Team-Specific Human Capital and Player Performance in Major League Baseball

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1 Introduction

Human capital, the knowledge and skills that a person possesses, represents an important predictor of performance in the workplace. One common workplace context is the team, where success depends on the way team members interact. This paper will explore one application of human capital to the team context: team-specific human capital, human capital that is developed by working on a team and is difficult to transfer to other teams or workplace environments.

More specifically, I will examine the salience of team-specific human capital in Major League Baseball by considering the effect of a player's tenure on an MLB team on the player's performance. The player's tenure will serve as a proxy for the team-specific human capital that a player has built up. To determine the effect of tenure on a player's performance, I will examine the effect of a player being traded during the season on the player's performance using a Difference-in-Difference Estimation. I will use data from 2021 and 2022 MLB game logs to determine player performance throughout the season for each player active during the year. Then, using a player being traded as the treatment, I will compare the performance of players who were traded to the performance of players who were not traded. This analysis will provide insight on whether team-specific human capital is a useful metric in the context of Major League Baseball.

This paper contributes to literature on human capital by evaluating whether one type of human capital, team-specific human capital, is a useful metric in Major League Baseball. Major League Baseball provides an interesting context for this analysis because, although baseball is a "team sport" where teammates rely on each other to succeed, players often change teams as a result of free agency or trades. Additionally, this paper is relevant to the decisionmaking surrounding these frequent transactions by providing additional insight into the likely performance of Major League Baseball players after changing teams.

2 Literature Review

Past research in economics has demonstrated the relevance of team-specific human capital in various team contexts. For example, using Medicare claims data, Chen (2021) finds that shared work experience between doctors who perform a medical procedure and doctors who provide care reduces patient mortality rates. Chen finds that repeated interaction, through a learning process, increases productivity with team members, likely serving as the mechanism through which team-specific human capital improves performance. However, on professional baseball teams, many opportunities for player productivity, such as at-bats, happen individually. Therefore, the effect of this mechanism is likely weaker between teammates on professional baseball teams. That said, this mechanism may have a larger effect on the relationship between players and managers, providing an interesting direction for future research. Applying team-specific human capital to US patent inventors, Jaravel, Petkova, and Bell (2018) find that team-specific capital is responsible for a large portion of many inventors' earnings and innovation. One interesting property of team-specific human capital that Jaravel et al. find is that team-specific human capital increases with time of collaboration. Furthermore, Jaravel et al. find that team-specific human capital improves innovation by reducing moral hazard through increased interdependence and increasing trust. Given the large financial, competitive, and reputational incentives Major League Baseball players have to perform, I do not expect moral hazard to have a large effect on player performance. However, trust between teammates may provide one mechanism for team-specific human capital in professional baseball players, though it is difficult to see how trust affects the often-individual opportunities baseball players have to perform.

In a study that evaluates the effect of tenure on baseball player performance, Hofmann, Jacobs, and Gerras (1992) find that batter performance increases linearly with tenure, age, and seniority before significantly declining. Additionally, Hofmann et al. find subgroups of individuals with opposite reactions to tenure: some whose performance improves with tenure and some whose performance declines. Because these subgroups may not be observed when evaluating mean performance, they create a challenge and potential limitation for this paper.

Like Chen, Bartel et al. (2014) find evidence of "unit-specific human capital" in the healthcare context. In particular, Bartel et al. find an association between the departure of experienced nurses, new hires, and temporary contract nurses and a decrease in productivity not attributable to skill and experience differences. Bartel et al. derive changes in staffing from exogenous absences such as vacations, sick days, and retirements. Although not included in this paper, a similar method could be used to evaluate team-specific human capital in the professional baseball context by, for example, using data from the roster changes that result from player injuries.

