# Peer Effects and Worker Visibility in Team Production

## Evidence from NBA Rookies

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# Motivation: Team Production and Visibility

- Worker careers depend on human-capital accumulation and the revelation of ability through performance signals.
- Production often occurs in teams, motivating a large literature on peer effects in the workplace.
- Much of this literature emphasizes positive peer channels:
  - knowledge spillovers (Jackson and Bruegmann, 2009; Azoulay et al., 2010; Papay et al., 2020; Sandvik et al., 2020),
  - social pressure and effort (Mas and Moretti, 2009; Bandiera et al., 2010; Cohen-Zada et al., 2024),
  - complementarities in production (Gould and Winter, 2009).
- We study an underexplored dimension of peer effects in settings with binding time constraints: **better peers may reduce a worker's visible active time.**
- Examples: consultants presenting to clients, academics presenting at conferences, and athletes playing in games.
- This matters because visible active time generates both experience and observable signals of ability.

# Empirical Challenges and Why the NBA?

- Studying the visibility channel is difficult in standard labor markets:
  - workers and firms sort into each other,
  - peer quality is typically not randomly assigned,
  - individual output is hard to separate from team output,
  - visible active time is rarely observed directly,
  - long-run labor-market outcomes are often unavailable.

- NBA rookies provide a useful setting:
  - rookies enter teams through the draft,
  - box-score statistics measure individual performance,
  - court time directly measures visibility,
  - post-rookie contracts measure market valuation.

# Contribution

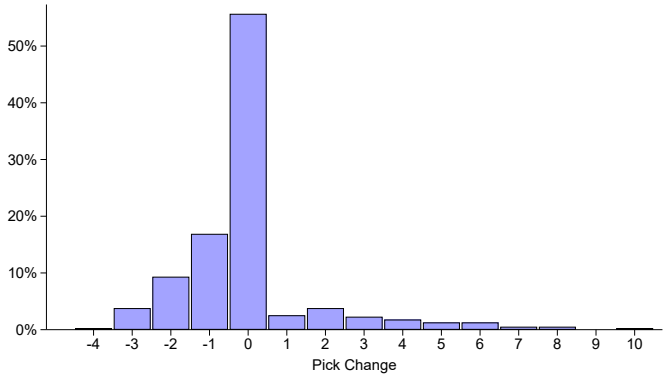
- We empiricall examine **visibility** as a channel through which peer quality affects early careers.
- We estimate effects of initial teammate quality on:
  - rookie playing time and performance,
  - salary and duration of the first freely negotiated contract.
- We exploit the NBA draft lottery as quasi-random variation in initial team assignment.
- We use Borusyak–Hull recentering to isolate lottery-induced variation in teammate quality (Borusyak and Hull, 2023).
- We develop a stylized model showing why stronger peers can reduce junior active time when time is scarce.
- The paper highlights a trade-off:

$$\underbrace{\text{positive peer channels}}_{+} \quad \text{vs.} \quad \underbrace{\text{reduced visibility}}_{-}.$$

# Institutional Background: The NBA Draft Lottery

- The NBA draft assigns incoming players to teams through an ordered sequence of picks.
- Lottery teams are the teams that miss the playoffs (13 teams before 2004, 14 teams from 2004 onward).
- Before the lottery, teams are ranked by regular-season record: weaker teams receive better pre-lottery positions and higher lottery odds.
- The lottery randomizes which teams receive the top 4 picks (top 3 before 2019).
- After the lottery-determined picks are assigned, the remaining lottery teams pick mechanically in reverse order of regular-season record.

# NBA Draft Lottery: Pick Changes




**How to read the figure**

- 0: team picked at its pre-lottery position.
- Positive values: team moved up in the draft order.
- Negative values: team moved down in the draft order.

# Data and Outcomes

- Sample:
  - lottery picks from 1995 to 2023,
  - picks 1–13 before 2004 and picks 1–14 from 2004 onward,
  - final full sample: 388 rookies.
- Restricted sample (used primarily for contract outcomes):
  - picks 1–3 before 2019 and picks 1–4 from 2019 onward,
  - 90 rookies for short-run outcomes; 73 rookies with post-rookie contract outcomes.
- Short-run outcomes:
  - visibility: minutes played,
  - performance: Efficiency Rating (EFF):

$$\text{EFF} = (\text{PTS} + \text{REB} + \text{AST} + \text{STL} + \text{BLK} - \text{Missed FG} - \text{Missed FT} - \text{TOV})/\text{GP},$$

- Long-run outcomes:
  - first-year salary in the first post-rookie contract (after the rookie-scale deal, which fixes initial pay and contract length by draft position),
  - contract duration.

