

Dang, Justin; Maeder, Nicolas; Mao, Chenyu; Yoo, Kwanjai

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## A Comment on "How Wage Announcement Affect Job Search - A Field Experiment"

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**July 2025**

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# A comment on “How Wage Announcement Affect Job Search - A Field Experiment”

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## Abstract

This report replicates the study by Belot et al. (2022), which investigates how posted wages affect labor supply through a field experiment using a job platform with varying wage postings. The paper’s main finding is that a higher wage increases job seekers’ interest in a vacancy, a result at odds with the same variables’ inverse relationship in the paper’s observational data.

This report assesses the computational and robustness reproducibility of the referenced paper’s results. Testing various empirical specifications and datasets, we find that all findings are, in fact, reproducible. Most importantly, the elasticity of a job posting’s saves/views with respect to its posted wage is consistently positive and statistically significant across all of our specifications and datasets.

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## 1 Introduction

[Belot et al. \(2022\)](#), henceforth BKM, study how a job opening's posted wage affects labor supply in a field experiment. With observational and experimental datasets, the authors investigate whether, all else equal, higher wages increase job seekers' interest in vacancies, thus providing first-hand empirical evidence on the shape of labor supply.

To motivate their study, BKM show that, in observational data, posted wages and labor supply are inversely related, a somewhat unexpected correlation. In turn, to allow for a causal investigation, BKM created their own job platform featuring thousands of actual, real-world vacancies with various pairs of fictitious postings interspersed. Specifically, to elicit the actual causal effect of the posted wage on labor supply, the only material difference within each fictitious pair of job postings lies in the posted wage. Ultimately, BKM find that labor supply is, in fact, increasing in a vacancy's posted wage and that this result is robust to a variety of empirical specifications (including which posting appears first on the platform and how the fictitious jobs are perceived by external raters). In effect, BKM's study not only provides important, first-hand evidence on the shape of labor supply, but it also serves as a particularly illustrative example of the fact that correlation is not causation.

In the present report prepared for the Institute for Replication as part of the recent Replication Games in Seattle ([Brodeur et al. \(2024\)](#)), we investigate the computational and robustness reproducibility of BKM's empirical results.<sup>1</sup> First and foremost, we test various modifications of BKM's empirical specifications to determine the wage elasticity and the probability of not saving a high-wage vacancy, conditional on saving a low-wage vacancy such as (1) restricting different samples using observational data with real vacancies, (2) estimating log-log and log-level regressions instead of Poisson regression with experimental data, (3) estimating probit and logit models instead of a linear probability model, and (4) changing various estimation parameters such as the granularity of the fixed effects when controlling for perception. Furthermore, since BKM provide all of their raw data,

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<sup>1</sup>Given the experimental nature of BKM's data, testing direct replicability or conceptual replicability lies beyond the scope of the report.

we are also able to re-run various parts of their analysis on differing sub- and supersets of the data used in their analysis.

In terms of its computational reproducibility, we found that all of BKM’s results were fully reproducible. More importantly, in terms of robustness reproducibility, we found that all of BKM’s results are also reproducible. In particular, although the relevant estimates vary across our various specifications, the main object of interest — the elasticity of a job posting’s total number of saves/views in the posted wage — is invariably positive, statistically, and economically significant.

## 2 Computational Reproducibility

In a first exercise, we successfully confirmed the computational reproducibility of all empirical results contained in the paper. To this end, we first cleaned all of the provided raw data using their respective .do files. In turn, we used the resulting cleaned data (in conjunction with a separate set of .do files) to reconstruct all of the tables included in the paper.

As part of our tests of computational reproducibility, we did not uncover any coding errors.<sup>2</sup>

## 3 Robustness Reproduction and Replication with Observational Data

### 3.1 Table 2: Effect of wage on number of saves with real vacancies

First, we focus on replicating and reproducing results with observational datasets, which are real vacancies posted during their study. In Table 2, the authors perform a Poisson regression of the number of saves ( $S_i$ ) on the logarithm of the offered wage ( $\log(w_i)$ ), controlling for vacancy characteristics ( $X_i$ ) such as whether the contract is temporary or part-time, and whether there is missing information in job ads:

$$S_i = \exp(\alpha + \beta \log(w_i) + \delta X_i + \epsilon_i)$$

We replicate Table 2 with the same observational data provided by the authors.

