What's My Employee Worth?

The Effects of Salary Benchmarking

Zoë Cullen (Harvard)
Shengwu Li (Harvard)
Ricardo Perez-Truglia (UC Berkeley)

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- U.S. legislation prohibits employers from sharing information on their employees' compensation with each other.
    - Concerns about coordinating to pay lower salaries.
- Companies are still allowed to use aggregated data (e.g., median salary by position) provided by third parties.
    - Practice known as **salary benchmarking**.

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  - Implications for how we model/understand labor markets.
  - Relevant for an ongoing policy debate.

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- Measure effects of benchmarking using administrative data.
    - Leverage the roll-out of a new benchmarking tool.
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  - Suggest significant effects on pay-setting.

- We offer a simple model that:
  - Can explain main findings.
  - Discusses implications for models of the labor market.
  - Discusses policy implications.

Related Literature

- Wage Dispersion. Diamond (1971); Rosen (1986); Krueger & Summers (1988); Murphy & Topel (1990); Mortensen & Pissarides (1994); Burdett & Mortensen (1998); Abowd et al. (1999); Mortensen (2005); Postel-Vinay & Robin (2006); Card et al. (2018); Roussille & Scuderi (2023); etc.

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- Pay transparency. Card et al. (2012); Mas (2017); Perez-Truglia (2020); Cullen & Pakzad-Hurson (2016); Cullen & Perez-Truglia (2018, 2021); Baker et al. (2019); Bennedsen et al. (2019); Caldwell & Harmon (2019); etc.

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- <u>Behavioral Firms.</u> Rounding (Dube et al., 2018); anchoring (Hjort et al., 2020; Hazell et al., 2021); downward rigidities (Grigsby et al., 2021; Kaur, 2019); uniform pricing (DellaVigna & Gentzkow, 2019); etc.

Institutional Context

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- Prominent in HR textbooks too (e.g., Zeuch, 2016).

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  - E.g., Abbott, Langer and Associates, Korn Ferry, Hayes Group, Mercer, Radford, Willis Towers Watson.
- More recently, free online tools became popular.
  - Based on crowd-sourced data.
  - E.g., Glassdoor, Comparably, and LinkedIn,

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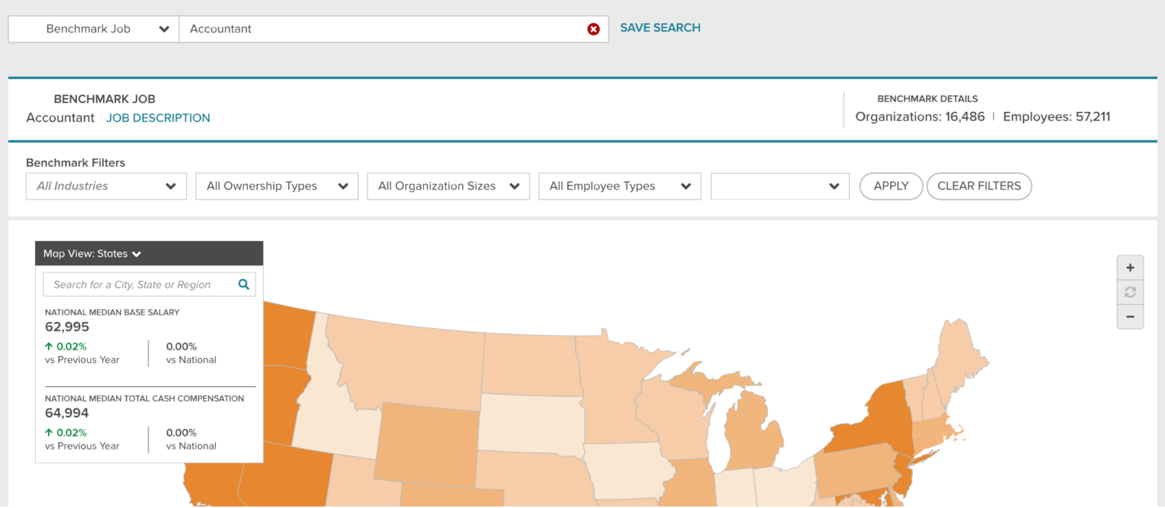
- Arguably the best tool on the market.
    - Administrative data (payroll records instead of surveys).
    - Massive sample sizes (650,000 firms and 20 million employees).
    - Highly responsive, due to high-frequency data. Comparison to Free Source

Screenshots of the Salary Benchmarking Tool



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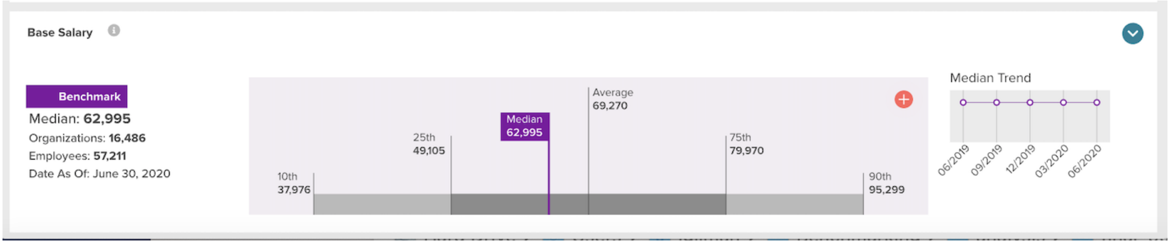

A Sketch of the Model

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- It is optimal to bid below own valuation.
- Whether to shade bid a little or a lot depends on what the firm thinks about the worker's *market value*.
  - Salary benchmark is useful information!

Quote from HR Textbook

"Using surveys to benchmark compensation levels ensures that the pay levels determined by the organization are not extraordinarily misaligned with market practice – i.e., pay is not too low or too high. Determining the appropriate amount of compensation is a balancing act. No organization wants to waste their financial resources by paying too high relative to the market; and those who pay too low risk unwanted turnover from employees looking for a better deal elsewhere." – Berger & Berger (2008), p. 125.

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- Prediction 2: The average salary could go up, down, or stay the same.

