

The wage elasticity of job applications: Quantity and quality margins

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Outline

Introduction

Setting and data

- Platform

- Sample

Conceptual framework

Diff-in-diff: the effect of wages on applications and hires

- Design

- Quantity

- Quality

- Hires

Structural decomposition

- From DiD to equilibrium effects

Motivation

- ▶ Persistent imbalances across local labour markets in terms of unemployment, tightness, hiring rates
- ▶ Wages are thought to be key to the reallocation process, by pushing/pulling workers across markets
- ▶ Research question: in the context of connected labour markets, what is the impact of a market-level increase in wages on labour supply?
 - ▶ Number of applications vs. quality of applications
 - ▶ Effect on affected market vs. spillovers

The paper in one slide

- ▶ What we do:
 - ▶ Online platform: lab in the field
 - ▶ We observe applications, offers, hires
 - ▶ Wages are set by the platform
 - ▶ Wage increase in one of the occupation, not others
 - ▶ Ideal for a diff-in-diff?
 - ▶ SUTVA is violated by design
 - ▶ Structural model to decompose effect on affected occupation vs. spillovers (and nature of spillovers)
 - ▶ Distinguish effect on number of applications vs. quality of applications
- ▶ What we find:
 - ▶ Reduced-form evidence
 - ▶ Wage elasticity of number of applications: 3.4
 - ▶ Wage elasticity of number of applications: between 0 (max quality in pool) and .5 (min quality in pool)
 - ▶ Wage elasticity of hires: 1.8
 - ▶ Structural estimation + decomposition
 - ▶ Spillovers are negative but modest (to be confirmed)

Contributions

- ▶ Labour-supply elasticities to wage increases:
 - ▶ hires/vacancy duration: Hirsch, Jahn, Manning and Oberfichtner (2025); Bassier, Manning and Petrongolo (2025); Mueller, Osterwalder, Zweimüller and Kettemann (2024); Datta (2025).
 - ▶ number of applications: Banfi and Villena-Roldan (2019); Marinescu and Wolthoff (2020); Belot, Kircher and Muller (2022); Beerli et al. (2026).
 - ▶ quality: Dal Bo, Finan and Rossi (2013); Balgova et al. (2025).
- ▶ Search and matching frameworks:
 - ▶ Endogenous occupation choices: Carrillo-Tudela and Visschers (2023)
 - ▶ Multidimensional skills and skill requirements: Baley, Figueiredo, and Ulbricht (2022)
 - ▶ Heterogeneous mobility: Amior, Elsby, Gottfries (2025)
- ▶ Collectively-bargained wages and sectoral/local minimum wages:
 - ▶ Dustmann et al. (2022); Engbom and Moser (2022); Derenoncourt and Weil (2025). Wage spillovers: Gopalan et al. (2021); Bassier (2022); Demir (2024); Giupponi and Machin (2026)
 - ▶ Providing information to foster occupational reallocation: Belot et al. (2019, 2025, 2026); Jäger et al. (2014); Klæui (2026)

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Extracadabra

- ▶ Online platform specialised in hospitality jobs in and around Paris
 - ▶ restaurants, bars, hotels, catering and events
 - ▶ main occupations: wait staff, bar staff, runners, receptionists
- ▶ Focus on *extra* jobs: short spells, often a few hours to a few days
- ▶ Workers usually operate as self-employed contractors
- ▶ Platform intermediates the match and acts as escrow after the job is performed

How matching happens

1. Employer creates a position: occupation, location, schedule, breaks, number of workers
2. Extracadabra runs a matching algorithm on the worker database
3. Matched workers receive an app notification and decide whether to apply
4. Employer browses applicants and selects one or more workers
5. After completion, employers can rate workers; high ratings affect future matching

Creating a job ad

Quel est le type de votre établissement ?

Cafés / Restaurants 	Bars / Clubs 	Hôtel 
Vente à emporter 	Retail / Vente 	Santé 
Restauration Collective 	Événementiel 	Autres 

Establishment type

Pour un poste en ...