3 Methodology

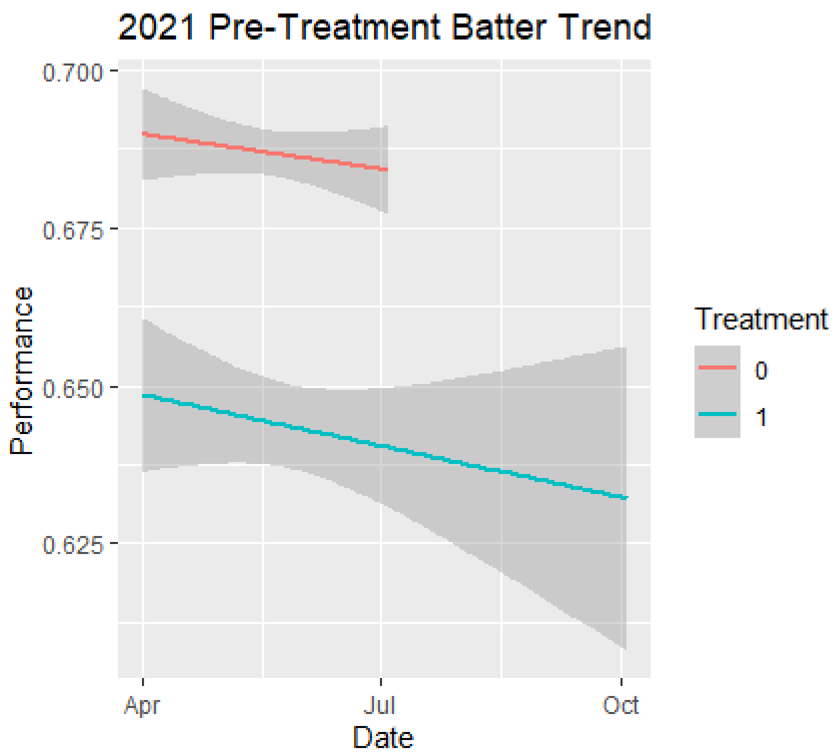
Because a team is more likely to let a poorly-performing player go, a player's tenure on a team is not independent of the player's performance. Therefore, I cannot directly compare a player's tenure on a team to the player's performance to infer the effect of team-specific human capital on player performance. Instead, I exploit player trades during the season as a source of variation in player tenure. Using in-season trades as the treatment, I use Difference-in-Difference Estimation to determine the causal effect of a player's tenure on a team to the player's performance.

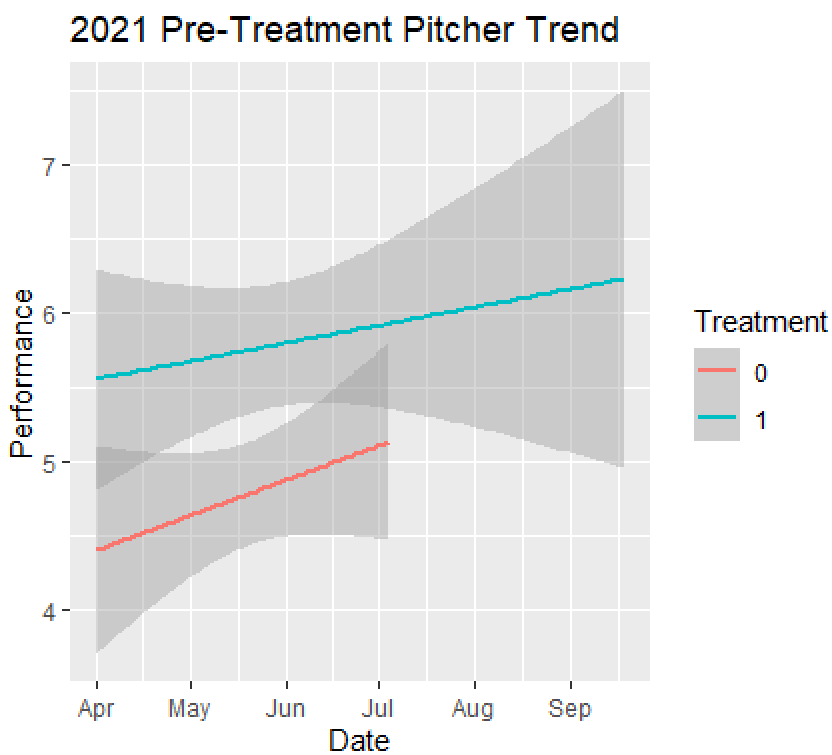
To perform my analysis, I use two separate datasets of MLB player game logs, one of all player logs from the 2022 season and one of all player logs from the 2021 season. From the 2021 and 2022 team pages on baseball-reference.com, I use the "Full-Season Roster and Games by Position" table for each team to create a list of players who appeared in a game for that team during the season. I evaluate the 2021 and 2022 players separately to avoid introducing a selection bias by selecting only players who appeared in both seasons. Then, I scraped the game log page on baseball-reference.com for each player during each season. For each player appearance, I recorded the player name, the date of the game, the player's team, and a performance indicator. For pitchers, I recorded Fielding Independent Pitching as a performance indicator and, for batters, I recorded On Base + Slugging Percentage as a performance indicator. Thus, I made the simplifying assumption that the bulk of a player's performance comes from pitching and batting instead of fielding. In total, I gathered data for 1505 players during the 2021 season and 1490 players during the 2022 season. Removing players who had missing performance data for either the before-treatment or after-treatment period, I included only 793 players in the 2021 dataset and 1014 players in the 2022 dataset.

