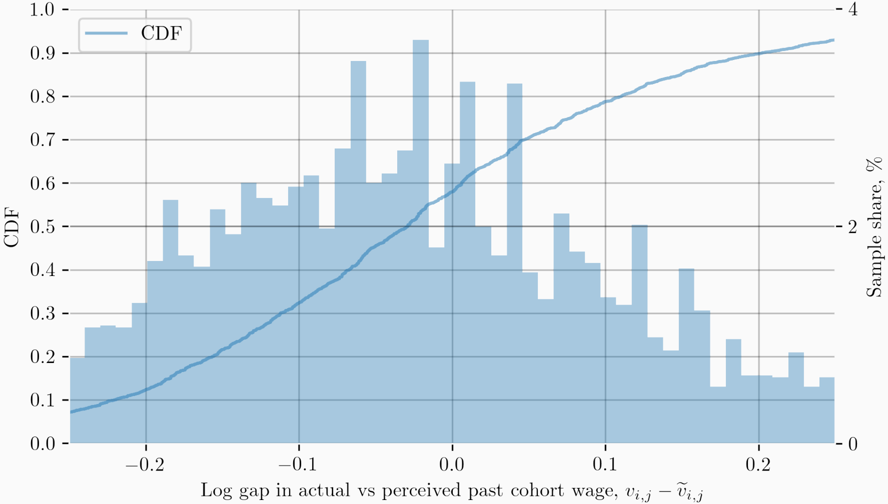
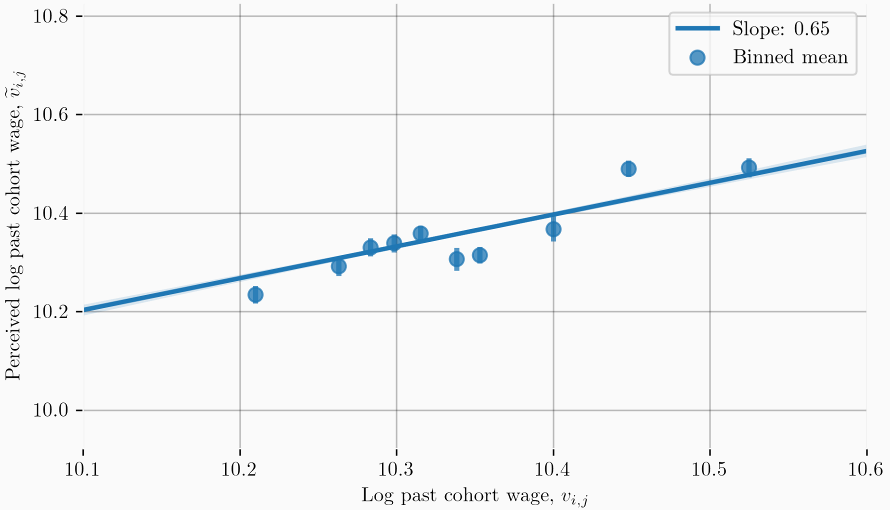
Misperceptions about wages for each job



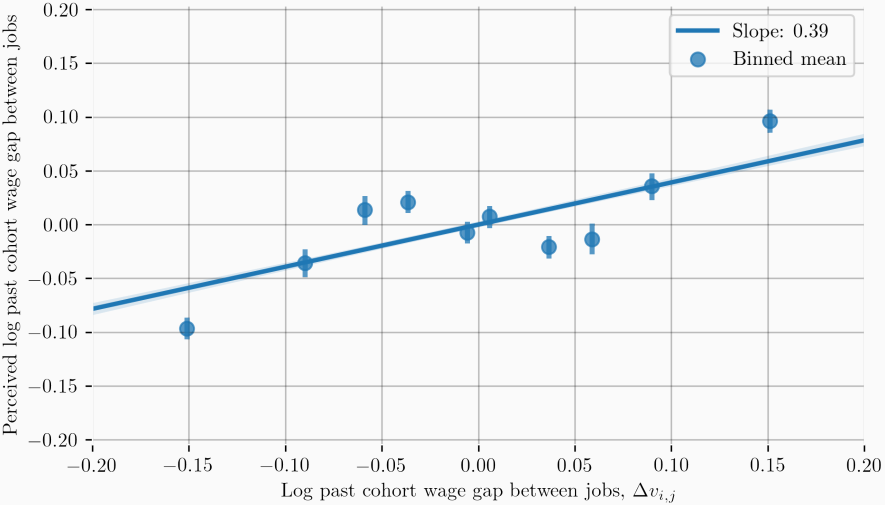
Get back Correlations Back to slides

Beliefs correlate with past cohort averages



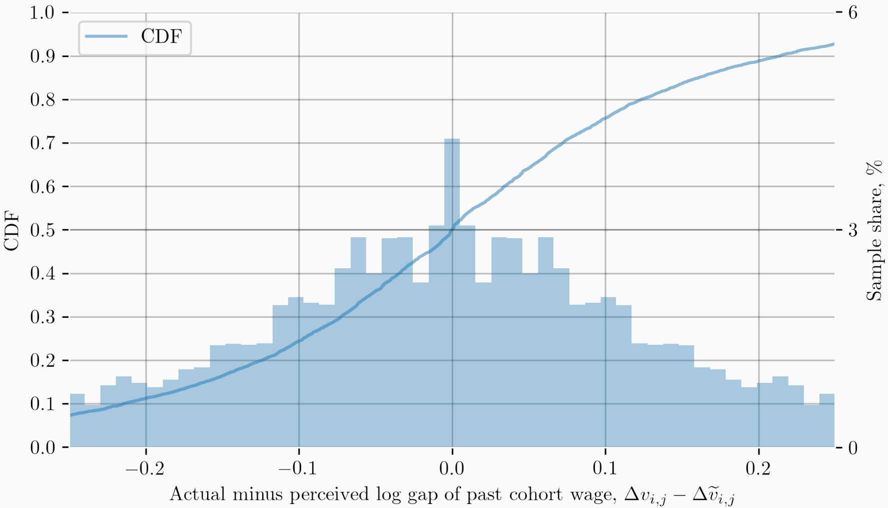
Histogram Back to slides

How beliefs correlate with past cohort averages at the job-pair level



Histogram | Unique job comparisons | Histogram with unique job comparisons | Back to slides