Data and Research Design

Data Sources

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  - Whether benchmark was "looked up" before the employee was hired.
- Benchmark Database: historical compensation benchmarks.
  - Exact benchmark value shown in the tool.

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    - Selected to match firms with access to the tool in key firm characteristics (e.g., size, state, industry).
- Sample is quite representative of medium and large firms. +

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- 534 firms gained access to the tool before 2019-Q4.
- 199 (37.3%) of these firms hired in at least one position during 2019-Q4.
- They looked up the salary for 20.8% of these new hires.

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- Average pre-treatment characteristics similar across three categories. +

Most Common Searched Positions

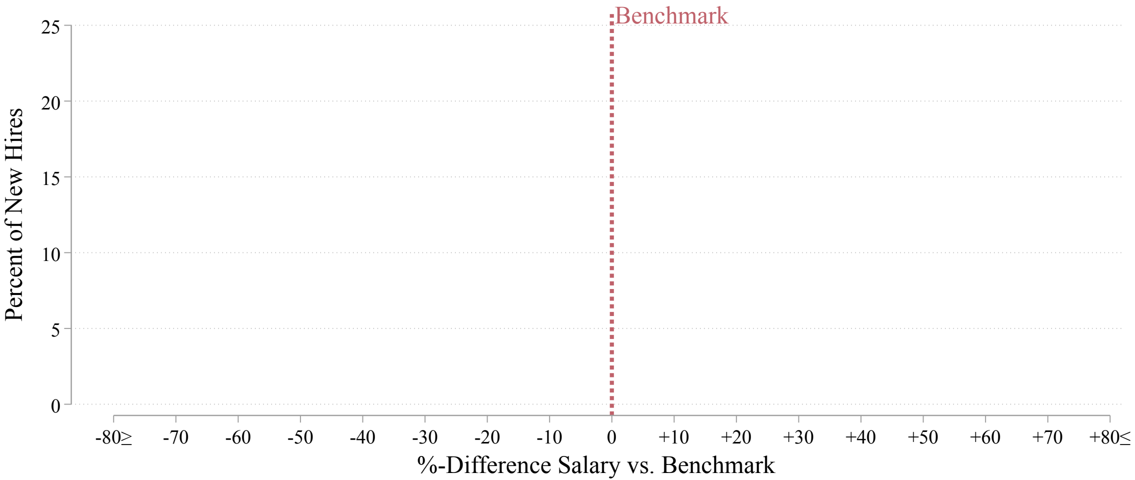
Position Title	(1) Searched	(2) Non-Searched	(3) Non-Searchable
Bank Teller	539 [12]	287 [24]	1,976 [87]
Customer Service Representative	468 [44]	4,401 [170]	4,012 [385]
Security Guard	286 [6]	139 [44]	6,263 [95]
Hotel Cleaner	208 [2]	379 [5]	1,058 [17]
Hand Packer	155 [4]	234 [17]	1,957 [55]
Patient Care Coordinator	117 [3]	103 [14]	133 [29]
Receptionist	93 [15]	310 [86]	2,911 [238]
Cook	86 [6]	334 [21]	1,606 [85]
Waiter/Waitress	84 [7]	1,113 [18]	2,986 [87]

Non-Searchable: Placebo Onboarding Dates

- Event-study analysis revolves around the onboarding date.
- Challenge: by definition, control firms do not have an onboarding date.
- Solution: assign a "placebo" on-boarding date.
    - Match treatment firm that is most similar in observables.
    - E.g., if Ford gains access but Fiat does not, we assume Fiat would have gained access when Ford did.

Effects on Compression

Searched Positions



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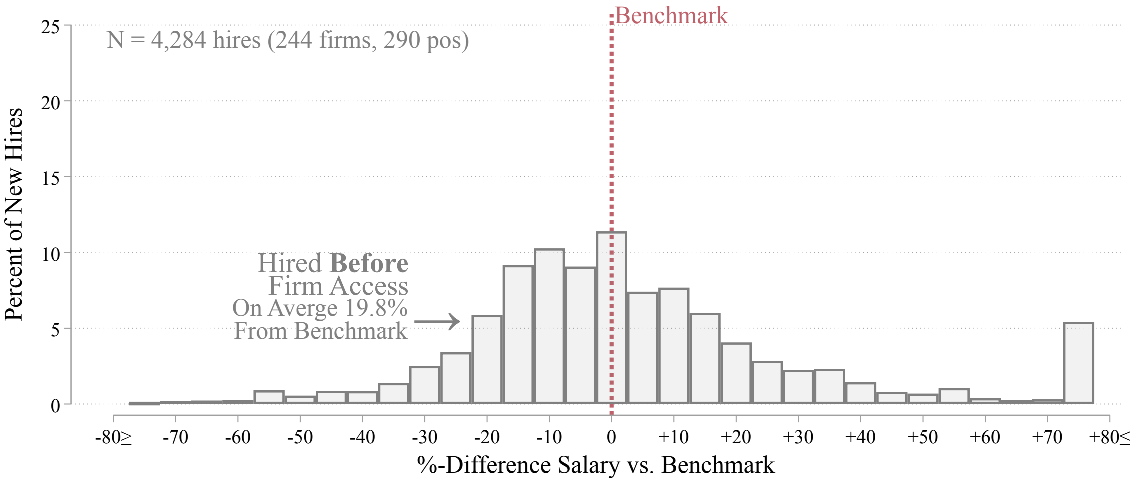