 Hôtel	 Cuisine	 Salle / Bar
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... En tant que

Chef de partie
Demi-chef de partie
Commis de cuisine
Second de cuisine
Chef de cuisine
Plongeur

[+ Voir plus de catégories](#)

Occupation

Soyez plus attractif

En prévision des JO, nous vous conseillons de booster vos demandes de +20% afin de réduire les refus et d'améliorer la qualité des profils reçus !

+10%	+20%	+30%	+50%	+100%
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Personnaliser %

Prestation

Durée totale	70h00
Pour 1 extra	
Prix horaire HT	17,90 €
Plongeur	
 Total HT* :	1253,00 €

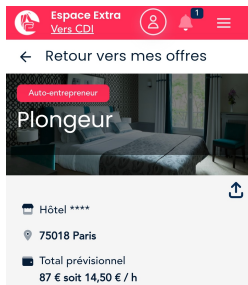
[*Qu'inclut le prix horaire ?](#)

Vous ne paierez qu'une fois la prestation du candidat effectuée

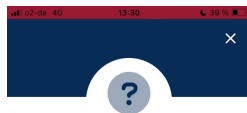
Suivant

Wage and boost

Applying and screening



Job details



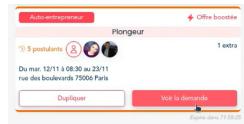
Tu es sur le point de postuler à la mission en tant que Serveur 🍷

Afin de valider ta candidature, merci de confirmer les informations suivantes :

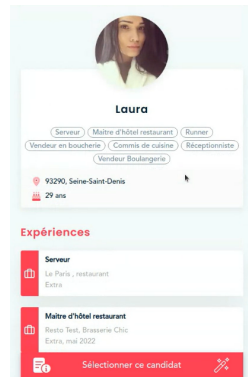
- ☐ Je suis disponible sur l'ensemble des créneaux
- ☐ J'ai pris connaissance des détails de la mission (horaires, tenues, adresse ...)
- ☐ J'ai lu la [charte de bonne conduite](#)

Soumettre ma candidature

Apply



Applications



Candidate profile

Data

- ▶ **Job-level data**

- ▶ wage, occupation, workplace postcode, precise schedule, unpaid breaks, posting time
- ▶ employer, venue, establishment category

- ▶ **Worker-level data**

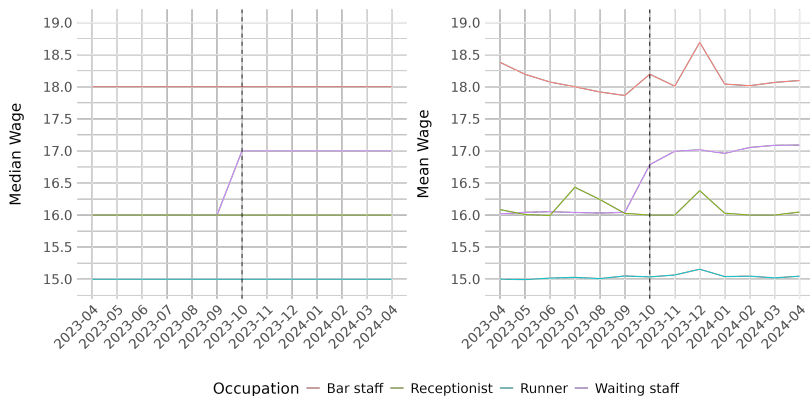
- ▶ age, gender, residence postcode, skills, ratings, platform and outside experience

- ▶ **Pair-level data**

- ▶ notifications, applications, employer decisions, hires, hours worked, final wage bill

The wage change

- ▶ Extracadabra sets default wages by precise occupation
- ▶ Wait-staff default wage increased from **16** to **17** euros per hour on **October 5, 2023**
- ▶ Default wages in neighbouring occupations remained fixed
- ▶ This provides occupation-level wage variation inside the same platform and local market



Analysis sample

- ▶ Jobs posted between **April 5, 2023** and **May 4, 2024**
- ▶ Four neighbouring service occupations:
 - ▶ treated occupation: wait staff
 - ▶ comparison occupations: bar staff, runners, receptionists
- ▶ 26,297 job adverts posted by 1,475 firms in 2,200 venues
- ▶ 5,632 workers and 320,833 applications
- ▶ 47% of jobs are filled with at least one worker