Between jobs wages log ratio, respondent beliefs vs. ground truth



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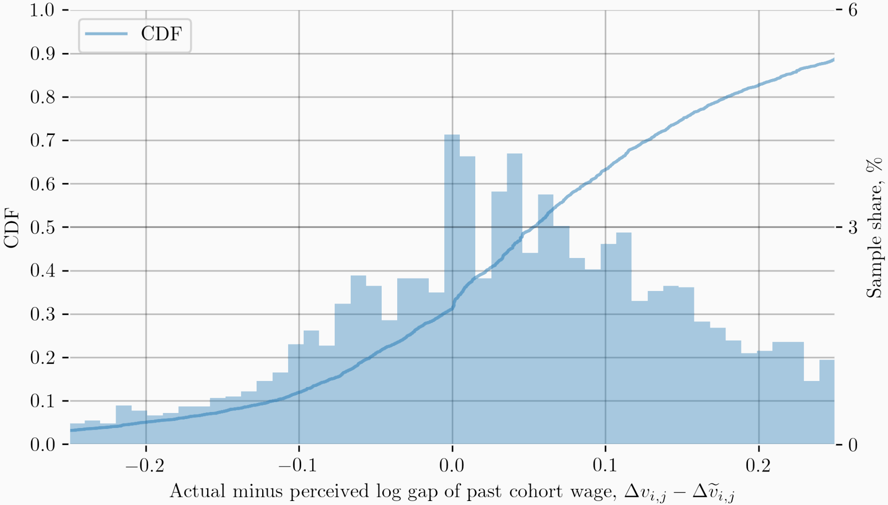
Between jobs wages log ratio, only keep $\Delta v_{i,j} > 0$



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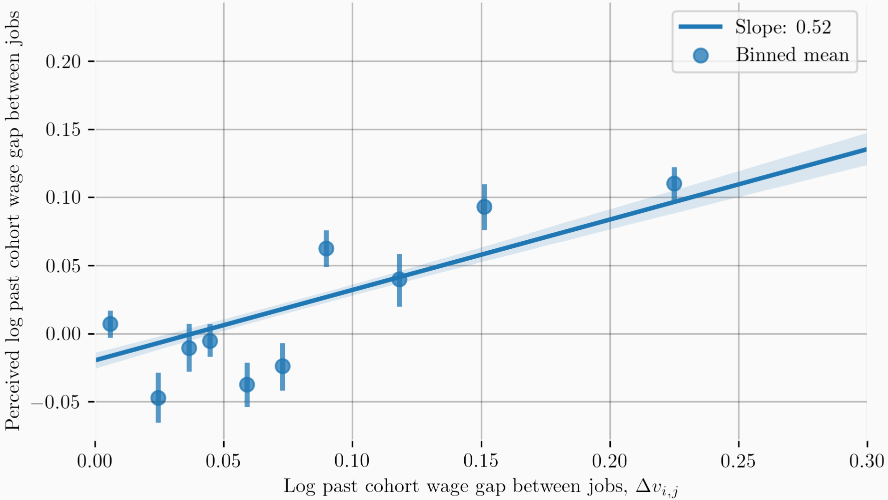
Between jobs wages log gaps, only keep $\Delta v_{i,j} > 0$



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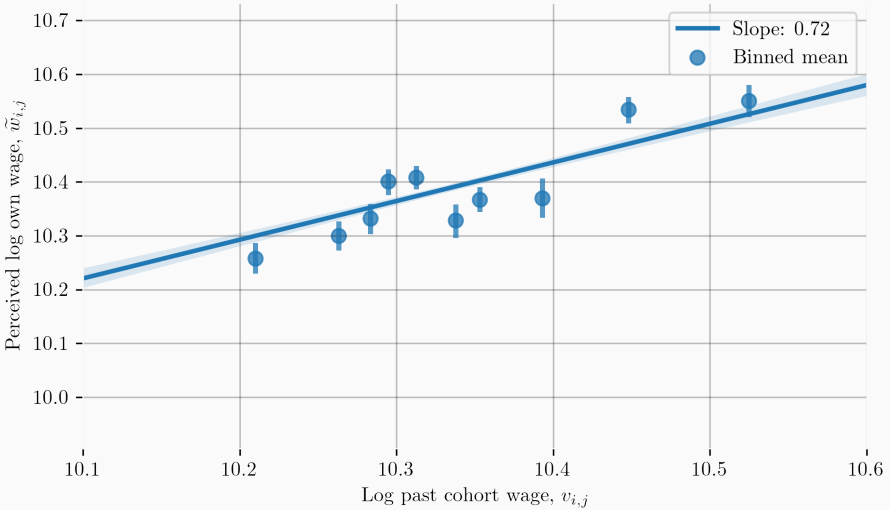
Perceived own and actual past cohort wage for control group



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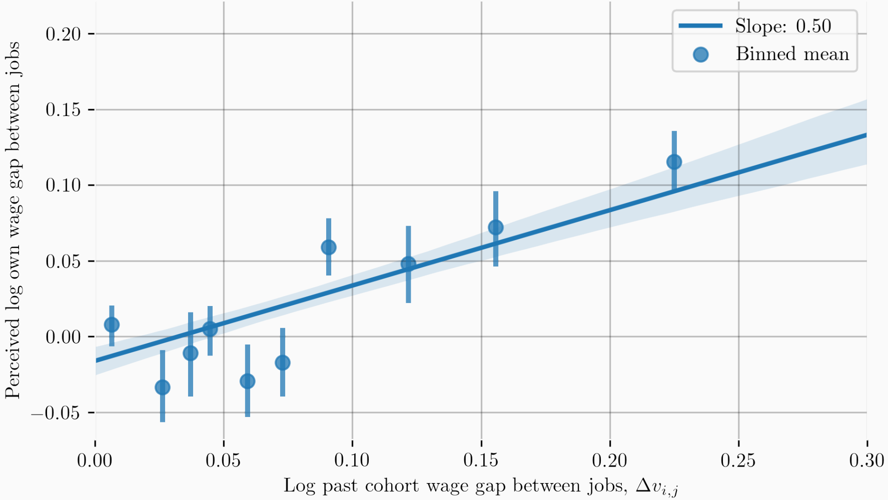
Perceived own and actual past cohort wage gaps for control group, only keep $\Delta v_{i,j} > 0$