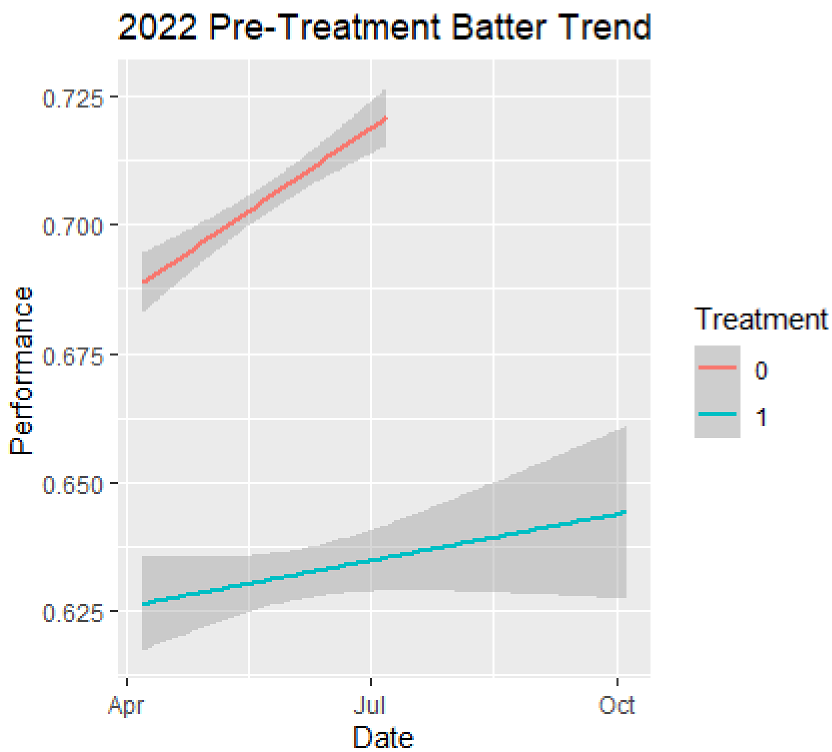
I choose to use Fielding Independent Pitching (FIP) as a performance indicator for pitchers to isolate pitcher performance from factors independent of pitcher performance such as quality of fielding that may skew other metrics such as Earned Run Average. I chose On-Base Plus Slugging (OPS) as an indicator for batting performance because OPS is a holistic statistic that reflects batting performance more completely than narrower statistics such as batting average.