Job ads and outcomes

	Wait staff	Bar staff	Receptionist	Runner	Non-wait staff
Postings	12,677	7,530	1,491	4,599	13,620
Workers notified	1,335	899	1,160	774	885
Applications	13.77	10.61	19.38	8.15	10.74
Hires	0.55	0.61	0.59	0.49	0.57
At least one hire	0.46	0.50	0.48	0.43	0.48
Work hours	5.75	5.86	6.08	6.91	6.24
Posted in Paris	0.66	0.69	0.88	0.71	0.72

Means by occupation. The non-wait staff group pools bar staff, receptionists, and runners.

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Why a model?

- ▶ A higher wage makes a job more attractive
- ▶ But it may also attract stronger competitors
- ▶ Workers choose whether to apply before knowing the realised applicant pool
- ▶ The model clarifies three margins:
 - ▶ quantity of applications
 - ▶ quality composition of the applicant pool
 - ▶ spillovers onto neighbouring occupations

Setting and decisions

- ▶ Worker type: productivity ranks $q = (q_A, q_B)$
 - ▶ Occupation A : wait staff, whose wage w_A increases
 - ▶ Occupation B : pooled comparison occupations,
- ▶ Workers are notified about jobs in occupation j at rate α_j and draw idiosyncratic ε_j : value of job is $w_j + \varepsilon_j$.
- ▶ Workers decide whether to apply and pay cost $\tilde{c}_j$.
 - ▶ The expected probability to apply to a job in j (conditional on being notified) is: λ_j
- ▶ Employers face the applicant pool: they draw an idiosyncratic ν_i for each applicant and hire the applicant with the highest $q_{ij} + \nu_i$
- ▶ After selection, the match happens with probability κ_j
 - ▶ The expected probability to be hired in a job in j is: p_j
- ▶ Workers that remain unmatched get instant utility b

Worker application rule

- ▶ Worker's value is:

$$u(q; w) = b + \sum_{j \in \{A, B\}} \alpha_j \mathbb{E}_{\varepsilon_j} [\max \{0, -\tilde{c}_j + \beta p_j(q_j; w)[w_j + \varepsilon_j - u(q; w)]\}],$$

- ▶ Apply when the expected surplus exceeds the application cost:

$$p_j(q_j; w) [w + \varepsilon_j - u(q; w)] \geq c_j$$

- ▶ Assuming ε_j is a logistic(s_j), application probability is:

$$\lambda_j(q; w) = \frac{1}{1 + \exp \{-[w_j - u(q; w) - c_j/p_j(q; w)]/s_j\}}$$

- ▶ The continuation value simplifies to:

$$u(q; w) = b - \sum_{k \in \{A, B\}} \alpha_k(q) \beta s_k p_k(q_k; w) \log[1 - \lambda_k(q; w)]$$

Competition among applicants

- ▶ Assume that ν_i is distributed as an EV(σ_j)
- ▶ Hiring probability depends on own productivity and competition from other applicants

$$p_j(q_j; w) = \kappa_j \frac{\exp(q_j/\sigma_j)}{\exp(q_j/\sigma_j) + D_j(w)}$$