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<sup>2</sup>Relative to the published paper, a small number of comments and table names were mislabeled, but all such instances were, of course, entirely inconsequential.

In the original study, the authors only used annual wage data to estimate the wage elasticity. In our reproduction, we used all the wages at different frequencies and converted them to annual frequency for robustness check.

The reproduction results (Table 1) are overall consistent with the original study. The magnitudes of the percentage effects are lower than the effects with only annual wage data but higher than the effects of using only hourly wage data, if we compare column (6) in Table 2 with column (6) in Table 1. The difference in magnitude might suggest a heterogeneity of labor supply elasticity on wages at different frequencies, while the main findings still suggest that a higher wage is associated with less job seeker interest.

Next, we restrict the sample to positive saves only and reproduce Table 2. We do this robustness check because we think there might be fundamental differences between zero saves and positive saves. Vacancies may receive zero saves because they look suspicious or hard to find, instead of having unattractive wages. Restricting the samples to only vacancies with positive saves may alleviate this concern, although it also significantly reduces the sample size.

In Tables 2 and 3, we show the results of restricting samples to only positive wages and additionally, including all wage frequencies. With positive wages only, the sample size reduces to around 25% of the original data. The estimated elasticity is still negative but with an even smaller magnitude (see Table 2). To make better use of the datasets, we further include vacancies with positive wages at all frequencies. In table 3, we find that wage elasticity estimated with control variables is not significantly negative.

Overall, we do not find many discrepancies with the reproduction using observational data. Even with the non-significant results in Table 3, it doesn't hinder the main argument of the paper, which is estimated better with the experimental data to control for unobserved vacancy characteristics.

## 4 Robustness Reproduction and Replication with Experimental Data

### 4.1 Effect of Wage Difference on Number of Saves/Views (Table 3)

In this section, we test the reproducibility of Table 3 using the experimental data in BKM. In Table 3, the authors estimate the following Poisson regression model:

$$S_{ip} = \exp(\alpha + \gamma_p + \beta \Delta w_{ip} + \epsilon_{ip}), \quad (1)$$

where  $S$  and  $\Delta w$  denote the number of saves and the percentage change in the wage, respectively, for vacancy  $i$  and vacancy pairs  $j$ . The model also includes pair fixed effects,  $\gamma_p$ . The parameter of interest,  $\beta$ , can be transformed to measure the percentage change in saves due to a 1 percent difference in the wage, or put simply the elasticity. We reproduce Table 3 using the experimental data as seen in Table 4 and obtain the same results in the original paper.

To check the robustness of the elasticity estimates found in BKM, we estimate three regression models by OLS. First, we estimate a log-level regression model:

$$\log(S_{ip} + c) = \alpha + \gamma_p + \beta \Delta w_{ip} + \epsilon_{ip}, \quad (2)$$

where  $\beta$  directly represents the elasticity and  $c$  is a constant that handles cases where  $S = 0$ . To be consistent with BKM, we set  $c = 0.1$ , although any constant can be used. Estimation results are reported in Table 5. Overall, the elasticity estimates obtained from a log-linear model are significantly positive, around 0.5 – 0.6, which are slightly smaller in magnitude compared to the elasticity estimates obtained from a Poisson model used in BKM.

Second, we estimate the following log-log regression model:

$$\log(S_{ip} + c) = \alpha + \gamma_p + \beta \log(\Delta w_{ip} + 1) + \epsilon_{ip}, \quad (3)$$

where  $\beta$  directly represents the elasticity and  $c = 0.1$  is a constant that handles cases where  $S = 0$ . Here, we transform the independent variable, wages, by adding one to the difference in wages to deal with zeroes when taking the logarithm. Estimation results are reported in Table 6. The elasticity estimates are slightly smaller around

0.5 for saves and around 0.7 for views compared to BKM elasticity estimates and are robust to the slightly adjusted specifications of the dependent and independent variables. All elasticity estimates are significantly positive for this specification and align with the results of BKM.

