# Who Gets Screened Out?

The Opioid Crisis and Employer Skill Requirements

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Discussant remarks by

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# The paper

## Question

How does the opioid crisis affect employers' job skill requirements for new hires?

## Design

Dynamic DID, 2007 + 2010–2019. **Treatment:** Firm-level exposure to the 2010 OxyContin reformulation (2006–09).

## Data

Lightcast online job postings × Compustat publicly traded firms (2,202 firms).

## Main result

1 SD $\uparrow$ exposure $\Rightarrow$ $-5.1\%$ firm employment, $+7.9\%$ cognitive skills, $+5.4\%$ computer skills required per posting. *Interpretation:* statistical discrimination — employers screen against drug-use risk via skill requirements.

# What the paper does well

## A genuinely new angle

The opioid–labor literature is extensive but has focused mainly on worker-side labor-supply and employment effects. This paper examines the *employer-side* response.

## Uniquely linked dataset

Fuzzy-matching Lightcast to Compustat at the firm level.

## Firm-level decomposition advantage

The firm-level approach separates *within-firm* adjustments from *cross-firm compositional* change, which is exactly the margin needed to interpret aggregate skill shifts.

# 1. The upskilling pattern: three candidate interpretations

All three are observationally equivalent in the paper's reduced-form regressions.

- **A. Statistical discrimination (paper's preferred).** Raise observable bar to screen out higher-risk applicants.
- **B. Productivity-substitution (p. 14).** Lower applicant productivity $\Rightarrow$ higher skill demand. Same signature, different mechanism. *Kim, Kim & Park (2024):* inflow is "entirely driven by less-skilled workers," and average local skill falls.
- **C. Capital–labor / task restructuring.** Footnote 8 rules out a capital-stock increase, not task restructuring or capital per worker.

# Suggestion #1: granular skill disaggregation

## “Computer skills” combines two mechanisms

- **Excel, Word, PowerPoint** $\Rightarrow$ raising basic-competency floor (screening).
- **Python, SQL, TensorFlow** $\Rightarrow$ technology adoption (not screening).

## Within “cognitive”

- Attention, accuracy, reliability $\Rightarrow$ screening.
- Advanced statistics, modeling $\Rightarrow$ technology adoption.

Disaggregating the keyword-level outcome would discriminate between screening (A) and productivity-substitution (B) more cleanly than the current six-category aggregation.

# 2. Identification

## **(a)** Exposure measure validity

CDC Schedule II is broader than OxyContin misuse; Figure A3 helps validate it, but Figure 14 is only state-level Alpert robustness. Report side-by-side average post coefficients and p-values?

## **(b)** Thin pre-period: missing 2008–2009

Lightcast does not cover 2008–09, leaving a single pre-year (2007) for skill outcomes. Compustat employment outcomes have 2005–08 as a separate pre-window.

## **(c)** Recession control not visualized

The paper controls for Hershbein–Kahn unemployment $\times$ year. Overlay the event-study with vs. without these controls?

## **(d)** Labor-supply controls may be bad controls

Appendix Tables 3/A3 condition on state-year LFP and wages. These are *post-treatment*, so treat them as a partial check, not proof that screening is isolated.

# 3. Aggregate reconciliation implies a reallocation

## The decomposition

$$\beta_{\text{total}} \approx s \cdot \beta_{\text{public}} + (1 - s) \cdot \beta_{\text{private}}$$

- $\beta_{\text{public}} = -5.1\%$ (this paper)
- $\beta_{\text{total}} \approx -1.2\%$ (Park & Powell 2021, 5-yr)
- $s \approx 1/3$ (Davis et al. 2006)

Solving: $\boxed{\beta_{\text{private}} \approx +0.75\%}$

## Implications

*Caveat:* back-of-envelope mapping; $\beta_{\text{total}}$ is per-capita and $\beta_{\text{public}}$ is firm-level.

- Reallocation is the implied missing margin.
- Does public-firm employment share fall in high-exposure counties?
- If less-skilled workers move from publicly traded firms to private firms, the wage–benefit gap is the relevant welfare margin.

# 4. The central distributional claim is asserted, not tested

## From the abstract

*"less-skilled workers may experience a disproportionate impact from the increased skill requirements, even among workers without a history of opioid use disorders."*

Three components, none directly tested:

1. **Less-skilled workers disproportionately affected.** Heterogeneity is by firm, not by worker. Figure 11 shows low-baseline-education *firms* upskill more — but low-education-firm $\neq$ less-skilled workers within firms. Without worker-level data, we cannot infer worker harm from firm characteristics.
2. **Mechanism is the increased skill requirement.** The 5% employment decline is not tied to raised requirements rather than reduced hiring, separations, or direct labor-supply effects.
3. **Non-user spillover is model-derived.** The paper does not observe drug-use status, so the non-user channel is inferred from Section 3.3 (Policy Implication 2) rather than tested in worker data.

# Suggestion #2: beyond skill requirements

## Additional firm-level analyses?

| **Outcome** | **What it tells us** |
|---|---|
| Revenue / worker | MPL: productive vs. defensive screening |
| Compensation / worker | Did remaining workers earn more? |
| Capital / worker | Capital deepening? |

## Potential extensions?

- TFP via Olley–Pakes
  - TFP ↑: productive screening; TFP ↓: defensive screening; TFP flat with composition shift: restructuring.
- Combine with Kim, Kim & Park (2024)
  - Worker-side companion paper (Lightcast Job Profile data) documents skilled-worker outflow, low-skill in-migration, and falling local skill levels.

# Thank you

Looking forward to the discussion.

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