- ▶ $D_j(w)$ proxies effective competition in occupation j

$$D_j(w) = \int \alpha_j(q_j) \exp(q_j/\sigma_j) \lambda_j(c; w) dF_j(q_j)$$

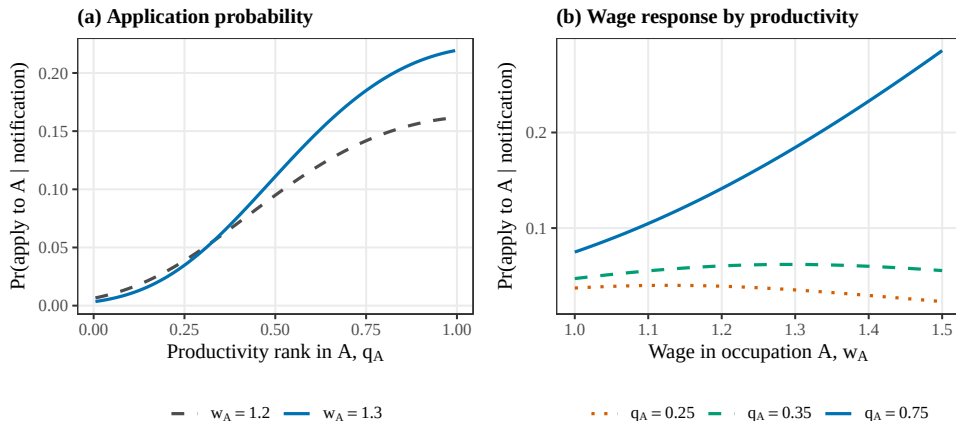
- ▶ Small σ_j : employers rank applicants more sharply by productivity
- ▶ Large σ_j : idiosyncratic employer-applicant fit matters more

How wages affect applications

$$\frac{d\lambda_j(q; w)}{dw_A} = \frac{\lambda_j(q; w)[1 - \lambda_j(q; w)]}{s_j} \left[\mathbf{1}\{j = A\} - \frac{du(q; w)}{dw_A} + \frac{c_j}{p_j(q_j; w)^2} \frac{dp_j(q_j; w)}{dw_A} \right]$$

1. Direct wage effect: the treated job pays more
2. Option-value effect: waiting for future jobs becomes more attractive
3. Competition effect: higher wages can lower hiring chances

Wages, hiring prospects, and applications



Illustrative calibration. Higher wages can attract high-productivity workers while discouraging some workers with low hiring probabilities.

From application rules to outcomes

- Applications per vacancy:

$$\mathcal{A}_j(w) = M_j \int \lambda_j(q; w) dF(q)$$

- Mean applicant quality:

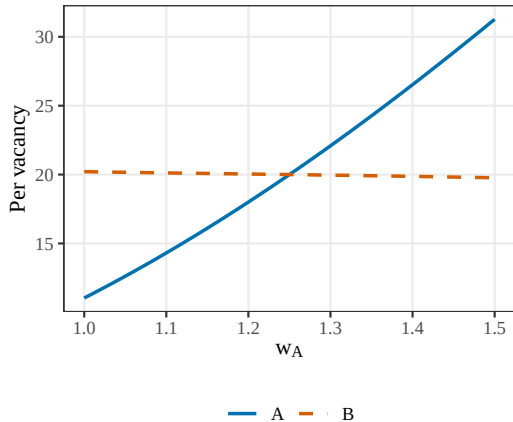
$$\overline{Q}_j(w) = \frac{\int q_j \lambda_j(q; w) dF(q)}{\int \lambda_j(q; w) dF(q)}$$

- Filling rate:

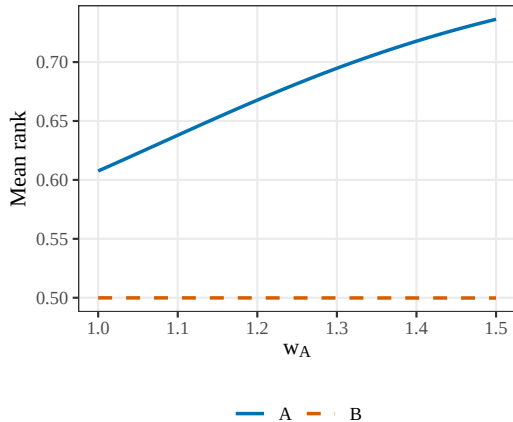
$$H_j(w) = \kappa_j [1 - \exp\{-\mathcal{A}_j(w)\}]$$

Spillovers

(a) Applications



(b) Applicant quality



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Difference-in-differences design

- ▶ Compare wait-staff ads to neighbouring service occupations
- ▶ Compare before and after the **October 5, 2023** default-wage increase
- ▶ Estimates are intention-to-treat:
 - ▶ most ads follow default wages
 - ▶ some firms use client-specific grids or wage boosts
- ▶ Main outcomes:
 - ▶ number of applications
 - ▶ mean, minimum, and maximum applicant quality