Lastly, we estimate a log-level regression model as our third robustness model specification.

$$\log(S_{ip}) = \alpha + \gamma_p + \beta \Delta w_{ip} + \epsilon_{ip}. \quad (4)$$

In this model, we do not add a constant to account for zeroes in the dependent variable. Therefore, the estimation of this log-level model will drop all observations where the dependent variable is zero.  $\beta$  still represents the wage elasticity. Estimation results are reported in Table 7. The elasticity estimates are smaller around 0.4 compared to BKM estimates, although all elasticities are still significantly positive even with the smaller sample sizes.

Overall, the BKM wage elasticity results from Table 3 are reproducible and reproducibly robust to various specifications of the regression model.<sup>3</sup> Although BKM obtain slightly higher wage elasticities, the estimates are significantly positive and robust to OLS estimations and alternative specifications of the dependent and independent variables.

## 4.2 Probability of not saving high-wage, conditional on saving low-wage (Table 5)

We replicate Table 5 in the paper and conduct a robustness check using different specifications. With experimental data, the authors investigate whether the reservation wage theory holds or not. In other words, they try to see if job seekers who apply for low-wage jobs also apply for high-wage jobs. The experimental data enables us to overcome potential endogeneity issues that might occur from other vacancy characteristics, such as non-pecuniary conditions or working hours, correlated with high-wage jobs. The authors make identical pairs of vacancies with only difference in wage.

The dependent variable of interest is the probability of not saving (viewing) the

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<sup>3</sup>We also reproduced Table 3 from BKM with the inclusion of both Edinburgh and Glasgow pairs (not shown), which produces the same wage elasticities as Table A11 from BKM.

high-wage jobs conditional on saving (viewing) the low-wage jobs, denoted by

$$P(S_h = 0|S_l = 1)$$

where  $S_h$  and  $S_l$  are dummy variables of saving (viewing) the high-wage job and low-wage job, respectively. In Table 5, the authors use a linear probability model with control of an indicator of high-wage jobs appearing first on the job posting website. We replicate Table 5 with the same data and regressor but use the logit and probit models instead of the linear probability model.

Table 8 and 9 show the predicted probability of each specification, thus allowing for a consistent comparison. The results are robust with both linear probability, logit, and probit models.

### 4.3 Controlling for perception (Tables 7, A12, A13)

Table 7 tests the robustness of the paper’s main finding — that a posting’s total number of views and saves is increasing in the posted wage — by controlling for how a particular job posting is perceived. To this end, the authors conducted a survey in which external evaluators were asked to rate each artificial job posting in terms of its perceived quality, competitiveness, and its working conditions.

Since participants’ “willingness to apply [...] to jobs in the Glasgow area is very small”, only job postings in Edinburgh were rated. In effect, unfortunately, we cannot test whether the findings in Table 7 are robust enough to include job postings in Glasgow. However, across their various specifications, the authors consistently construct FE dummies for postcodes with more than 8 observations only. As part of our analysis, we can thus test whether the paper’s main results are robust to a more granular specification.<sup>4</sup>

As shown in Table 10, the number of postcode dummies does not have a material impact on the paper’s primary object (or any other variable) of interest. Indeed, as shown in Table 11 and Table 12, the same is true when the perception controls are run individually (akin to Tables A12 and A13 in the original paper).

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<sup>4</sup>This effectively tests whether the published results are chiefly driven by variation across postcodes within the set of observations from postcodes with only a few observations.

## 5 Conclusion

All of the robustness checks conducted as part of this report point in the same direction, namely that BKM's main results are robust to a wide range of alternate specifications. To some degree, this may be owed to their simple nature of the research question — how do wages impact labor supply? — but, at least to some degree, it is also owed to the original authors' diligent execution (and outstanding documentation) of their analysis.

The main limitation of our own analysis lies in the fact that we, just like BKM, relied heavily on the available experimental data. To further investigate BKM's main results and, in particular, to test said results' external validity beyond Scotland, new data would need to be collected. This lies, of course, well beyond the scope of a replication report and, as such, must be left for future work.

## References

- Belot, M., Kircher, P. and Muller, P.: 2022, How wage announcements affect job search—a field experiment, *American Economic Journal: Macroeconomics* **14**(4), 1–67.
- Brodeur, A., Mikola, D., Cook, N. and et al.: 2024, Mass reproducibility and replicability: A new hope, *I4R Discussion Paper 107* .