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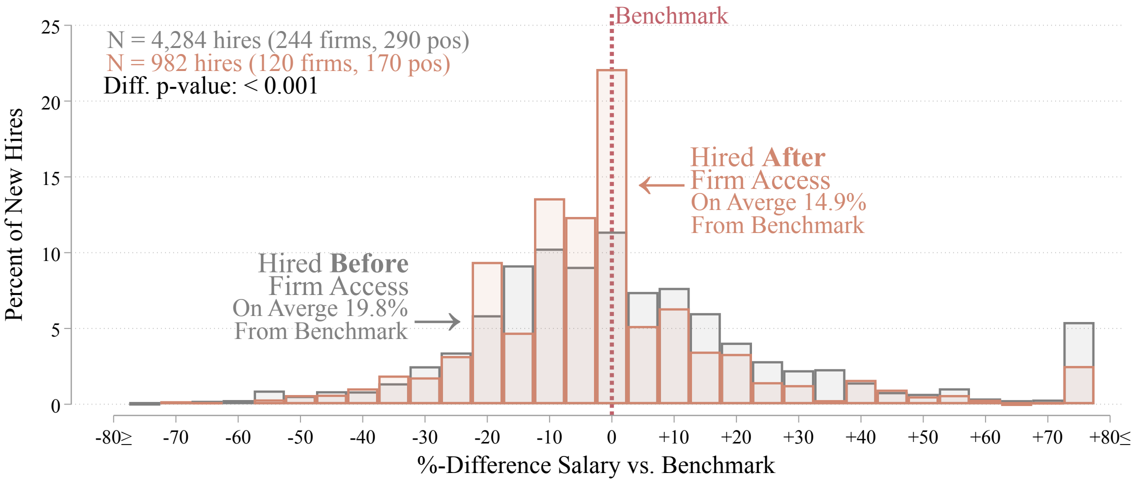

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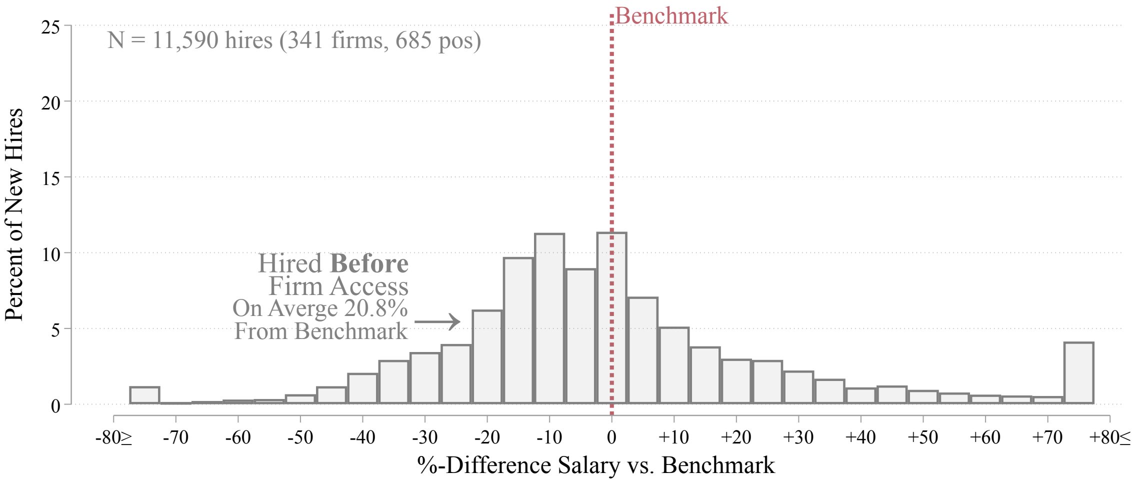

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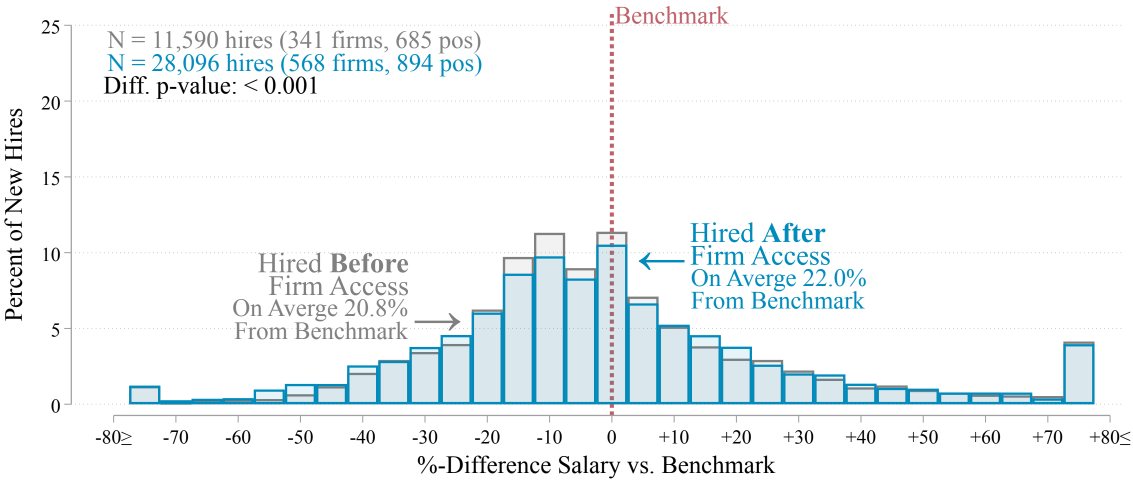

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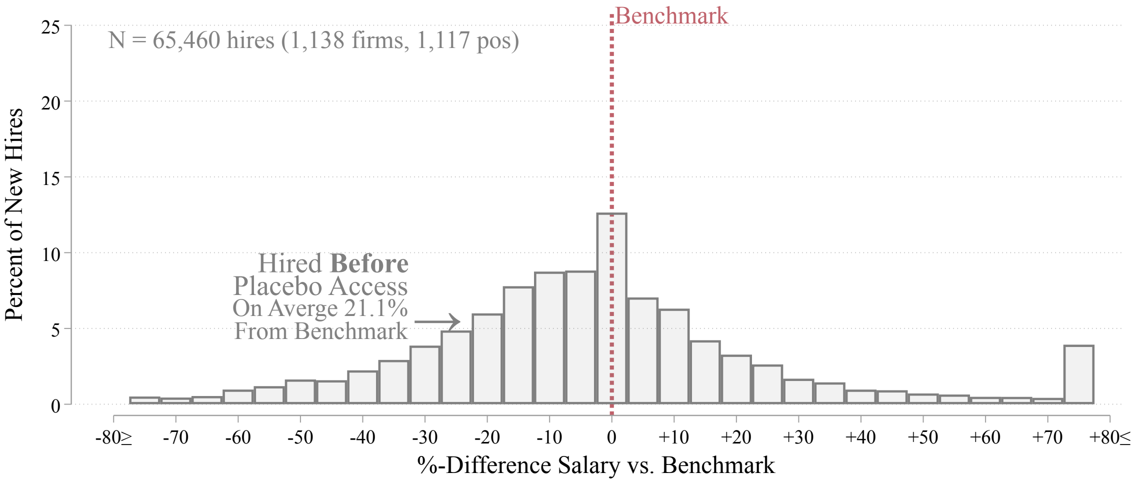