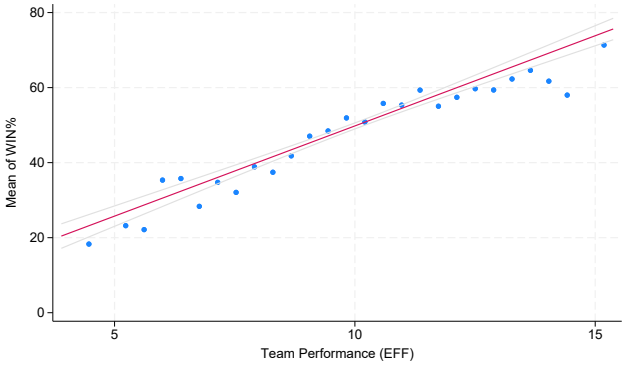
# Measuring Team Quality

**Baseline measure: average veteran teammate quality**

$$Q_{t,s} = \frac{1}{N_{t,s-1}} \sum_{j \in \text{veterans of } t} EFF_{j,s-1}.$$

- The measure uses veterans on the rookie's initial roster, but evaluates them using performance from the season before the rookie joins the team.
- In the baseline specification, all veteran teammates receive equal weight. In robustness checks, we weight veteran quality by minutes played, games played, and games started.
- We also use team-level proxies: previous season win-loss record and preseason Wins O/U, the betting-market forecast of a team's regular-season wins.

# Does the Team-Quality Measure Capture Team Strength?




**Validation check**

- Higher lagged veteran EFF is strongly associated with higher current-season win percentage.
- This suggests that the measure captures meaningful variation in team strength.
- It is more flexible than last season's win-loss record because it uses updated roster information.
- It also allows us to separate same-position and different-position teammates.

# Formula Treatment

**Treatment: team quality assigned to draft slot $r$ in season $s$**

$$q_{s,r} = f_r(L_s; E_s) = \sum_{t \in \mathcal{T}_s} \mathbf{1}\{L_{s,r} = t\} Q_{t,s}.$$

- $L_s$: lottery realization, i.e. which team receives each lottery pick.
- $E_s$: the rest of the assignment environment:

$$E_s = \{\text{lottery teams}, \text{lottery odds}, \text{trades}, \text{team quality}, \dots\}.$$

## General problem

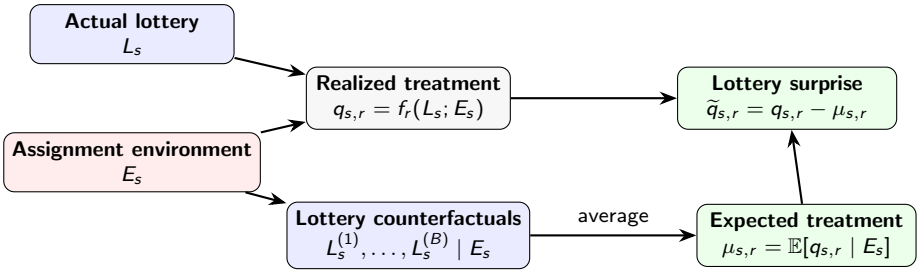
The lottery randomizes one input into the treatment, $L_s$. It does not directly randomize the treatment $q_{s,r}$.

- A pick slot receives a team quality value through the mapping $f_r(L_s; E_s)$.
- The same lottery shock can generate different treatment values under different $E_s$.
- High or low assigned team quality may therefore reflect:

$$\underbrace{\text{the lottery realization}}_{\text{shock}} \quad \text{and} \quad \underbrace{\text{the exposure mapping}}_{\text{assignment environment}}.$$

- This is the Borusyak and Hull (2023) "formula treatment" problem: random shocks can produce nonrandom treatment exposure.

# Applying Borusyak and Hull (2023) to the NBA Lottery




**Expected exposure: replay the lottery many times**

$$\mu_{s,r} = \mathbb{E}[f_r(L_s; E_s) \mid E_s] \approx \frac{1}{B} \sum_{b=1}^{B} f_r(L_s^{(b)}; E_s),$$

where $L_s^{(b)}$ is a simulated lottery draw using the actual NBA lottery rules.

## BH idea

Use the known shock assignment process to remove the part of treatment that is predictable from exposure.

# What Can Enter $E_s$?

## Rule

$E_s$ must be determined before the lottery draw, or otherwise independent of the lottery realization.

**Can enter $E_s$**

- lottery teams, lottery odds, and pre-lottery records.
- trades or pick transfers agreed before the lottery realization.
- predetermined measures of team quality.

**Cannot enter $E_s$**

- transactions that respond to the lottery realization.
- post-lottery roster changes made to fit the selected rookie.
- contemporaneous team quality measures affected by the rookie.