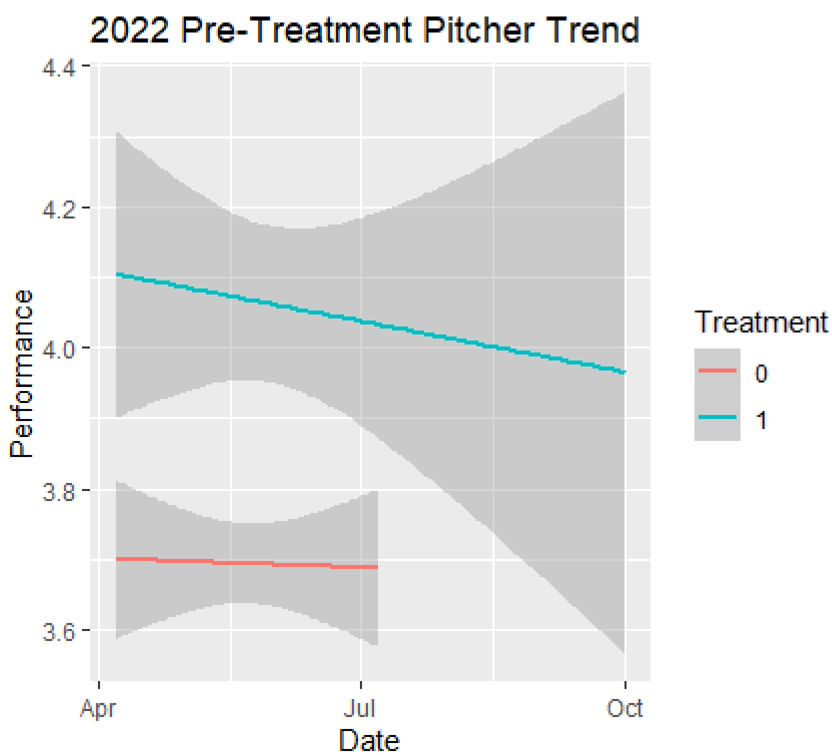
In order to use Difference-in-Difference Estimation, I must verify the following assumptions. First, the allocation of the intervention cannot be determined by the outcome. Intuitively, this assumption seems weak in the MLB player trade context. Professional baseball teams are more willing to trade players who are not performing well and less likely to trade players who are performing well. To check this assumption, I compare the mean performance of players in the treatment group prior to the treatment to the mean performance of players in the control group. I calculate $\widehat{\text{FIP}}_{\text{Control}} = 5.63$, $\widehat{\text{FIP}}_{\text{Treatment}} = 6.88$, $\widehat{\text{OPS}}_{\text{Control}} = 0.558$, and $\widehat{\text{OPS}}_{\text{Control}} = 0.482$. Since a lower FIP and higher OPS indicate better performance, there does seem to be selection towards worse-performing players in the treatment/traded group.

Second, the treatment and control groups must have parallel trends in outcome. As in the graphics, the 2021 batter treatment group has a slightly larger downward performance trend than the 2021 batter control group. The 2021 pitcher treatment group seems to improve performance compared to the 2021 pitcher control group. The 2022 batter control group has a steeper upward performance trend compared to the treatment group. The 2022 pitcher treatment group seems to improve performance more than the control group.


2021 Pre-Treatment Batter Trend
0.700
0.675
0.650
0.625
Performance
Apr
Jul
Oct
Date
Treatment
0
1


2021 Pre-Treatment Pitcher Trend
7
6
5
4
Performance
Apr
May
Jun
Jul
Aug
Sep
Date
Treatment
0
1





Third, the composition of intervention and comparison groups must be stable for repeated crosssectional design. To limit composition changes, I include only players who play in both the pre-treatment and post-treatment periods. Since the period of study is limited to only one year, changes in performance due to age, salary differences, and other factors should be limited. However, being traded can affect a players performance in ways separate from changing team-specific human capital. For example, a player may get less playing time or may not adjust to the environment well. These potential effects limit what can be learned about team-specific human capital from MLB player trades.

Fourth, there cannot be spillover effects. As established in De Grip, Sauermann, and Sieben (2016), the tenure of a team's members affects overall team performance. Thus, there is a potential spillover effect on control group members of a team when a new player joins the team.

I calculate the DID estimator using two methods. First, I use the following formula.

$$\widehat{\beta}_1^{\text{diffs-in-diffs}} = (\overline{Y}^{\text{treatment, after}} - \overline{Y}^{\text{treatment, before}}) - (\overline{Y}^{\text{control, after}} - \overline{Y}^{\text{control, before}})$$