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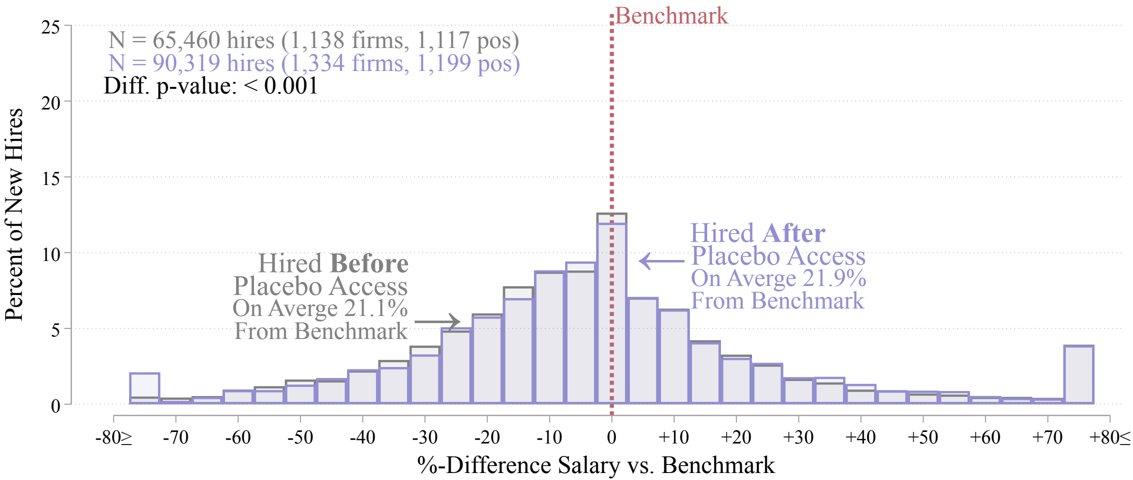
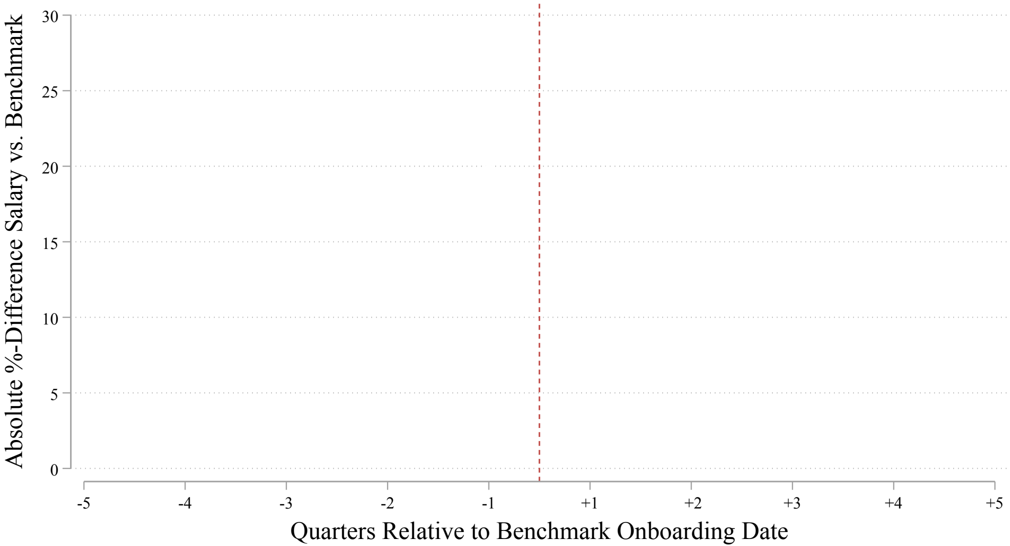


DiD Specification

$$Y_{i,j,t} = \sum_{s\in S} \alpha_{1,s}^{k} \cdot A_{j,t}^{s} \cdot T_{i,j} + \sum_{s\in S} \alpha_{2,s}^{k} \cdot A_{j,t}^{s} + \alpha_3^k \cdot T_{i,j} + X_{i,j,t}\alpha_4^k + \delta_t^k + \psi^k + \epsilon_{i,j,t}^k$$

- $Y_{i,j,t}$: abs. distance to benchmark.
- $T_{i,j}$: dummy for Searched positions.
- $A_{j,t}^{s}$: event-study dummies for onboarding.
- $k = 1$: Searched vs. Non-Searchable.
- $k = 2$: Searched vs. Non-Searched.

Searched vs. Non-Searched



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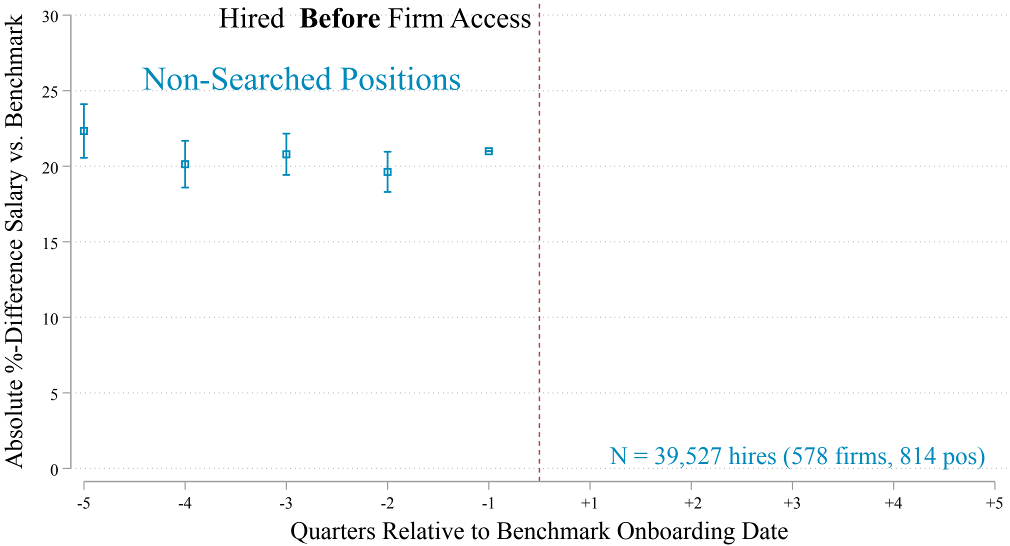