**Check: are post-lottery moves related to the draw?**

| | Roster turnover | | Trade | |
|---|---|---|---|---|
| | Full | Restricted | Full | Restricted |
| Pick change | -0.0297 | 0.173 | -0.00398 | -0.00673 |
| | (0.0840) | (0.108) | (0.0102) | (0.0163) |
| Observations | 388 | 90 | 388 | 90 |

Notes: Coefficients from regressions on pick change. Roster turnover measures changes in the roster after the lottery. Trade indicates whether the pick/player is traded after the lottery. Standard errors in parentheses.

# Main Findings

The visibility penalty appears early, affects performance, and carries over to future labor-market outcomes.

**A one-standard-deviation increase in teammate quality:**

- reduces rookie playing time by about **2 minutes per game**, roughly **9%** of average rookie playing time.
- reduces rookie performance by about **0.9 EFF points**, roughly **9%** relative to the sample mean.
- lowers first-year salary in the first post-rookie contract by about **2.2 percentage points** of the salary cap. For the 2018 draft class, this corresponds to roughly **$2.8 million** less in first-year pay.
- shortens contract duration by about **0.8 years**, relative to an average contract length of 4.27 years.

# Short-Run Effects: Visibility and Performance

| | Minutes played | Performance (EFF) |
|---|---|---|
| **Panel A: Baseline team quality** | | |
| Team Performance (EFF) | -1.34*** | -0.584*** |
| | (0.250) | (0.183) |
| **Panel B: Position decomposition** | | |
| Team Performance (EFF), same position | -0.145** | -0.066* |
| | (0.054) | (0.038) |
| Team Performance (EFF), different position | 0.002 | -0.0007 |
| | (0.018) | (0.014) |
| Player controls | Yes | Yes |
| Control function ($\mu_{s,r}$) | Yes | Yes |
| Pick FE, position FE, season FE | Yes | Yes |
| Observations | 388 | 388 |

# Robustness: EFF Components

| | Points | FTA | FT | FGA | FG | Rebounds | Steals | Blocks | Turnovers |
|---|---|---|---|---|---|---|---|---|---|
| Team Performance (EFF) | -0.671*** | -0.235*** | -0.177*** | -0.618*** | -0.258*** | -0.234*** | -0.019 | -0.046** | -0.146*** |
| | (0.170) | (0.068) | (0.051) | (0.130) | (0.058) | (0.080) | (0.013) | (0.017) | (0.028) |
| Player controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control function ($\mu_{s,r}$) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Pick FE, position FE, season FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 388 | 388 | 388 | 388 | 388 | 388 | 388 | 388 | 388 |

# Long-Run Effects: First Freely Negotiated Contract

| | Restricted sample: Picks 1–3(4) | | |
|---|---|---|---|
| Specification | (1) | (2) | (3) |
| **Panel A: Salary (% of salary cap)** | | | |
| Team Performance (EFF) | -1.48* | -1.76** | -1.50* |
| | (0.722) | (0.766) | (0.778) |
| **Panel B: Contract duration** | | | |
| Team Performance (EFF) | -0.504*** | -0.554*** | -0.531*** |
| | (0.136) | (0.139) | (0.173) |
| Player controls | No | No | Yes |
| Control function ($\mu_{s,r}$) | No | Yes | Yes |
| Pick FE, season FE | Yes | Yes | Yes |
| Observations | 73 | 73 | 73 |

# Robustness: Alternative Measures of Team Quality

- In the baseline specification, all veteran teammates receive equal weight.
- We now re-estimate the main specification using alternative team-quality measures.
- First, we use team-level proxies:
  - previous season win-loss record,
  - preseason Wins O/U, the betting-market forecast of a team's regular-season wins.
- Second, we construct usage-weighted measures of veteran quality:
  - Wt. A: weights based on minutes played,
  - Wt. B: weights based on games played,
  - Wt. C: weights based on games started.
- Because usage weights are measured contemporaneously, we instrument them with their lagged values.
- All specifications include the same controls, fixed effects, and BH control function.