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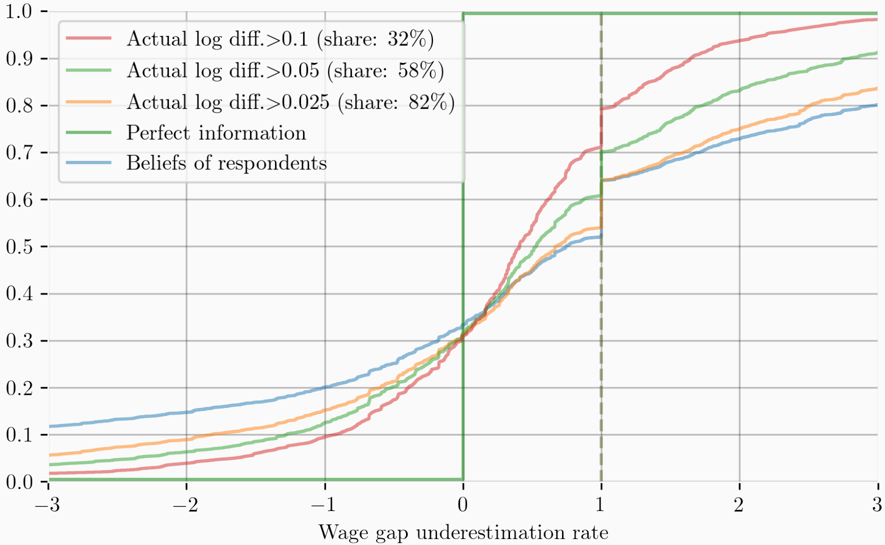
Misperceptions about the difference between jobs, conditional on data gap



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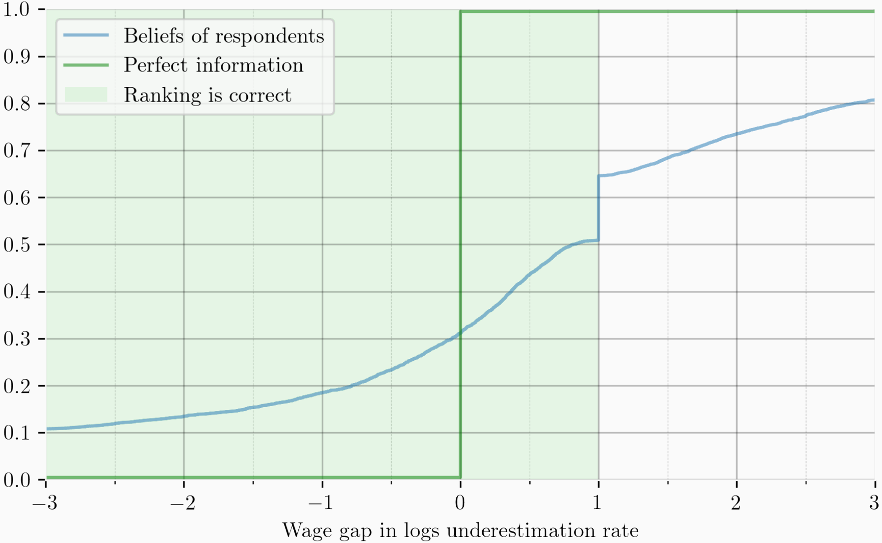
Misperceptions about the difference between jobs in logs



Misperceptions about the difference between jobs

	Absolute log wage gap underestimation		Wage gap under-estimation rate	Overestimated the wage gap by $> 50\%$	Underestimated the wage gap by $> 50\%$	Underestimated the wage gap by $> 100\%$	Unique:	
	Mean	Std. Dev.	Median	Share in $\%$	Share in $\%$	Share in $\%$	Persons	Job-pairs
Full sample	0.135	0.112	0.747	25.10	55.17	36.12	1902	5706
Actual log diff.$>$ 0.05	0.144	0.120	0.528	20.15	51.10	30.02	1583	2456
Actual log diff.$>$ 0.1	0.153	0.128	0.408	17.30	45.68	20.86	1046	1471
2 most frequent job types	0.134	0.111	0.864	25.29	55.36	36.23	1902	3804
Full sample, typos corrected	0.132	0.108	0.741	24.88	55.13	36.24	1901	5703
Active job seekers	0.135	0.112	0.770	26.46	55.27	35.89	1237	3711
Near and recent graduates	0.134	0.109	0.676	24.69	54.44	35.43	1303	3909
Good understanding of all job types	0.131	0.109	0.665	24.47	54.17	34.54	1019	3057
Is close to someone in all job types	0.140	0.119	0.622	28.21	53.21	33.33	436	1308
Correct answer to test	0.128	0.104	0.646	27.58	52.42	34.98	1135	3405
Incorrect answer to test	0.136	0.119	1.000	22.73	60.84	40.88	349	1047

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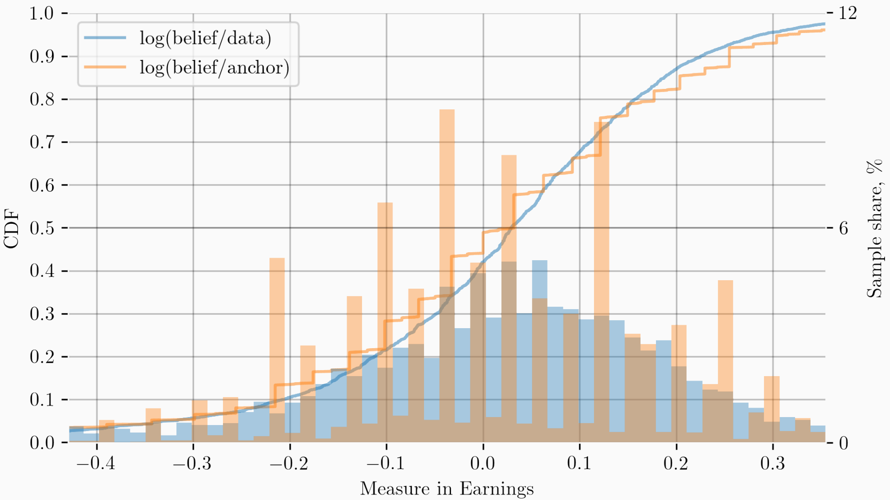
Belief and data relative to anchor



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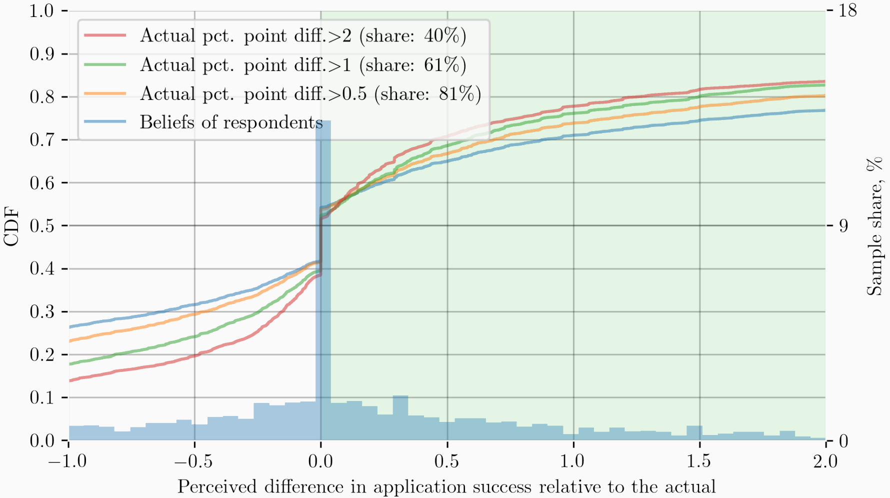
Relative misperceptions gap for likelihood of a successful application