## 6 Tables

Table 1: Table 2 Reproduction with all wage frequencies

	Poisson regression						Log-log regression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Salary)	-0.69*** (0.0070)	-0.59*** (0.039)	-0.51*** (0.049)	-0.51*** (0.049)	-0.51*** (0.053)	-0.51*** (0.053)	-0.27*** (0.057)
Temporary contract			-0.093 (0.072)	-0.064 (0.076)	-0.074 (0.070)	-0.074 (0.070)	-0.069 (0.054)
Part time			0.41*** (0.14)	0.44*** (0.13)	0.43*** (0.13)	0.43*** (0.13)	0.42*** (0.072)
No company name			-0.27*** (0.064)	-0.34*** (0.063)	-0.34*** (0.059)	-0.34*** (0.059)	-0.23*** (0.060)
No contacts in ad				0.52*** (0.14)	0.56*** (0.14)	0.56*** (0.14)	0.23*** (0.063)
Constant	73016.4*** (16219.8)						0.52 (0.54)
Sample	All wages	All wages	All wages	All wages	All wages	All wages	All wages
Occupation f.e.	No	Yes	Yes	Yes	Yes	Yes	Yes
Month f.e.	No	No	No	No	Yes	Yes	Yes
N	13272	13017	12819	12819	12819	12819	13073

Notes: Standard errors in parentheses. Columns 1–6 are Poisson regressions where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Column 7 is a log-log regression where the independent variable is  $\log(\text{saves} + 0.1)$ . Authors' calculations using data from [Belot et al. \(2022\)](#). The sample converts all wages into annual frequency.

Table 2: Table 2 Reproduction with positive save numbers

	Poisson regression						Log-log regression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Salary)	-0.41*** (0.024)	-0.36*** (0.046)	-0.29*** (0.046)	-0.29*** (0.045)	-0.29*** (0.043)	-0.027 (0.025)	-0.24*** (0.044)
Temporary contract			-0.014 (0.067)	0.0041 (0.067)	0.037 (0.070)	-0.16*** (0.045)	0.021 (0.053)
Part time			0.20** (0.10)	0.20** (0.10)	0.17* (0.10)	0.081 (0.074)	0.15** (0.064)
No company name			-0.29*** (0.041)	-0.31*** (0.041)	-0.30*** (0.039)	-0.0069 (0.053)	-0.27*** (0.040)
No contacts in ad				0.23** (0.097)	0.24*** (0.095)	0.26*** (0.077)	0.15*** (0.055)
Constant	488.7*** (199.8)						2.68*** (0.45)
Sample	Annual wages	Annual wages	Annual wages	Annual wages	Annual wages	Hourly wages	Annual wages
Occupation f.e.	no	yes	yes	yes	yes	yes	yes
Month f.e.	no	no	no	no	yes	yes	yes
N	1721	1685	1650	1650	1650	1601	1686

Notes: Standard errors in parentheses. Columns 1–6 are Poisson regressions where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Column 7 is a log-log regression where the independent variable is  $\log(\text{saves})$ , with only the positive number of saves. Authors' calculations using data from [Belot et al. \(2022\)](#). Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 3: Table 2 Reproduction with positive wages + all wage frequencies

			Poisson regression				Log-log regression
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Salary)	-0.079*** (0.0091)	-0.048* (0.027)	-0.032 (0.027)	-0.030 (0.028)	-0.031 (0.027)	-0.031 (0.027)	-0.024 (0.025)
Temporary contract			-0.035 (0.037)	-0.010 (0.037)	-0.0078 (0.036)	-0.0078 (0.036)	-0.0033 (0.032)
Part time			0.14** (0.075)	0.16*** (0.068)	0.17*** (0.069)	0.17*** (0.069)	0.16*** (0.046)
No company name			-0.16*** (0.034)	-0.21*** (0.032)	-0.20*** (0.031)	-0.20*** (0.031)	-0.19*** (0.031)
No contacts in ad				0.27*** (0.054)	0.27*** (0.052)	0.27*** (0.052)	0.18*** (0.031)
Constant	4.75*** (0.56)						0.34 (0.26)
Sample	All wages	All wages	All wages	All wages	All wages	All wages	All wages
Occupation f.e.	no	yes	yes	yes	yes	yes	yes
Month f.e.	no	no	no	no	yes	yes	yes
N	3648	3615	3509	3509	3509	3509	3542