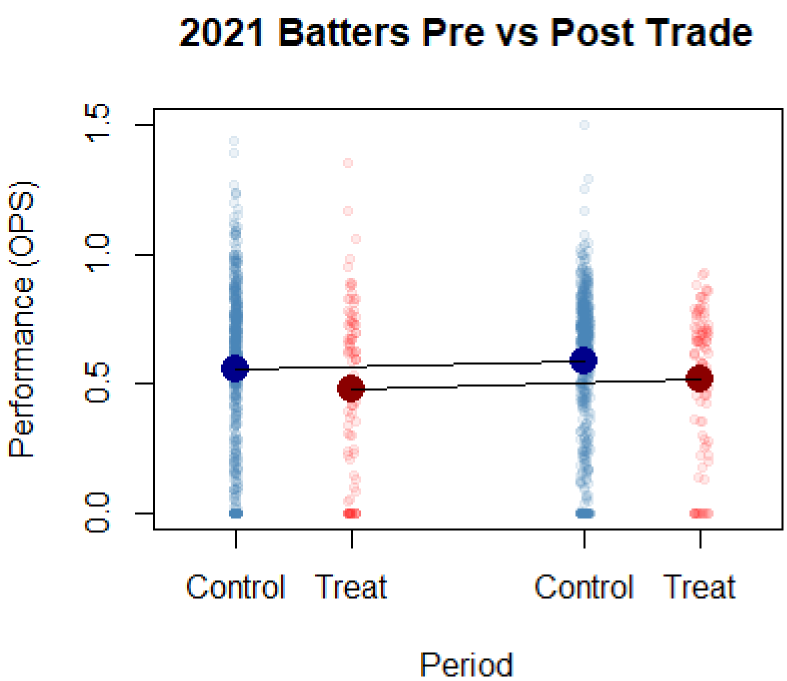
I define the cutoff between the before/after groups for the treatment group as being traded and for the control group by comparing the date to the mean date for all the data.

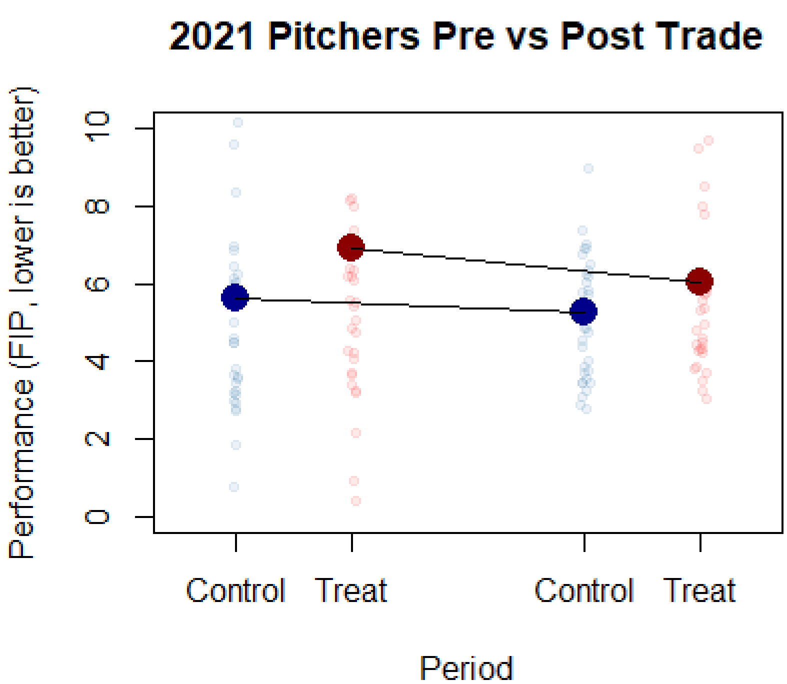
Second, I use regression to calculate the estimator again.