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General model

The value of applying for a job of type j, for person i, is:

$$A_{i,j} = P_{i,j}Y_{i,j} + (1 - P_{i,j})\,U_i = P_{i,j}S_{i,j} + U_i \tag{E.1}$$

Where $S_{i,j}$ is the surplus value:

$$S_{i,j} = Y_{i,j} - U_i = \kappa_i Z_{i,j} W_{i,j}^{\delta} \tag{E.2}$$

Job seekers operate under uncertainty and we therefore assume they have perceptions about these values, and are subject to extreme value taste shocks:

$$\begin{aligned} \widetilde{A_{i,j}} &= \widetilde{P_{i,j}}\widetilde{S_{i,j}} + \widetilde{U_i} - \xi_{i,0} \\ \widetilde{S_{i,j}} &= \kappa_i \widetilde{W_{i,j}}^{\delta} \widetilde{Z_{i,j}} \xi_{i,j} \end{aligned}$$

The value of not applying for any job is:

$$\widetilde{A_{i,0}} = \widetilde{U_i} \tag{E.3}$$

General model - choice probabilities

$$j_i^* = \arg\max_j \widetilde{A_{i,j}} = \arg\max_j \frac{\log\left(\widetilde{A_{i,j}} - U_i + \xi_{i,0}\right)}{\sigma} \tag{E.4}$$

For $j = 1, 2, 3$ we have:

$$\frac{\log\left(\widetilde{A_{i,j}} - U_i + \xi_{i,0}\right)}{\sigma} = \log\left(\left(\kappa_i \widetilde{W_{i,j}}^{\delta} \widetilde{Z_{i,j}} \widetilde{P_{i,j}}\right)^{\sigma^{-1}}\right) + \sigma^{-1} \log \xi_{i,j}$$

For $j = 0$ we have

$$\frac{\log\left(\widetilde{A_{i,0}} - U_i + \xi_{i,0}\right)}{\sigma} = \sigma^{-1} \log \xi_{i,0}$$

General model - choice probabilities

We assume $\xi_{i,j} \overset{i.i.d.}{\sim} F_{EV_{II}}(x) = \exp\left(-x^{-1}\right)$ meaning that $\ln \xi_j \overset{i.i.d.}{\sim} F_{EV_I}(x) = \exp\left(-\exp(-x)\right)$.
This gives the choice probabilities:

$$\Pi^*_{i,j} = \frac{\left(\kappa_i \widetilde{W_{i,j}}^{\delta} \widetilde{Z_{i,j}} \widetilde{P_{i,j}}\right)^{\sigma^{-1}}}{1 + \sum_{j'=1,2,3} \left(\kappa_i \widetilde{W_{i,j'}}^{\delta} \widetilde{Z_{i,j'}} \widetilde{P_{i,j'}}\right)^{\sigma^{-1}}} \tag{E.5}$$

and for $j = 0$ we have

$$\Pi^*_{i,0} = \frac{1}{1 + \sum_{j'=1,2,3} \left(\kappa_i \widetilde{W_{i,j'}}^{\delta} \widetilde{Z_{i,j'}} \widetilde{P_{i,j'}}\right)^{\sigma^{-1}}} \tag{E.6}$$

General model - specification

Taking logs and differencing between jobs gives:

$$\Delta \pi_{i,j,j'} = \beta_1 \Delta \widetilde{w_{i,j,j'}} + \Delta \varepsilon_{i,j,j'} \tag{E.7}$$

With $\beta_1 \equiv \sigma^{-1}\delta$ and $\varepsilon_{i,j} \equiv \sigma^{-1}\left(\widetilde{p_{i,j}} + \widetilde{z_{i,j}}\right)$.

With IV controls this becomes:

$$\Delta \pi_{i,j,j'} = \beta_1 \Delta \widetilde{w_{i,j,j'}} + \beta_2(\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}) + \Delta \epsilon_{i,j,j'} \tag{E.8}$$

Where $\Delta \epsilon_{i,j,j'} = \Delta \varepsilon_{i,j,j'} - \beta_2 \left(\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}\right)$ Appendix TOC Regression slide

Beliefs updating framework

I assume wages for a given person in a given job type, will be the true mean times a person-specific ability adjustment and a person-job-specific adjustment:

$$W_{i,j} = \exp(a_i)\exp(a_{i,j}) \cdot \bar{W}_{i,j} \tag{F.1}$$

$$\Leftrightarrow w_{i,j} = a_i + \bar{w}_{i,j} + a_{i,j} \tag{F.2}$$

The respondent's prior is that $\bar{w}_{i,j}$ is normally distributed: $\bar{w}_{i,j}|\widetilde{v_{i,j}} \sim \mathcal{N}(\widetilde{v_{i,j}}, \frac{1}{\rho})$. Treatment is a is a noisy signal $v_{i,j} = \bar{w}_{i,j} + n_{i,j}$, with the noise being $n_{i,j} \sim \mathcal{N}(0, \frac{1}{\rho_n})$. Both ρ and ρ_n are commonly known. Then the posterior after a signal is given, $\bar{w}_{i,j}|\{\widetilde{v_{i,j}}, v_{i,j}\}$, is also normally distributed and has posterior precision and mean:

$$\rho' = \rho + \rho_n\,,\ \widetilde{v}^p_{i,j} = \frac{\rho_n}{\rho + \rho_n} v_{i,j} + \frac{\rho}{\rho + \rho_n} \widetilde{v_{i,j}} \tag{F.3}$$

Updating can be written as:

$$\underbrace{\widetilde{v}^p_{i,j} - \widetilde{v_{i,j}}}_{\text{Updating}} = \frac{\rho_n}{\rho + \rho_n} (\underbrace{v_{i,j} - \widetilde{v_{i,j}}}_{\text{Perception gap}}) \tag{F.4}$$