# Robustness: Alternative Team Quality Measures, Minutes

| | Team-level proxies | | Usage-weighted EFF | | |
|---|---|---|---|---|---|
| Team quality measure | Team W/L | Wins O/U | EFF Wt. A | EFF Wt. B | EFF Wt. C |
| | -0.146** | -0.231*** | -0.205*** | -0.119*** | -0.150*** |
| | (0.054) | (0.063) | (0.041) | (0.032) | (0.035) |
| Player controls | Yes | Yes | Yes | Yes | Yes |
| Control function ($\mu_{s,r}$) | Yes | Yes | Yes | Yes | Yes |
| Pick FE, position FE, season FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 386 | 370 | 388 | 388 | 388 |

# Robustness: Alternative Team Quality Measures, Performance

| | Team-level proxies | | Usage-weighted EFF | | |
|---|---|---|---|---|---|
| Team quality measure | Team W/L | Wins O/U | EFF Wt. A | EFF Wt. B | EFF Wt. C |
| | -0.073** | -0.100** | -0.105*** | -0.065*** | -0.074*** |
| | (0.032) | (0.039) | (0.027) | (0.019) | (0.024) |
| Player controls | Yes | Yes | Yes | Yes | Yes |
| Control function ($\mu_{s,r}$) | Yes | Yes | Yes | Yes | Yes |
| Pick FE, position FE, season FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 386 | 370 | 388 | 388 | 388 |

# Mechanism: A Model of Active Time Allocation

- A team consists of $R$ agents. At most $n < R$ agents can be active at the same time.
- Each lineup $i$ in the set of possible lineups $\mathcal{L}$ is active for time $t_i$, with $t_i \in [0, 1]$, and

$$\sum_{i \in \mathcal{L}} t_i = 1.$$

- Lineup $i$ has skill vector $s_i$ and produces performance

$$f_i(s_i, t_i).$$

- The principal observes skills and allocates active time across lineups so as to maximize the probability of team success:

$$\max_{\{t_i\}_{i \in \mathcal{L}}} \; p\left(f_1(s_1, t_1), f_2(s_2, t_2), \ldots\right) \quad \text{s.t.} \quad \sum_{i \in \mathcal{L}} t_i = 1.$$

# Special Case: One Junior and Two Senior Coworkers

- We study the simplest case that captures the trade-off: $R = 3$ agents, with $n = 2$ active at a time.
- There is one junior worker, 1, and two senior coworkers, 2 and 3.
- The possible lineups are

$$A = \{1, 2\}, \qquad B = \{1, 3\}, \qquad C = \{2, 3\}.$$

- The principal allocates active time across lineups, $t_A + t_B + t_C = 1$.
- The junior's active time is the total time spent in lineups that include him:

$$t_b = t_A + t_B.$$

**Question**

How does the junior's optimal active time $t_b^*$ change when senior peer skill increases?

# Comparative Statics: When Does Peer Skill Reduce Visibility?

We rewrite the allocation problem in terms of

$$t_a = t_A, \qquad t_b = t_A + t_B, \qquad t_C = 1 - t_b.$$

The principal solves

$$T(s) = \arg \max_{(t_a, t_b) \in S'} p\Big(f_A(s_{-3}, t_a), f_B(s_{-2}, t_b - t_a), f_C(s_{-1}, 1 - t_b)\Big),$$

where

$$S' = \{(t_a, t_b) : 0 \le t_a \le t_b \le 1\}.$$

The model gives a clean comparative statics result under three conditions:

- diminishing returns to active time in lineups,
- senior skill raises the marginal value of senior-senior time,
- senior skill raises junior-senior time less than senior-senior time.

**Result**

Under these conditions, the junior's optimal active time $t_b^*$ decreases as senior peer skill increases.

# Why Does the Junior Receive Less Time?

When senior peer skill increases, two forces matter.

- **Senior-senior lineups become more valuable.**

  High-skill seniors are especially productive when paired with each other.

- **Junior-senior lineups become relatively less attractive.**

  The marginal value of additional junior time may fall when the skill gap between junior and seniors is large.

- **Total active time is fixed.**

  More time for senior-senior lineups mechanically means less time for lineups involving the junior.

# From Visibility to Performance and Contracts

- The allocation model delivers a prediction for active time:

$$\frac{\partial t_b^*}{\partial s_k} < 0, \qquad k \in \{2, 3\}.$$

- To interpret effects on performance, we add a mapping from active time to individual output that gives the decomposition

$$\frac{\partial P_1}{\partial s_k} = \underbrace{\frac{\partial F_1}{\partial s_k}}_{\text{peer spillover } (+)} + \underbrace{\frac{\partial F_1}{\partial t_b}\frac{\partial t_b^*}{\partial s_k}}_{\text{visibility effect } (-)}.$$

- Better peers may improve the junior, e.g. through learning and mentorship.
- But better peers also reduce active time.
- If the visibility effect dominates, performance declines.

# Conclusion

- We study how peer quality affects early-career visibility in team production.
- Using NBA draft-lottery variation and Borusyak–Hull recentering, we find that stronger initial teams reduce rookie visibility and performance, with consequences for later contracts:
  - fewer minutes per game and lower rookie performance,
  - lower first-year salary and shorter first post-rookie contracts.
- The results point to a visibility mechanism: when active time is scarce, stronger peers can crowd out juniors from meaningful participation.

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