Notes: Standard errors in parentheses. Columns 1–6 are Poisson regressions where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Column 7 is a log-log regression where the independent variable is  $\log(saves)$ , with only the positive number of saves. Authors' calculations using data from [Belot et al. \(2022\)](#). The sample converts all wages into annual frequency. Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 4: Table 3 Reproduction: Effect of Wage Difference on Number of Saves/Views

	Saves			Views		
	(1)	(2)	(3)	(4)	(5)	(6)
Salary difference (in %)	0.70** (0.44)	0.69* (0.45)	0.92*** (0.43)	0.70** (0.35)	0.71** (0.36)	0.86*** (0.29)
Appearing first			0.58*** (0.13)			0.50*** (0.075)
Pair fixed effects	yes	yes	yes	yes	yes	yes
Postal code f.e.	no	yes	yes	no	yes	yes
N	240	240	240	304	304	304

Notes: Clustered standard errors (by pair) in parentheses. All regressions are Poisson models where  $\exp(\beta) - 1$  is reported (which is the percentage effect). Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 5: Table 3 Reproduction Using Log-Level Model: Effect of Wage Difference on Number of Saves/Views

		Saves			Views	
	(1)	(2)	(3)	(4)	(5)	(6)
Salary difference (in %)	0.57** (0.25)	0.57** (0.26)	0.54** (0.25)	0.66** (0.28)	0.66** (0.28)	0.62** (0.26)
Appearing first			0.48*** (0.085)			0.49*** (0.088)
Pair fixed effects	yes	yes	yes	yes	yes	yes
Postal code f.e.	no	yes	yes	no	yes	yes
N	322	322	322	322	322	322

Notes: Clustered standard errors (by pair) in parentheses. All regressions are log-level regression models where the dependent variable is  $\log(saves + 0.1)$  or  $\log(views + 0.1)$ , the main independent variable is *salary\_diff*, and  $\beta$  is reported (which is the percentage effect). Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 6: Table 3 Reproduction Using Log-Log Model: Effect of Wage Difference on Number of Saves/Views

	Saves			Views		
	(1)	(2)	(3)	(4)	(5)	(6)
Salary difference (in %)	0.58** (0.26)	0.58** (0.26)	0.53** (0.27)	0.77** (0.32)	0.77** (0.32)	0.72** (0.29)
Appearing first			0.48*** (0.086)			0.49*** (0.088)
Pair fixed effects	yes	yes	yes	yes	yes	yes
Postal code f.e.	no	yes	yes	no	yes	yes
N	322	322	322	322	322	322

Notes: Clustered standard errors (by pair) in parentheses. All regressions are log-log regression models where the dependent variable is  $\log(\text{saves} + 0.1)$  or  $\log(\text{views} + 0.1)$ , the main independent variable is  $\log(\text{salary\_diff} + 1)$ , and  $\beta$  is reported (which is the percentage effect). Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 7: Table 3 Reproduction Using Log-Level Model (Not Adjusting for Zeroes): Effect of Wage Difference on Number of Saves/Views

	Saves			Views		
	(1)	(2)	(3)	(4)	(5)	(6)
Salary difference (in %)	0.41* (0.23)	0.37 (0.25)	0.47** (0.22)	0.41** (0.19)	0.37* (0.20)	0.38** (0.19)
Appearing first			0.39*** (0.075)			0.37*** (0.054)
Pair fixed effects	yes	yes	yes	yes	yes	yes
Postal code f.e.	no	yes	yes	no	yes	yes
N	188	188	188	251	251	251

Notes: Clustered standard errors (by pair) in parentheses. All regressions are log-level regression models where the dependent variable is  $\log(\text{saves})$  or  $\log(\text{views})$ , the main independent variable is  $\text{salary\_diff}$ , and  $\beta$  is reported (which is the percentage effect). Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 8: Table 5 Reproduction - Saves

	Saves		
	Original study	Logit	Probit
High appears first	-0.292*** (0.0532) [0.000]	-1.286*** (0.257) [0.000]	-0.789*** (0.154) [0.000]
Constant	0.529*** (0.0374) [0.000]	0.118 (0.150) [0.432]	0.0738 (0.0939) [0.432]
Predicted probability			
High appears first = 1	0.237	0.237	0.237
High appears first = 0	0.529	0.529	0.529
Observations	267	267	267
(pseudo) $R^2$	0.077	0.0618	0.0618