Updating formula

If we include spurious learning (ϱ), and that beliefs are given by the function:

$$f(\widetilde{v}^p_{i,j}, T_i, a_i, a_{i,j}) \equiv a_i + \psi_1 \widetilde{v}^p_{i,j} + \psi_2 T_i \widetilde{v}^p_{i,j} + a_{i,j} \tag{F.5}$$

The suggested first stage becomes:

$$\widetilde{w_{i,j}} = a_i + \psi_1 \widetilde{v_{i,j}} + \psi_1 \varrho(\widetilde{v_{i,j}} - v_{i,j}) + \psi_2 T_i \widetilde{v_{i,j}} + \left(\frac{\rho_n(\psi_1 + \psi_2)}{\rho + \rho_n} \right) T_i (v_{i,j} - \widetilde{v_{i,j}}) + a_{i,j} \tag{F.6}$$

Assuming $\psi_1 = \psi_2 = 0$ gives:

$$\widetilde{w}_{i,j} = a_i + \psi_1 \varrho(v_{i,j} - \widetilde{v_{i,j}}) + \left(\frac{\rho_n \psi_1}{\rho + \rho_n} \right) T_i (v_{i,j} - \widetilde{v_{i,j}}) + a_{i,j} \tag{F.7}$$

Appendix TOC Information treatment

Full table main specification

	(1) Base	(2) Control for $\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}$ squared and cubed	(3) Pre-experiment controls
First stage: Perceived gap in individual wages $\Delta \widetilde{w_{i,j,j'}}$			
$T_i \cdot (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}})$	0.315***	0.314***	0.312***
	(0.037)	(0.036)	(0.036)
Reduced form: Gap in log likelihood of applying $\Delta \pi_{i,j,j'}$			
$T_i \cdot (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}})$	1.313***	1.302***	1.344***
	(0.465)	(0.452)	(0.435)
Second stage: Gap in log likelihood of applying $\Delta \pi_{i,j,j'}$			
$\Delta \widetilde{w_{i,j,j'}}$	4.175***	4.141***	3.917***
	(1.441)	(1.417)	(1.405)
First stage F-stat	73.69	74.83	71.80
Average elasticity $\widehat{\mathcal{E}}^a$	2.91	2.89	2.73
Educations	83	83	83
Persons	1902	1902	1902
N	11412	11412	11412

Controls are the same pre-treatment variables as in the balance checks, plus fixed effects on education level and field, the variables are interacted with Underestimation of prior cohort gap in logs, $\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}$ Std. errors are clustered by person * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

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Controlling for spillovers

	(1) Base	(2) Control for $\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}$ squared and cubed	(3) Pre-experiment controls	(4) Spill-over controls	(5) Non-pecuniary spill-over controls
First stage: Perceived gap in individual wages $\Delta \widetilde{w_{i,j,j'}}$					
$T_i \cdot (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}})$	0.305***	0.304***	0.301***	0.179***	0.299***
	(0.038)	(0.037)	(0.037)	(0.032)	(0.037)
$\Delta p_{i,j,j'}$	0.002	0.002	0.002	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Reduced form: Gap in log likelihood of applying $\Delta \pi_{i,j,j'}$					
$T_i \cdot (\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}})$	1.321***	1.302***	1.188***	0.445	1.198***
	(0.462)	(0.451)	(0.443)	(0.424)	(0.434)
$\Delta p_{i,j,j'}$	0.547***	0.545***	0.543***	0.377***	0.379***
	(0.032)	(0.032)	(0.032)	(0.029)	(0.031)
Second stage: Gap in log likelihood of applying $\Delta \pi_{i,j,j'}$					
$\Delta \widetilde{w_{i,j,j'}}$	4.330***	4.277***	3.505**	2.484	4.006***
	(1.473)	(1.454)	(1.478)	(2.372)	(1.429)
$\Delta p_{i,j,j'}$	0.536***	0.535***	0.533***	0.376***	0.376***
	(0.030)	(0.031)	(0.031)	(0.029)	(0.030)
First stage F-stat	65.62	66.87	62.12	32.28	63.85
Average elasticity $\widehat{\mathcal{E}}^a$	3.01	2.97	2.43	1.73	2.78
Educations	82	82	82	82	82
Persons	1859	1859	1859	1850	1859
N	10762	10762	10762	10712	10762

Controls are the same pre-treatment variables as in the balance checks, plus fixed effects on education level and field, the variables are interacted with Underestimation of prior cohort gap in logs, $\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}$ Std. errors are clustered by person
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Reduced form, $\Delta\pi_{i,j,j'}$

	(1) Base	(2) Control for $\Delta v_{i,j,j'} - \Delta\widetilde{v_{i,j,j'}}$ squared and cubed	(3) Pre-experiment controls
$T_i \cdot (\Delta v_{i,j,j'} - \Delta\widetilde{v_{i,j,j'}})$	1.313***	1.302***	1.344***
	(0.465)	(0.452)	(0.435)
Educations	83	83	83
Persons	1902	1902	1902
N	11412	11412	11412

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OLS full, $\Delta\pi_{i,j,j'}$

	Difference in log likelihood of applying, $\Delta\pi_{i,j,j'}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\widetilde{w_{i,j,j'}}$	4.281***	4.286***	3.774***	3.764***	3.590***	3.549***	3.431***	3.945***
	(0.290)	(0.291)	(0.354)	(0.291)	(0.288)	(0.288)	(0.288)	(0.273)
$\Delta v_{i,j,j'} - \Delta\widetilde{v_{i,j,j'}}$	-2.356***	-2.316***	-1.485***	-1.983***	-2.081***	-1.849***	-1.797***	-1.472***
	(0.248)	(0.245)	(0.359)	(0.243)	(0.241)	(0.236)	(0.230)	(0.230)
$\Delta p_{i,j,j'}$		0.536***			0.535***	0.485***	0.377***	0.374***
		(0.030)			(0.031)	(0.031)	(0.031)	(0.030)
$\Delta\widetilde{v_{i,j,j'}}$			1.388***					
			(0.465)					
$\Delta \ln$ Hours				2.688***	3.187***	2.998***	2.746***	1.965***
				(0.351)	(0.344)	(0.333)	(0.322)	(0.326)
Δ Colleagues						0.373***	0.273***	0.269***
						(0.031)	(0.030)	(0.030)
Δ Performance							0.375***	0.366***
							(0.025)	(0.025)
Δ Yearly wage growth								13.519***
								(1.493)
Average elasticity $\widehat{\mathcal{E}}^a$	2.99	2.98	2.63	2.62	2.49	2.46	2.38	2.73
Educations	83	82	83	82	82	82	82	82
Persons	1902	1859	1902	1855	1824	1824	1824	1819
N	11412	10762	11412	10998	10500	10500	10500	10470