Estimating equation

- ▶ Number of applications: Poisson model with offset for notifications

$$Y_j = \exp(\beta \text{WaitStaff}_j \times \text{Post}_j + X_j\gamma + \lambda_{o(j)} + \lambda_{t(j)} + \text{FE} + \ln M_j)$$

- ▶ Quality outcomes: linear model with the same treatment indicator and controls
- ▶ Controls include schedule, hours, breaks, posting time, expected duration, number of working days, and shift type
- ▶ Richest specification uses venue fixed effects

Identification

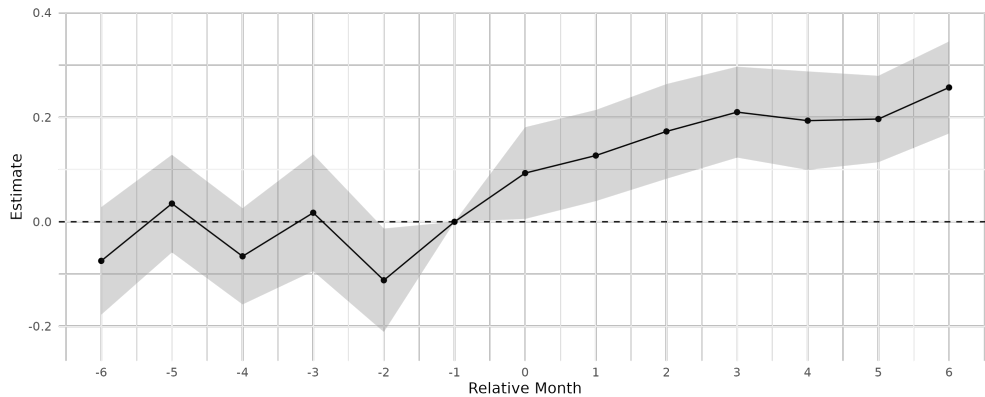
- ▶ Parallel trends: without the wait-staff wage increase, treated and comparison occupations would have evolved similarly
- ▶ Why plausible here:
 - ▶ same platform and short time window
 - ▶ largely same local hospitality market
 - ▶ many firms post in several service occupations
 - ▶ some workers apply across occupations
- ▶ Main concern: SUTVA may fail
 - ▶ applications gained by wait-staff jobs may partly come from comparison jobs
 - ▶ structural section decomposes this reduced-form contrast

Impact on number of applications

	(1)	(2)	(3)	(4)
Post $\times$ Treated	0.266*** (0.020)	0.195*** (0.020)	0.207*** (0.021)	0.210*** (0.022)
Approx. effect	+30.5%	+21.5%	+23.0%	+23.4%
Observations	26,297	26,112	25,921	25,461
Dependent mean	12.2	12.2	12.3	12.2
Category FE		✓	✓	
Postcode FE		✓	✓	
Category $\times$ postcode FE			✓	
Venue FE				✓

Poisson regressions with occupation and week fixed effects, controls, and notification offset. With a 6.25% wage increase, the preferred log-point estimate implies an elasticity of roughly 3.4.

Event study: applications



Event study with specification (4), with venue FE.

Defining applicant quality

- ▶ Goal: measure quality as perceived by employers for a given job
- ▶ Revealed-preference approach:

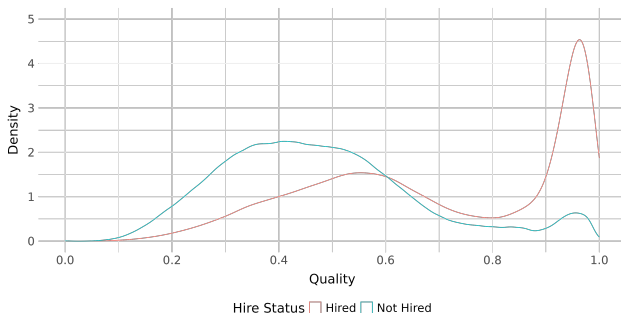
$$h_{ij}^* = X_{ij}\gamma + u_{ij}$$

where $h_{ij} = 1$ if applicant i is hired for job j

- ▶ Predictors include:
 - ▶ previous work and approval by the firm
 - ▶ distance, ratings, occupation and establishment-type experience
 - ▶ gender, age, skills, language, recent connection to the app
 - ▶ occupation-firm fixed effects
- ▶ Quality is pair-specific: the same worker can be high quality for one job and not another