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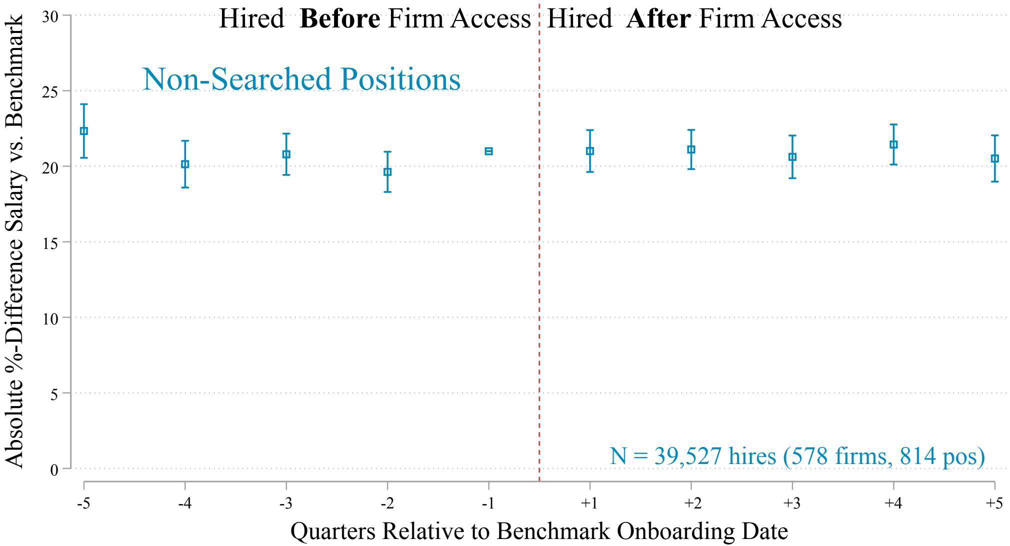

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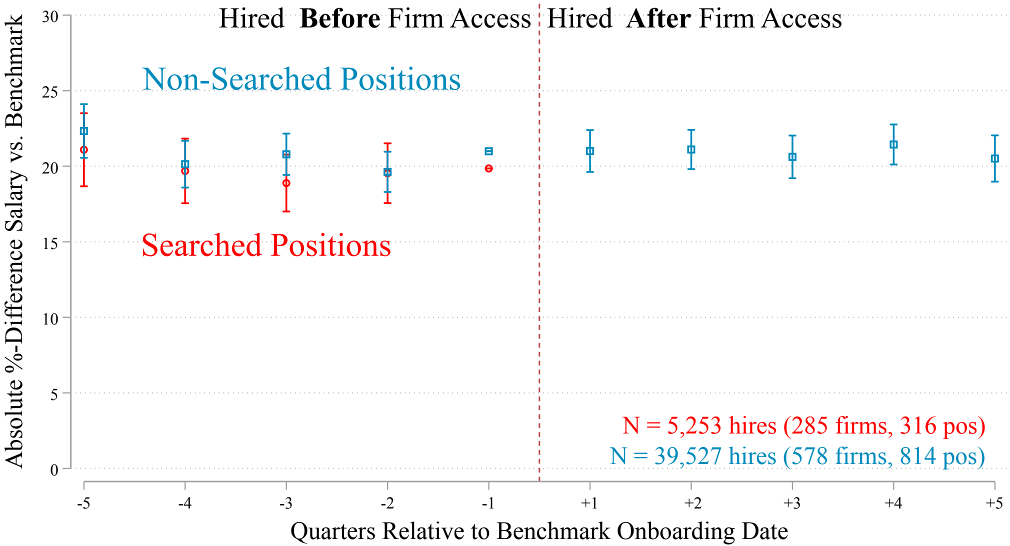

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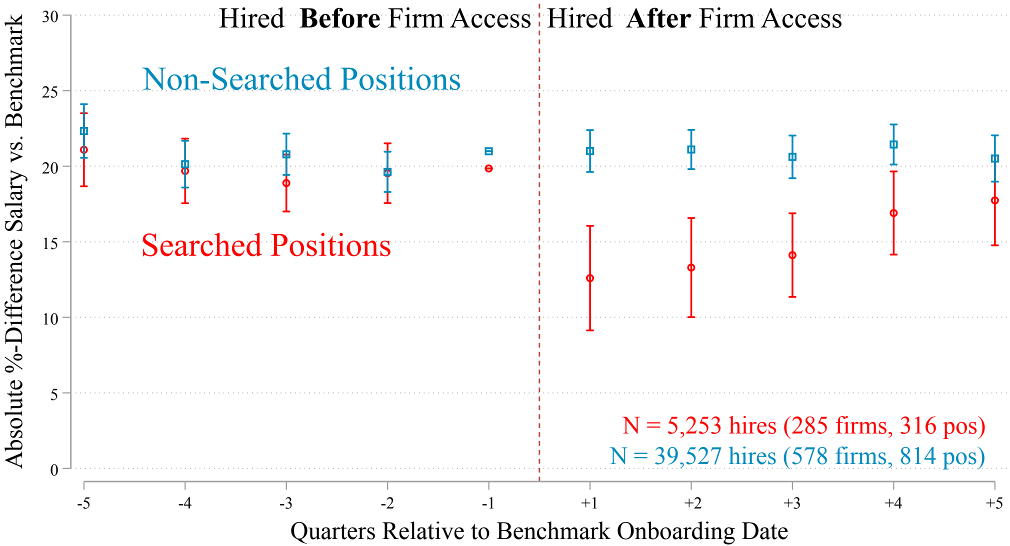