$\Delta\widetilde{p_{i,j,j'}}$ is the difference in perceived probability of receiving an offer if the respondent applies to the job type relative to another job. *Yearly wage growth*, uses perceived wages in 5 years and perceived initial wages to calculate an equivalent yearly wage growth. $\ln$ Hours is the log of the stated expected monthly hours worked, observations are excluded if wages in 5 years or hours were stated to be zero. *Colleagues* is how they think they would get on with their colleagues in the job type, scalled from 1-6. *Performance* is how well they think they would perform in the job type, scalled from 1-6. The sample is the survey population from educations that were eligible for treatment. Std. errors are clustered at person.
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

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Naive treatment effect at the job level

	log perceived wage, $\widetilde{w_{i,j}}$				Log propensity to apply, $\pi_{i,j}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment, T_i	-0.056***	-0.057***	0.045***	0.038***	-0.070	-0.080*	0.115*	0.119**
	(0.010)	(0.007)	(0.012)	(0.009)	(0.044)	(0.043)	(0.062)	(0.059)
Controls		✓		✓		✓		✓
Overestimated	Yes	Yes	No	No	Yes	Yes	No	No
Underestimated	No	No	Yes	Yes	No	No	Yes	Yes
Avg. $v_{i,j} - \widetilde{v}_{i,j}$:	-0.133	-0.133	0.138	0.138	-0.133	-0.133	0.138	0.138
Persons	1547	1547	1288	1288	1547	1547	1288	1288
N	3303	3303	2403	2403	3303	3303	2403	2403

Controls are the same pre-treatment variables as in the balance checks, plus fixed effects on education level and field The sample is the survey population from educations that were eligible for treatment. Std. errors are clustered at person. * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

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Elasticity

$$\mathcal{E}_{i,j} = \frac{\partial \pi_{i,j}}{\partial \widetilde{w_{i,j}}} = \frac{\partial \left(\sigma^{-1} \log \left(\kappa_i \widetilde{W_{i,j}}^{\delta} \widetilde{Z_{i,j}} \widetilde{P_{i,j}} \right) - \ln \left(1 + \sum_{j'=1,2,3} \left(\kappa_i \widetilde{W_{i,j'}}^{\delta} \widetilde{Z_{i,j'}} \widetilde{P_{i,j'}} \right)^{\sigma^{-1}} \right) \right)}{\partial \widetilde{w_{i,j}}} \tag{H.1}$$

$$= \frac{\delta}{\sigma} - \frac{1}{\left(1 + \sum_{j'=1,2,3} \left(\kappa_i \widetilde{W_{i,j'}}^{\delta} \widetilde{Z_{i,j'}} \widetilde{P_{i,j'}} \right)^{\sigma^{-1}} \right)} \frac{\partial \left(1 + \sum_{j'=1,2,3} \left(\kappa_i \widetilde{W_{i,j'}}^{\delta} \widetilde{Z_{i,j'}} \widetilde{P_{i,j'}} \right)^{\sigma^{-1}} \right)}{\partial \widetilde{w}_{i,j}} \tag{H.2}$$

$$= \frac{\delta}{\sigma} - \frac{\left(\kappa_i \widetilde{W_{i,j}}^{\delta} \widetilde{Z_{i,j}} \widetilde{P_{i,j}} \right)^{\sigma^{-1}}}{\left(1 + \sum_{j'=1,2,3} \left(\kappa_i \widetilde{W_{i,j'}}^{\delta} \widetilde{Z_{i,j'}} \widetilde{P_{i,j'}} \right)^{\sigma^{-1}} \right)} \frac{\partial \left(\sigma^{-1} \log \left(\kappa_i \widetilde{W_{i,j}}^{\delta} \widetilde{Z_{i,j}} \widetilde{P_{i,j}} \right) \right)}{\partial \widetilde{w_{i,j}}} \tag{H.3}$$

$$= \frac{\delta}{\sigma} \left(1 - \Pi_{i,j} \right) \tag{H.4}$$

Averaging the elasticity

With $\frac{\delta}{\sigma} \equiv \beta_1$, we calculate the average elasticity in the sample following Train (2009)[ch. 2.6.1]:

$$\widehat{\mathcal{E}}^a(\hat{\beta}_1) = \frac{1}{N \cdot J} \sum_{i=1,j=1}^{N,J} \hat{\beta}_1 \left(1 - \Pi_{i,j}\right) = \hat{\beta}_1 \frac{1}{N \cdot J} \sum_{i=1,j=1}^{N,J} \left(1 - \Pi_{i,j}\right) \tag{H.5}$$

Appendix TOC | Get back to slide | Log odds approach

Log odds ratio

Writing the model in log odd ratio approach:

$$\ln \frac{\Pi_{i,j}}{1-\Pi_{i,j}} = \ln \frac{\left(\widetilde{S_{i,j}}\widetilde{P_{i,j}}\right)^{-\sigma}}{\sum_{j'\in J}\left(\widetilde{S_{i,j'}}\widetilde{P_{i,j'}}\right)^{-\sigma}} - \ln\left(1-\frac{\left(\widetilde{S_{i,j}}\widetilde{P_{i,j}}\right)^{-\sigma}}{\sum_{j'\in J}\left(\widetilde{S_{i,j'}}\widetilde{P_{i,j'}}\right)^{-\sigma}}\right) \tag{H.6}$$

$$= \ln \frac{\left(\widetilde{S_{i,j}}\widetilde{P_{i,j}}\right)^{-\sigma}}{\sum_{j'\in J}\left(\widetilde{S_{i,j'}}\widetilde{P_{i,j'}}\right)^{-\sigma}} - \ln\left(\frac{\sum_{j'\neq j}\left(\widetilde{S_{i,j'}}\widetilde{P_{i,j'}}\right)^{-\sigma}}{\sum_{j'\in J}\left(\widetilde{S_{i,j'}}\widetilde{P_{i,j'}}\right)^{-\sigma}}\right) \tag{H.7}$$

$$= \ln \kappa_i + \frac{\delta}{\sigma}\widetilde{w_{i,j}} + \frac{1}{\sigma}\left(\widetilde{z_{i,j}} + \widetilde{p_{i,j}}\right) - \ln\left(\sum_{j'\neq j}\left(\widetilde{S_{i,j'}}\widetilde{P_{i,j'}}\right)^{-\sigma}\right) \tag{H.8}$$

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2stage, Log odds ratio, full