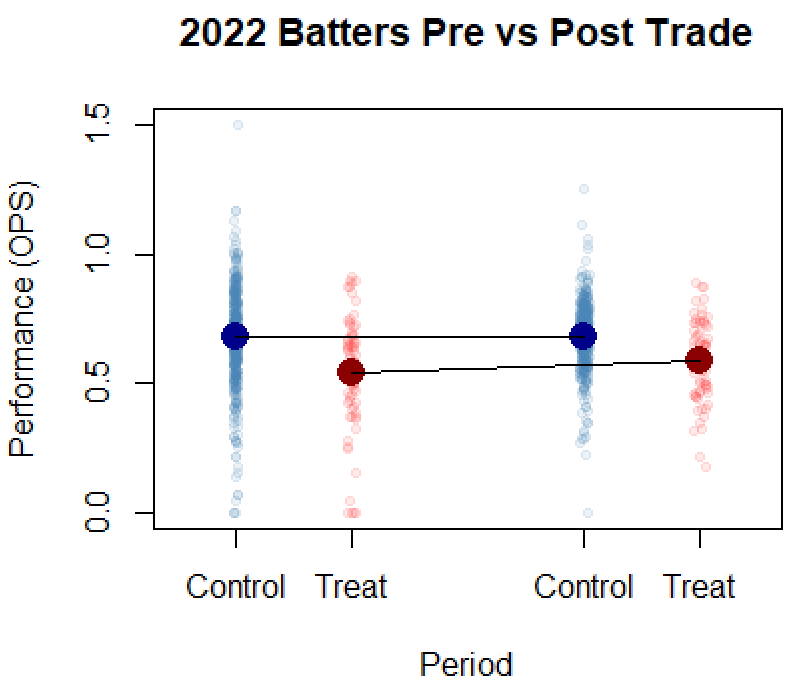
4 Results

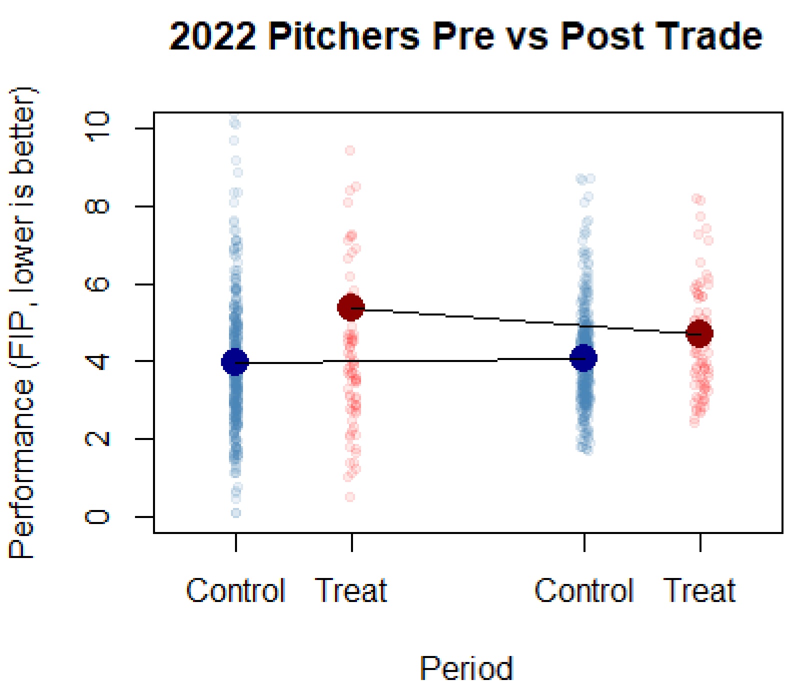
Table 1: Manual DID Estimator

	Batter	Pitcher
2021	0.0097	-0.4702
2022	0.0388	-0.7510


2021 Batters Pre vs Post Trade
Performance (OPS)
0.0
0.5
1.0
1.5
Control
Treat
Control
Treat
Period


2021 Pitchers Pre vs Post Trade
Performance (FIP, lower is better)
0
2
4
6
8
10
Control
Treat
Control
Treat
Period





In both years, both batters and pitchers slightly improve following a trade. The 2021 regression

Table 2: 2021 Regression

	Dependent variable: Perf. Diff	
	Batter	Pitcher
	(1)	(2)
Trade	0.010	-0.470
	(0.017)	(0.820)
Constant	0.027***	-0.371
	(0.006)	(0.558)
Observations	1,448	138
R^2	0.0002	0.002
Adjusted R^2	-0.0005	-0.005
Residual Std. Error	0.219 (df = 1446)	4.804 (df = 136)
F Statistic	0.348 (df = 1; 1446)	0.329 (df = 1; 136)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3: 2022 Regression

	Dependent variable: Perf. Diff	
	Batter	Pitcher
	(1)	(2)
Trade	0.039***	-0.751***
	(0.013)	(0.221)
Constant	0.006	0.117
	(0.005)	(0.093)
Observations	1,014	1,014
R^2	0.008	0.011
Adjusted R^2	0.007	0.010
Residual Std. Error (df = 1012)	0.152	2.677
F Statistic (df = 1; 1012)	8.558***	11.550***
Note:		*p<0.1; **p<0.05; ***p<0.01

supports the null hypothesis since $p_{2021} >> \alpha = 0.05$ but the 2022 regression supports the alternate hypothesis since $p_{2022} < \alpha = 0.05$. However, $R^2 < 1.1$ for all cases, so the player trades are not a good indicator of player performance.