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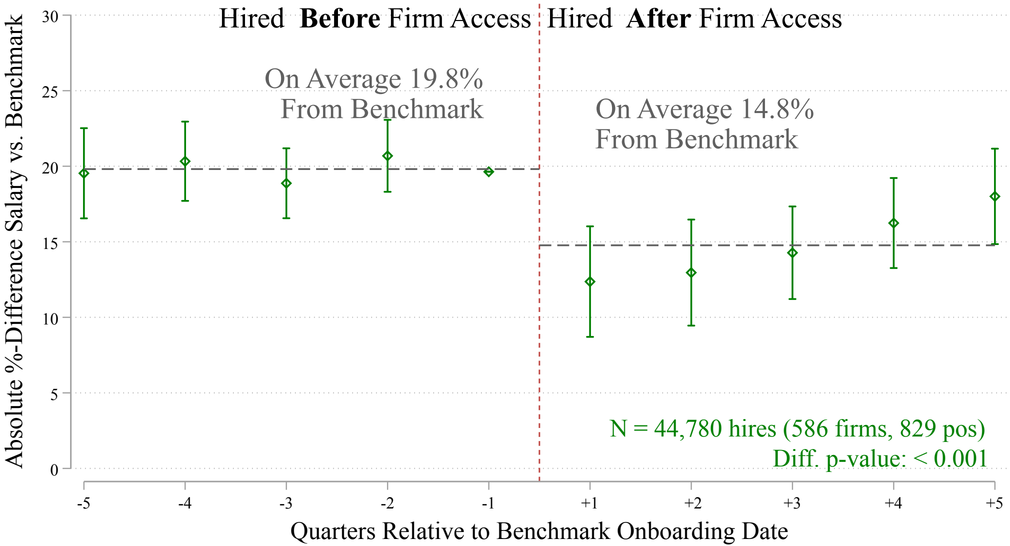

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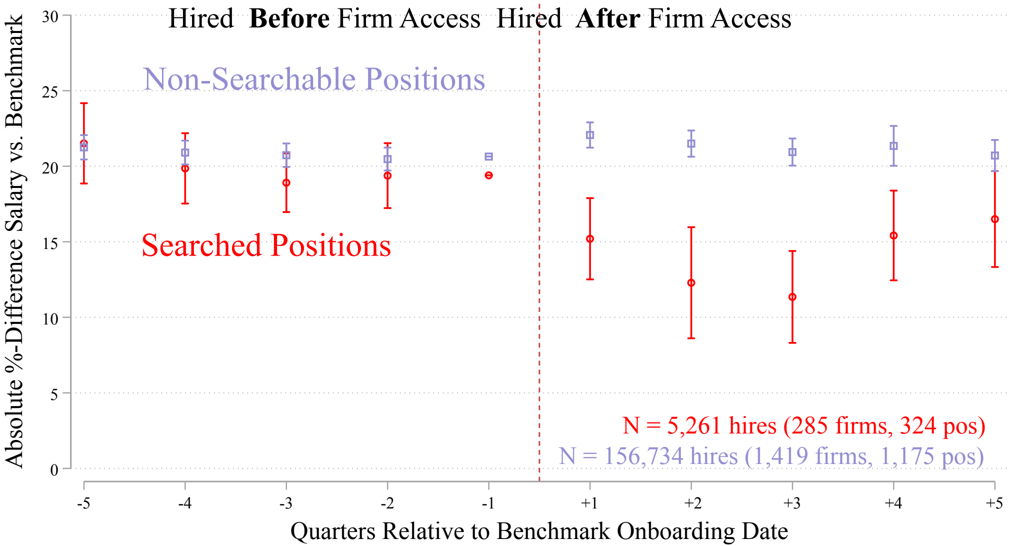

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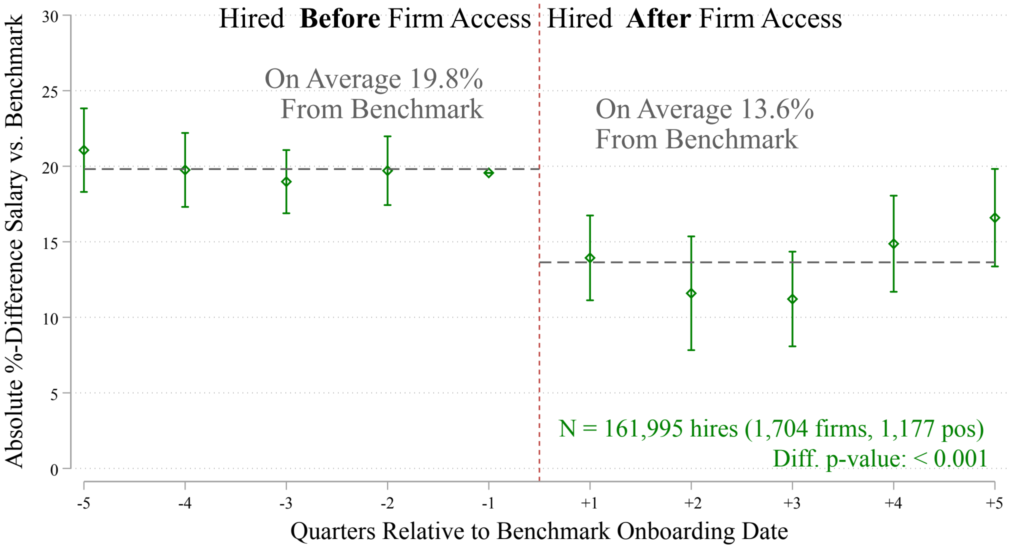

Complementary Survey Experiment

- In the SHRM survey, we embedded a survey experiment.
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  - We measure if they change their salary offer in response to the benchmark.
- Survey results indicate significant compression toward benchmarks.
  - Consistent in direction and magnitude with the results from the natural experiment. +