Notes: Clustered standard errors in parentheses. Authors' calculations using data from [Belot et al. \(2022\)](#) for columns 2 and 3. Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 9: Table 5 Reproduction - Views

	Views		
	Original study	Logit	Probit
High appears first	-0.272*** (0.0460) [0.000]	-1.242*** (0.228) [0.000]	-0.756*** (0.136) [0.000]
Constant	0.487*** (0.0342) [0.000]	-0.0533 (0.137) [0.696]	-0.0334 (0.0856) [0.696]
Predicted probability			
High appears first = 1	0.215	0.215	0.215
High appears first = 0	0.487	0.487	0.487
Observations	500	500	500
(pseudo) $R^2$	0.073	0.0591	0.0591

Notes: Clustered standard errors in parentheses. Authors' calculations using data from [Belot et al. \(2022\)](#) for columns 2 and 3. Significant at the \*\*\*[1%] \*\*[5%] \*[10%] level.

Table 10: Reproduction of Table 7 with more postcode dummies

	Saves		Views	
	(1)	(2)	(3)	(4)
Salary difference from original salary	0.92*** (0.43)	0.73* (0.58)	0.86*** (0.29)	0.72** (0.37)
Q1 (quality) standardized		-0.057 (0.18)		0.13 (0.17)
Q2 (competition) standardized		-0.083 (0.15)		-0.16 (0.098)
Q3 (working conditions) standardized		0.36* (0.23)		0.31** (0.14)
Appearing first	0.57*** (0.13)	0.58*** (0.13)	0.50*** (0.075)	0.50*** (0.075)
Pair fe	yes	yes	yes	yes
Postal code fe	yes	yes	yes	yes
N	240	240	304	304

Notes: Table 10 reproduces the authors' original Table 7, but features a dummy for each postcode featuring more than 4 (instead of 8) observations. All results still hold. Perception variables Q1-Q3 are unavailable for Glasgow.

Table 11: Reproduction of Table A12 with more postcode dummies

	(1)	(2)	(3)	(4)	(5)
Salary difference from original salary	0.92*** (0.43)	0.73* (0.58)	0.84** (0.47)	0.97** (0.64)	0.53 (0.41)
Q1 (quality) standardized		-0.057 (0.18)	0.074 (0.21)		
Q2 (competition) standardized		-0.083 (0.15)		-0.015 (0.16)	
Q3 (working conditions) standardized		0.36* (0.23)			0.29* (0.20)
Appearing first	0.57*** (0.13)	0.58*** (0.13)	0.57*** (0.13)	0.57*** (0.13)	0.57*** (0.13)
Pair fe	yes	yes	yes	yes	yes
Postal code fe	yes	yes	yes	yes	yes
N	240	240	240	240	240

Notes: Table 11 reproduces the authors' original Table A12, which features *saves* as the dependent variable. In the above, a dummy is created for each postcode featuring more than 4 (instead of 8) observations. All results still hold. Perception variables Q1-Q3 are unavailable for Glasgow.

Table 12: Reproduction of Table A13 with more postcode dummies

	(1)	(2)	(3)	(4)	(5)
Salary difference from original salary	0.86*** (0.29)	0.72** (0.37)	0.62** (0.31)	1.08*** (0.44)	0.46** (0.28)
Q1 (quality) standardized		0.13 (0.17)	0.23 (0.19)		
Q2 (competition) standardized		-0.16 (0.098)		-0.073 (0.11)	
Q3 (working conditions) standardized		0.31** (0.14)			0.28** (0.13)
Appearing first	0.50*** (0.075)	0.50*** (0.075)	0.49*** (0.078)	0.50*** (0.075)	0.49*** (0.075)
Pair fe	yes	yes	yes	yes	yes
Postal code fe	yes	yes	yes	yes	yes
N	304	304	304	304	304

Notes: Table 12 reproduces the authors' original Table A13, which features *views* as the dependent variable. In the above, a dummy is created for each postcode featuring more than 4 (instead of 8) observations. All results still hold. Perception variables Q1-Q3 are unavailable for Glasgow.