	Log odds acceptance likelihood $\ln \frac{\pi_{i,j}}{1-\pi_{i,j}}$				
	(1)	(2)	(3)	(4)	(5)
$\ln$ perceived wage, $\tilde{w}_{i,j}$	1.660*	5.401**	5.547**	5.430**	5.552***
	(0.850)	(2.413)	(2.344)	(2.323)	(2.076)
Perception gap, $\tilde{w}^a_{i,j} - w^a_j$	1.447***	4.030***	2.079	2.046	1.542
	(0.506)	(1.143)	(1.739)	(1.741)	(1.267)
$\ln$ perceived avg. wage, $\tilde{w}^a_{i,j}$			2.513	2.611	1.031
			(2.427)	(2.418)	(2.075)
Yearly wage growth					19.413***
					(4.318)
$\ln$ Hours					3.604***
					(0.754)
Appl likelihood					0.019***
					(0.004)
Colleagues					0.429***
					(0.049)
Performance					0.684***
					(0.052)
Person FE		✓	✓	✓	✓
Constant	✓				
N	5706	5706	5706	5706	5514
First stage F(K-P)	33.184	52.803	64.607	34.910	54.082
Average elasticity $\widehat{\mathcal{E}}^a$	1.655	5.384	5.530	5.414	5.535
Instruments:					
$T_i(\tilde{w}^a_{i,j} - w^a_j)$	✓	✓	✓	✓	✓
$T_i\tilde{w}^a_{i,j}$				✓	

This table shows the second stage estimates instrumenting log of the perceieved wage, $\ln \tilde{w}_{i,j}$, with the variable indicated by the two lowest columns. The outcome variable is the log odds of the likelihood of accepting a job. $\widehat{\mathcal{E}}^a$ is the sample-average elasticity of the likelihood of accepting a job with respect to the perceived wage suggested by the estimate. *Yearly wage growth*, uses perceived wages in 5 years and perceived initial wages to calculate an equivalent yearly wage growth. $\ln$ Hours is the log of the stated expeceted monthly hours worked. Observations are excluded in column (5) if wages in 5 years or hours were stated to be zero. *Appl likelihood* is the stated likelihood between 0 and 100 that given that they had applied to the job, how likely it would be that they would have received a job offer, graded from 0-100. *Colleagues* is how they think they would get on with their colleagues in the job type from 1-6. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

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OLS, Log odds ratio, full

	Log odds acceptance likelihood $\ln \frac{\pi_{i,j}}{1-\pi_{i,j}}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln$ perceived wage, $\tilde{w}_{i,j}$	1.365***	6.590***	5.730***	5.729***	1.837***	7.896***	6.851***
	(0.174)	(0.557)	(0.519)	(0.587)	(0.196)	(0.487)	(0.457)
Perception gap, $\tilde{w}^a_{i,j} - w^a_j$	1.579***	3.612***	2.131	1.595			
	(0.424)	(0.830)	(1.605)	(1.144)			
$\ln$ perceived avg. wage, $\tilde{w}^a_{i,j}$			2.359	0.879			
			(1.428)	(1.146)			
Yearly wage growth				19.752***			22.845***
				(2.193)			(1.976)
$\ln$ Hours				3.564***			3.671***
				(0.522)			(0.517)
Appl likelihood				0.019***			0.018***
				(0.004)			(0.004)
Colleagues				0.428***			0.448***
				(0.048)			(0.050)
Performance				0.683***			0.678***
				(0.049)			(0.049)
Person FE		✓	✓	✓		✓	✓
Constant	✓				✓		
N	5706	5706	5706	5514	5706	5706	5514
Average elasticity $\widehat{\mathcal{E}}^a$	1.361	6.570	5.712	5.712	1.831	7.872	6.830

This table shows OLS estimates. The outcome variable is the log likelihood of accepting a job, relative to rejecting all of them. $\widehat{\mathcal{E}}^a$ is the sample-average elasticity of the likelihood of accepting a job with respect to the perceived wage suggested by the estimate. *Yearly wage growth*, uses perceived wages in 5 years and perceived initial wages to calculate an equivalent yearly wage growth. $\ln$ Hours is the log of the stated expeceted monthly hours worked. Observations are excluded in column (5) if wages in 5 years or hours were stated to be zero. *Appl likelihood* is the stated likelihood between 0 and 100 that given that they had applied to the job, how likely it would be that they would have received a job offer, graded from 0-100. *Colleagues* is how they think they would get on with their colleagues in the job type from 1-6. * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

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Fixed effects versions

$$\pi_{i,j} - \pi_{i,0} = \ln \kappa_i + \frac{\delta}{\sigma}\widetilde{w_{i,j}} + \frac{1}{\sigma}\left(\widetilde{z_{i,j}} + \widetilde{p_{i,j}}\right) \tag{H.9}$$

With $\frac{1}{\sigma}\left(\widetilde{z_{i,j}} + \widetilde{p_{i,j}}\right) = \varepsilon_{i,j}$

The first stage in levels is:

$$\widehat{\widetilde{w_{i,j}}} = a_i + \tau_1 T_i(\widetilde{v_{i,j}} - v_{i,j}) + \tau_2(\widetilde{v_{i,j}} - v_{i,j}) + a_{i,j} \tag{H.10}$$

Is just the fixed effects version of the first difference regression.

Both are consistent under strict exogeneity $\mathbb{E}\left[\varepsilon_{i,j} | \widetilde{w}_{i,0}, \widetilde{w}_{i,1}, \widetilde{w}_{i,2}\right] = 0$. (The condition for FD is slightly more lenient but with $J = 3$ its almost the same ($\mathbb{E}\left[\varepsilon_{i,j} | \widetilde{w}_{i,j-1}, \widetilde{w}_{i,j}, \widetilde{w}_{i,j+1}\right] = 0$) They give the same estimates and if $J = 2$ they would be the exact same.

They are efficient under different circumstances. FE is efficient if $\varepsilon_{i,j}$ is serially uncorrelated. FD is efficient if $\varepsilon_{i,j}$ is a unit root process ($\varepsilon_{i,j} - \varepsilon_{i,j'}$ is serially uncorrelated).