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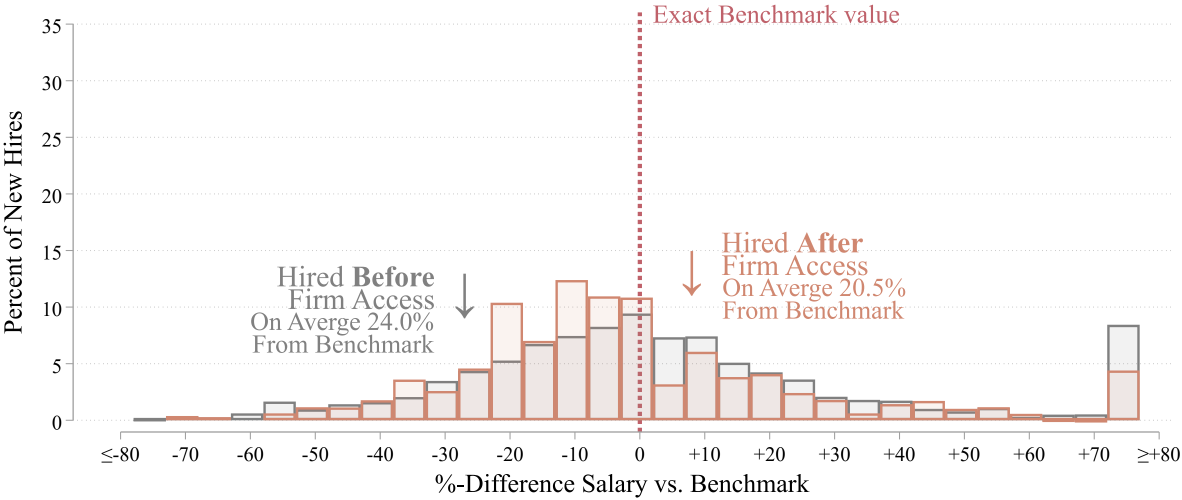
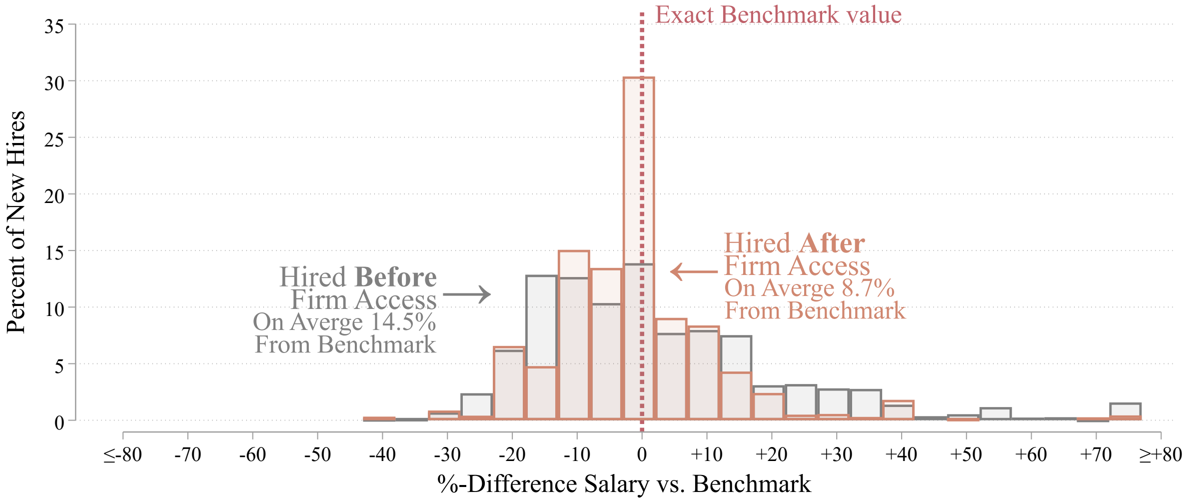
- 58% of the sample categorized as high-skill.
    - E.g.: Software Developer, Ophthalmic Technician, Production Operations Engineer.

High Skill



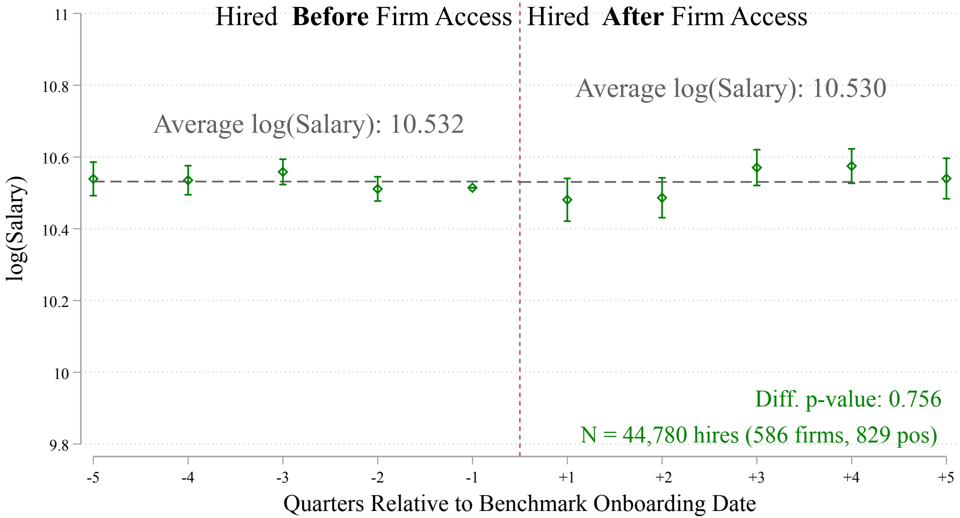
Exact Benchmark value
Percent of New Hires
35
30
25
20
15
10
5
0
Hired **Before**
Firm Access
On Averge 24.0%
From Benchmark
Hired **After**
Firm Access
On Averge 20.5%
From Benchmark
≤-80
-70
-60
-50
-40
-30
-20
-10
0
+10
+20
+30
+40
+50
+60
+70
≥+80
%-Difference Salary vs. Benchmark