Quality score: validation

- ▶ Logistic model
- ▶ Estimation sample: 361,689 applications
- ▶ Metrics:
 - ▶ AUC: .76
 - ▶ Specificity: .785
 - ▶ Sensitivity: .605
- ▶ Strong predictors:
 - ▶ already approved by same establishment
 - ▶ past experience in related qualifications
 - ▶ ratings and recent app activity

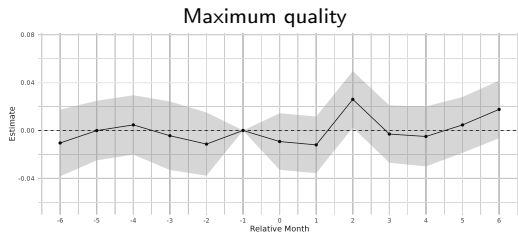
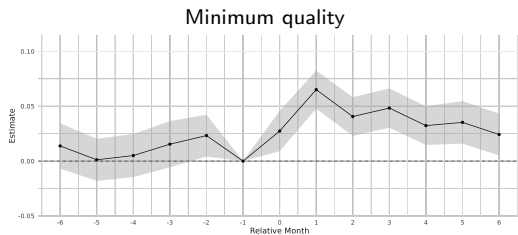
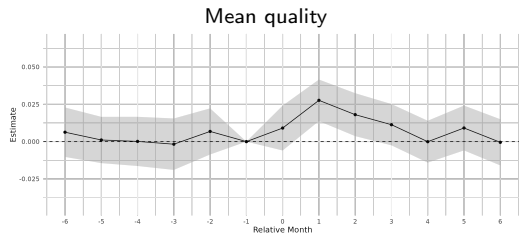


Impact on applicant quality

	(1)	(2)	(3)	(4)
Mean quality				
Post $\times$ Treated	0.0065** (0.0031)	0.0128*** (0.0030)	0.0107*** (0.0032)	0.0095*** (0.0034)
Minimum quality				
Post $\times$ Treated	0.0292*** (0.0036)	0.0349*** (0.0037)	0.0329*** (0.0039)	0.0307*** (0.0043)
Maximum quality				
Post $\times$ Treated	0.0042 (0.0052)	0.0095* (0.0051)	0.0060 (0.0053)	0.0065 (0.0057)
Observations	19,503	19,388	19,207	18,773

OLS regressions. The wage change raises average quality modestly and shifts the lower tail more strongly.

Event studies: applicant quality



Hires: why this is different

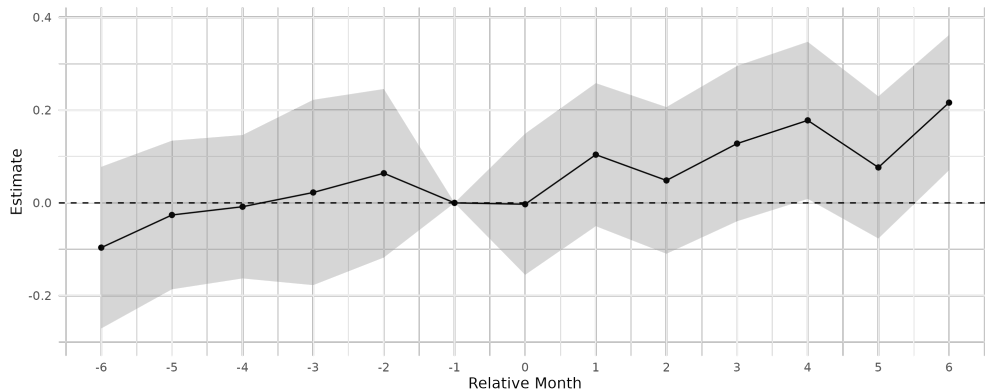
- ▶ Applications are a worker-side response to posted wages and amenities
- ▶ Hires combine worker behaviour with employer decisions
- ▶ Firms may also adjust:
 - ▶ screening effort
 - ▶ hiring standards
 - ▶ willingness to leave the job unfilled
- ▶ Estimated hiring effects therefore combine:
 - ▶ more and better applicants
 - ▶ employer selection over the changed applicant pool