5 Experiment Proposal

A potential experiment to test for the effect of team-specific human in the context of a baseball team is to randomly assign athletes to new teams during the season. Then, the researcher could compare indicators for performance, such as Wins Above Replacement (WAR) or Win Probability Added (WPA), between players, adjusting for factors such as previous performance, position, age, etc. Tenure would be defined as a binary variable, whether the player was assigned a new team during the season. Randomly reassigning only a small fraction of players would ensure that the control group retains the effect of team-specific human capital. Alternatively, the researcher could reserve 'control teams' that do not add or trade any players to completely isolate the control group from spillover effects. Randomly assigning players to the treatment and control group would ensure that being traded is independent of previous performance, unlike the natural situation in Major League Baseball.

Player performance could be modeled using the following function

$$Y = \beta_0 D + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + U$$

where Y is an indicator for performance, β_0 is effect size, D is tenure, X_1 is salary, X_2 is difference between player age and mean age, X_3 is a performance indicator for the previous year, $\beta_1, \beta_2, \beta_3$ are coefficients, and U is the error term.

To conduct a power analysis for this experiment, I use speculative but plausible values for each variable. I set $\beta_0 = -1$ and sample D from the binomial distribution with probability of success = 0.25. I use the lognormal distribution with meanlog = 4,000,000 and sdlog = 0.5 to generate player salary values since average MLB player salary is around \$4,000,000 [1]. I set $\beta_1 = 0.4$ because I expect salary to be moderately correlated with performance. I use the normal distribution with mean = 0 and standard deviation = 4 to generate X_2, which is similar to the age standard deviation of 3.5 in

[1] https://www.statista.com/statistics/236213/mean-salaray-of-players-in-majpr-league-baseball/

a previous study on professional baseball players[2]. I set $\beta_2 = -0.1$ since I expect the other factors to have a larger effect on player performance. I sample from the normal distribution with mean = 1.5 and standard deviation = 1 to generate X_3 to reflect average MLB player WAR[3]. I set $\beta_3 = 0.6$ because I expect previous year WAR to have the largest effect on player performance.

Using grid search, I calculated the smallest possible sample size with power > 0.8 such that power was within 0.01 of 0.8. This calculation resulted in sample size = 9500 with power = 0.808.

[2]https://pubmed.ncbi.nlm.nih.gov/16516219/

[3]https://library.fangraphs.com/misc/war/

References

Bartel, Ann P. et al. (Apr. 2014). "Human Capital and Productivity in a Team Environment: Evidence from the Healthcare Sector". en. In: *American Economic Journal: Applied Economics* 6.2, pp. 231–259. ISSN: 1945-7782, 1945-7790. DOI: 10.1257/app.6.2.231. URL: https://pubs.aeaweb.org/doi/10.1257/app.6.2.231 (visited on 06/28/2023).

Chen, Yiqun (Dec. 2021). "Team-Specific Human Capital and Team Performance: Evidence from Doctors". en. In: *American Economic Review* 111.12, pp. 3923–3962. ISSN: 0002-8282. DOI: 10.1257/aer.20201238. URL: https://pubs.aeaweb.org/doi/10.1257/aer.20201238 (visited on 06/28/2023).

De Grip, Andries, Jan Sauermann, and Inge Sieben (June 2016). "The role of peers in estimating tenure-performance profiles: Evidence from personnel data". en. In: *Journal of Economic Behavior & Organization* 126, pp. 39–54. ISSN: 01672681. DOI: 10.1016/j.jebo.2016.03.002. URL: https://linkinghub.elsevier.com/retrieve/pii/S0167268116300154 (visited on 06/28/2023).

Hofmann, David A., Rick Jacobs, and Steve J. Gerras (Apr. 1992). "Mapping individual performance over time." en. In: *Journal of Applied Psychology* 77.2, pp. 185–195. ISSN: 1939-1854, 0021-9010. DOI: 10.1037/0021-9010.77.2.185. URL: http://doi.apa.org/getdoi.cfm?doi=10.1037/0021-9010.77.2.185 (visited on 06/28/2023).

Jaravel, Xavier, Neviana Petkova, and Alex Bell (Apr. 2018). "Team-Specific Capital and Innovation". en. In: *American Economic Review* 108.4-5, pp. 1034–1073. ISSN: 0002-8282. DOI: 10.1257/aer.20151184. URL: https://pubs.aeaweb.org/doi/10.1257/aer.20151184 (visited on 06/28/2023).