Low Skill


Exact Benchmark value
Percent of New Hires
35
30
25
20
15
10
5
0
Hired **Before**
Firm Access
On Averge 14.5%
From Benchmark
Hired **After**
Firm Access
On Averge 8.7%
From Benchmark
≤-80
-70
-60
-50
-40
-30
-20
-10
0
+10
+20
+30
+40
+50
+60
+70
≥+80
%-Difference Salary vs. Benchmark

Effects on Levels

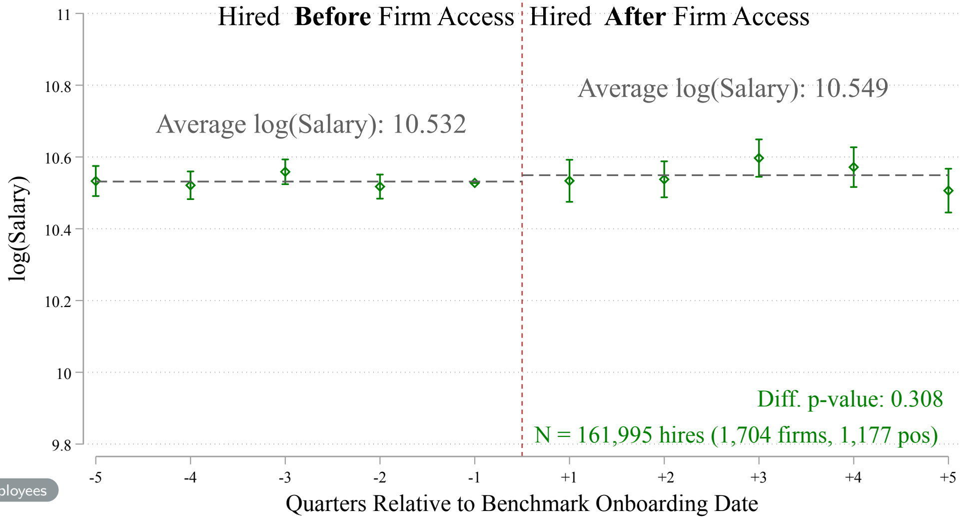
Searched vs. Non-Searched



Forecast

+

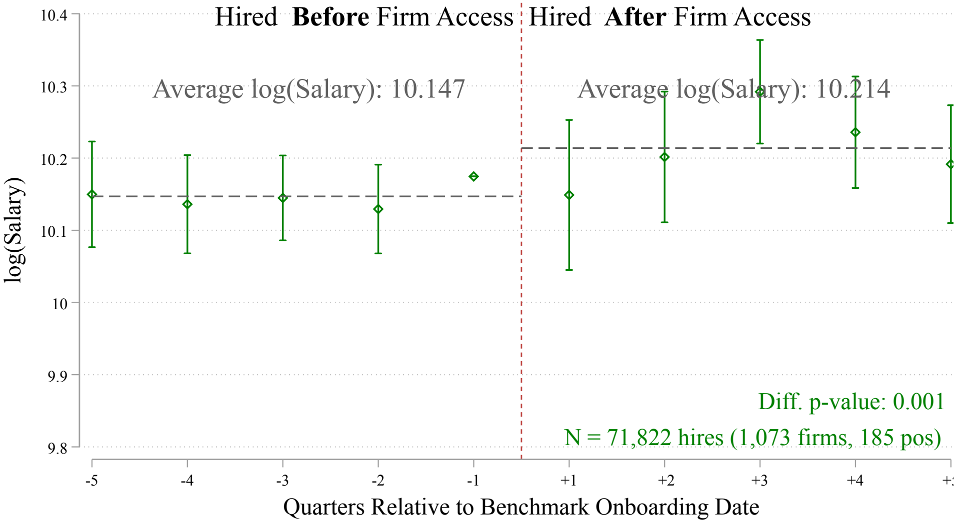
Searched vs. Non-Searchable



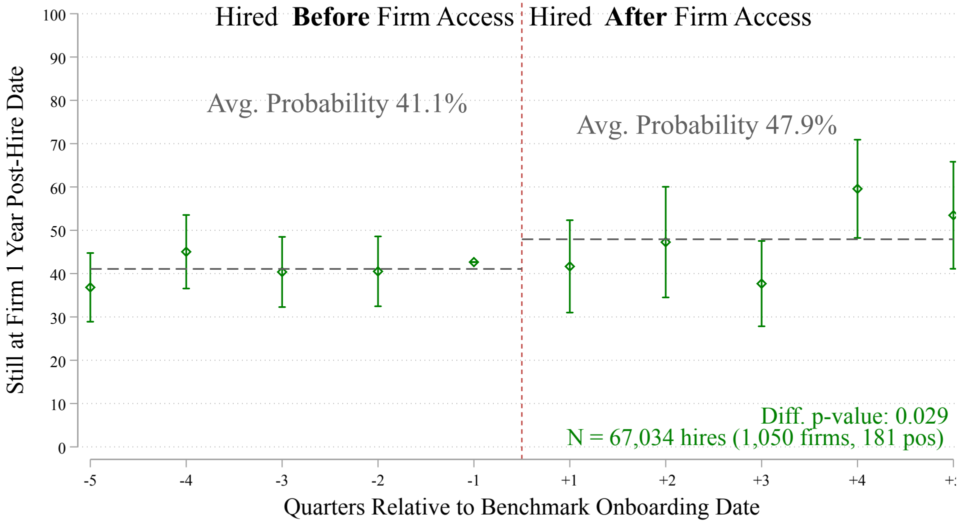
Existing Employees

+

Low-Skill Salary (Searched vs. Non-Searchable)



Low-Skill Retention (Searched vs. Non-Searchable)



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  - Effects are surprising, according to a forecast survey with experts.
- We provide a model that can fit the main facts.
  - Highlight that salary dispersion can be, at least in part, attributed to information frictions.

Policy Implications

- In recent years, the FTC, DOJ and White House have revised their statements and policies about salary benchmarking.
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  - Our model formalizes the pro-competitive argument: average salary goes up in equilibrium.
  - Evidence suggests some desirable effects even in partial equilibrium: average salary and retention go up for low-skill positions.