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Spillovers in expectations

	Gap between jobs in:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\widetilde{w_{i,j,t+5}}$	Hours≤ 35	Hours$\in (35, 40)$	Hours≥ 40	Log appl likelihood	Colleagues	Performance
$\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}$	-0.508***	0.308***	0.316***	-0.547***	0.087	-0.736***	-0.534**
	(0.027)	(0.052)	(0.082)	(0.077)	(0.207)	(0.168)	(0.216)
$T_i \left(\Delta v_{i,j,j'} - \Delta \widetilde{v_{i,j,j'}}\right)$	0.225***	-0.063	-0.042	0.069	0.362	0.126	0.184
	(0.040)	(0.082)	(0.126)	(0.111)	(0.282)	(0.242)	(0.320)
Persons	1850	1850	1850	1850	1850	1850	1850
N	10712	10712	10712	10712	10712	10712	10712

This table shows first stage regressions, replacing the outcome variable with perceived job amenities. $\tilde{w}_{i,j,t+5}$ is the log of the perceived earnings in 5 years after starting to work in the job type. *Hours* is how many hours they think they would work each week if they were hired. *Log appl likelihood* is the log of the how likely they thing their application would be successful. *Colleagues* is how they think they would get on with their colleagues in the job type, scaled from 1-6. *Performance* is how well they think they would perform in the job type, scaled from 1-6. The sample is the survey population from educations that were eligible for treatment. Std. errors are clustered at person. * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$.

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Correlation between log perceived starting wage and other amenities

	(1) $\Delta\widetilde{w_{i,j,t+5}}$	(2) Hours≤ 35	(3) Hours$\in (35, 40)$	(4) Hours≥ 40	(5) Appl likelihood	(6) Colleagues	(7) Performance
Panel A: Full eligible sample							
$\Delta\widetilde{w_{i,j,j'}}$	0.852***	-0.332***	-0.671***	0.916***	0.085	0.500***	0.675***
	(0.030)	(0.042)	(0.074)	(0.071)	(0.143)	(0.141)	(0.167)
N	10712	10712	10712	10712	10712	10712	10712
Panel B: Control sample							
$\Delta\widetilde{w_{i,j,j'}}$	0.881***	-0.372***	-0.727***	1.020***	0.140	0.534***	0.659***
	(0.043)	(0.060)	(0.099)	(0.095)	(0.197)	(0.193)	(0.229)
N	5466	5466	5466	5466	5466	5466	5466
Panel C: Treatment sample							
$\Delta\widetilde{w_{i,j,j'}}$	0.814***	-0.277***	-0.596***	0.775***	0.011	0.455**	0.697***
	(0.042)	(0.059)	(0.114)	(0.108)	(0.209)	(0.204)	(0.244)
N	5246	5246	5246	5246	5246	5246	5246

Notes: This table shows the person-adjusted correlation between amenities and log of perceived wages in the job type. Panel A uses the full eligible sample. Panel B uses the control group. Panel C uses the treatment group. *Hours* is how many hours they think they would work each week if they were hired. *Colleagues* is how they think they would get on with their colleagues in the job type, scalled from 1-6. *Performance* is how well they think they would perform in the job type, scalled from 1-6.

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$\ln$ perceived wage, $\tilde{w}_{i,j}$, controlling for misperceptions in other treated jobs

	(1)	(2)	(3)	(4)
Treatment, T_i	-0.015**	-0.015**		
	(0.007)	(0.007)		
$\ln$ perceived avg. wage, $\tilde{w}^a_{i,j}$	0.843***	0.843***	0.843***	0.843***
	(0.045)	(0.045)	(0.045)	(0.045)
Perception gap, $\tilde{w}^a_{i,j} - w^a_j$	-0.173***	-0.173***	-0.117**	-0.145**
	(0.055)	(0.055)	(0.058)	(0.055)
T_i X perception gap, $T_i(\tilde{w}^a_{i,j} - w^a_{i,j})$	-0.339***	-0.339***	-0.335***	-0.337***
	(0.033)	(0.033)	(0.043)	(0.045)
$\tilde{w}^a_{i,j'} - w^a_{j'}$	-0.028		0.027	
	(0.019)		(0.020)	
$T_i(\tilde{w}^a_{i,j'} - w^a_{i,j'})$	-0.003		0.002	
	(0.026)		(0.029)	
$\tilde{w}^a_{i,j''} - w^a_{j''}$	-0.055***			-0.027
	(0.020)			(0.020)
$T_i(\tilde{w}^a_{i,j''} - w^a_{i,j''})$	-0.004			-0.002
	(0.024)			(0.029)
$\frac{1}{2}\left((\tilde{w}^a_{i,j'} + w^a_{i,j'}) + (\tilde{w}^a_{i,j'} - w^a_{i,j'})\right)$		-0.083**		
		(0.033)		
$T_i\frac{1}{2}\left((\tilde{w}^a_{i,j'} - w^a_{i,j'}) + (\tilde{w}^a_{i,j'} - w^a_{i,j'})\right)$		-0.007		
		(0.040)		
Education FE	✓	✓		
Person FE			✓	✓
N	5706	5706	5706	5706

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

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Wage spill over issue

Say for a given variable $x_{i,j} = (\widetilde{v_{i,j}} - v_{i,j})$, with $J = 3$, the demean of the variable for the first job, $x_{i,j}$, is equal to the sum of the demean of the variable for the two other jobs $x_{i,j'} + x_{i,j''}$:

$$
\begin{aligned}
&- \left(x_{i,j'} - \frac{1}{3}(x_{i,j} + x_{i,j'} + x_{i,j''}) \right) - \left(x_{i,j''} - \frac{1}{3}\left(x_{i,j} + x_{i,j'} + x_{i,j''}\right)\right) \\
&= \frac{2}{3}x_{i,j} + \frac{2}{3}(x_{i,j'} + x_{i,j''}) - x_{i,j'} - x_{i,j''} = x_{i,j} - \frac{1}{3}\left(x_{i,j} + x_{i,j'} + x_{i,j''}\right)
\end{aligned}
$$

I can also not include the mean of the variable for the 2 other jobs, $\frac{1}{2}(x_{i,j'} + x_{i,j''})$, because when you demean that, it is equal to the demeaned $x_{i,j}$ divided by -2:

$$
\begin{aligned}
x_{i,j} - \frac{1}{3}\left(x_{i,j} + x_{i,j'} + x_{i,j''}\right) &= -2 \cdot \left(\frac{1}{2}(x_{i,j'} + x_{i,j''}) - \frac{1}{3}\frac{1}{2}\left(2x_{i,j} + 2x_{i,j'} + 2x_{i,j''}\right) \right) \\
&= -2 \cdot \frac{1}{3}\left(x_{i,j} + x_{i,j'} - x_{i,j''}\right) - x_{i,j'} + x_{i,j''} \\
&= x_{i,j} - \frac{1}{3}\left(x_{i,j} + x_{i,j'} + x_{i,j''}\right)
\end{aligned}
$$

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