Impact on number of hires

	(1)	(2)	(3)	(4)
Post $\times$ Treated	0.103*** (0.034)	0.109*** (0.034)	0.148*** (0.035)	0.109*** (0.038)
Approx. effect	+10.8%	+11.5%	+16.0%	+11.5%
Observations	26,297	25,938	25,509	24,629
Dependent mean	0.6	0.6	0.6	0.6
Category FE		✓	✓	
Postcode FE		✓	✓	
Category $\times$ postcode FE			✓	

Poisson regressions with occupation and week fixed effects, controls, and notification offset.

Event study: hires



Event-study: specification (4) with venue fixed effects.

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What the reduced form bundles together

- ▶ The DiD estimate compares wait-staff jobs to neighbouring occupations
- ▶ But neighbouring occupations may themselves respond to the wait-staff wage increase
- ▶ The model decomposes:

$$\tau_Y^M = \underbrace{\Delta Y_A}_{\text{effect on treated occupation}} + \underbrace{(-\Delta Y_B)}_{\text{control-group spillover}}$$

- ▶ If comparison applications fall, the DiD overstates the treated-occupation effect

Parameters and moments

- ▶ Observed/calibrated:
 - ▶ notifications per vacancy
 - ▶ cell-specific notification rates
 - ▶ match duration
 - ▶ discount factor
 - ▶ empirical joint productivity cells
- ▶ Estimated:

$$\theta = (b, c_A, c_B, s_A, s_B, \sigma_A, \sigma_B)$$

Parameter	Interpretation	Estimate
b	Search value, level	0.91
c_A	Application cost, A	0.10
c_B	Application cost, B	0.09
s_A	Worker dispersion, A	0.50
s_B	Worker dispersion, B	0.31
σ_A	Employer dispersion, A	0.79
σ_B	Employer dispersion, B	0.74

Identification in the model

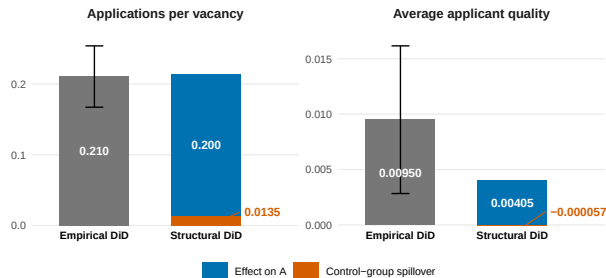
- ▶ Slope of hiring probabilities across productivity ranks identifies employer selectivity
- ▶ Conditional application rates identify worker-side costs and payoff dispersion
- ▶ DiD moments are additional moments (not strictly needed for identification)

Model fit

Moment	Data	Model
Pre-reform applications per vacancy, A	10.270	9.626
Pre-reform applications per vacancy, B	7.735	7.481
DiD: applications per vacancy	0.210	0.213
DiD: average applicant quality	0.0095	0.0040

- ▶ Model solved on empirical productivity cells with cell notification rates
- ▶ The current version matches the application response closely
- ▶ The quality response is under-predicted

Decomposition



Outcome	DiD	Effect A	Effect B
Applications	0.214	0.200	-0.013
Avg. quality	0.004	0.004	0.000

- ▶ In the current estimates, most of the application DiD is an effect on wait-staff jobs
- ▶ Spillovers onto the comparison occupation are negative but modest
- ▶ Quality decomposition remains preliminary because the model under-fits the reduced-form quality response

Conclusions so far

- ▶ If we take the results of the model seriously: diff-in-diff estimates are not far from labour-supply elasticities
- ▶ Elasticities:
 - ▶ Number of applications: 3.5
 - ▶ Quality: .3 at the mean, much higher at the lower end of distribution
 - ▶ Hires: 2
- ▶ Why is elasticity of hires lower than number of applications?
 - ▶ Because marginal applicants are low quality?
 - ▶ Because firms' hiring standards have increased?
- ▶ Could these elasticities explain why some occupations remain low-paying high-tightness?