Does Not Playing Hockey Make You Worse At Hockey? Investigating the Impact of the COVID-19 Pandemic on Hockey Player Development

Abstract

During 2020-2021, many hockey leagues had shortened seasons or no seasons due to the restrictions on play caused by the COVID-19 pandemic. The Ontario Hockey League did not play any games during this "COVID" season, which raises the question of whether not playing games during the 2020-2021 COVID season negatively impacted player development (or even caused players to get worse). Statistical and causal inference methods were employed to assess the impact of not playing during the COVID season, including Ordinary Least Squares, Gamma, Mixed Effects, and matched regression models, as well as a Bayesian Additive Regression sum of Trees model. All models pointed to no significant difference in post-COVID performance for treated (played during COVID season) vs control (did not play during COVID season) groups. Future research should focus on studying other populations, experimenting with alternative variable definitions, and studying player development curves to more thoroughly assess treatment impact.

Keywords: sports analytics, causal inference, Coronavirus pandemic

1 Introduction

Joyce (2021) Lefebvre et al. (2022) Joyce (2021), Lefebvre et al. (2022)

During 2020-2021, many hockey leagues had shortened seasons or no seasons due to the restrictions on play caused by the COVID-19 pandemic. Among these leagues were National Hockey League (NHL) feeder leagues, such as the Ontario Hockey League (OHL), the Western Hockey League, and the Quebec Major Junior Hockey League. Some players experiencing restrictions on play participated in other leagues or tournaments during the 2020-21 season, while others did not. This raises the question of whether not playing games during the 2020-2021 COVID season negatively impacted player development (or even caused players to get worse).

To answer this question, we examined data from the OHL, which did not play any games during the 2020-21 season due to the state of the COVID-19 pandemic (1). Some players from this league found leagues abroad (U.S. or Europe) to play in, while others recorded no games during 2020-2021, which we will call the COVID season. While some leagues may have played a partial season, OHL players either played in another league, or they did not play at all. This provided a natural experiment, allowing us to not only use traditional statistical inference but also causal inference methods.

There has been much speculation from coaches, scouts, sports commentators, and fans about the effects of the COVID season on player development Joyce (2021). The question many asked prior to the COVID season remains (at least quantitatively) unanswered: "what will be the impact on athletes unable to compete for well over a year during a key stretch of their development?" (2). Some coaches theorized that players would become better and stronger having had time off to reevaluate their individual performance and work on more skill, speed, and strength training (2), while others feared the lack of game play may have dulled the sharpening hockey skills and IQ of developing players (3). There have been plenty of skaters who had to take time off from their hockey career due to injury and came back better and stronger than before (4, 5). However, these are typically NHL players with access to extensive training and rehabilitation resources, something that not all OHL players may have had. Additionally, these players are typically not taking time off during pivotal developmental years; they are already well-established professional players.

2 Previous Work

Previous work in this area has investigated the impact of injury on player development and important psychological aspects of player development. Much work has focused on psychological aspects in player development, such as mutual trust and respect between athletes and their coaches, or frameworks through which players develop (6, 10). But little research was found on pivotal developmental years or typical development curves for ice hockey players, though some work has been done to investigate development progression in swimming (7). This research pointed to significant development from ages 10 to roughly 17 depending on the group analyzed. The prior research most similar to our research investigated the performance impacts of concussions in the NHL. Neustadtl et al. found no significant differences in pre- and post-concussion performance for the 269 NHL players studied (8). Buckley at al. again found no significant difference in pre and post- performance for players who missed playing time due to injury and those who missed playing time due to non-injury reasons (9). However, no research was found investigating the impact of reduced playing time in developing (major junior) hockey players.

3 Data

Our dataset includes skaters (excludes goalies) who played in the Ontario Hockey League (OHL) during both the pre-COVID (2019-2020) and post-COVID (2021-2022) seasons. The dataset also contains information regarding other leagues they have participated in during their career. There is data about season, team, league, points, games played, position, and drafted status. Each row is a player on a certain team in a specific season. There are 219 observations in the dataset. The data was sourced from Elite Prospects and was supplied by our external advisor, Dr. Sam Ventura.

3.1 Added Variables

If a skater played for several teams during one season, including the COVID season, the team for which they played the most games was selected. Statistics for all other teams were dropped. This was done to control for team effect on performance.

Table 1: Sample data rows and variables

first_name	last_name	position	ppg_19	gp_21	age_continuous	treatment	ppg_21
Shane	Wright	F	1.1379310	63	15.98904	Played	1.492063
Logan	Mailloux	D	0.0000000	12	16.71311	Played	0.750000
Wyatt	Johnston	F	0.5660377	68	16.63388	Played	1.823529
Brandt	Clarke	D	0.6666667	55	16.89315	Played	1.072727

Player performance: To approximate player performance in the post-COVID season, we calculated each player's points per game (PPG) as PPG = (goals + assists)/games played in the post-COVID season.

Previous player performance: To approximate player performance in the pre-COVID season, we computed each player's PPG in the pre-COVID season.

Treatment: We defined a player as treated if they participated in at least one game during the post-COVID season. This allowed us to retain players who recorded relatively few games in elite competitions like the IIHF World Junior Championship as treated. Thus ensuring we were not obscuring the effects of these competitions on development. There are 67 treated players and 152 control players.

Age: We defined age as the continuous age of the player as of January 1st, 2020. Previous Player Performance : To control for player performance in the pre-COVID season, we approximated player performance using player PPG in the pre-COVID season.

Drafted: Whether a player was drafted in 2020 or earlier Relative PM : Relative plus-minus (PM) is defined as a player's PM relative to the average PM of their team.

Ranked PM: Ranked plus-minus defines how a player's PM ranks among those of their teammates. If there are n players on a team, each player will receive a PM ranking 1-n.

3.2 Data Integrity

Through analysis and comparison with OHL records, we estimate that we have 99% of the data from the 2019-2020 and 2021-2022 regular seasons.

Table 2: Missing goals for each OHL team in the 2019-2020 and 2021-2022 regular seasons

team_name	goals_19	true_goals_19	difference_19	goals_21	true_goals_21	difference_21
Ottawa 67's	293	296	3	194	199	5
Saginaw Spirit	289	289	0	231	234	3
Flint Firebirds	272	274	2	285	286	1
London Knights	265	265	0	260	264	4
Kitchener Rangers	260	264	4	235	236	1
Sudbury Wolves	258	259	1	221	223	2
Soo Greyhounds	252	253	1	293	295	2
Windsor Spitfires	252	256	4	302	305	3
Peterborough Petes	250	250	0	239	240	1
Sarnia Sting	243	244	1	233	234	1
Owen Sound Attack	233	235	2	233	235	2
Hamilton Bulldogs	232	235	3	296	300	4
Oshawa Generals	228	229	1	209	215	6
Erie Otters	227	229	2	222	223	1
Mississauga Steelheads	220	223	3	228	229	1
Barrie Colts	217	220	3	243	245	2
Guelph Storm	214	218	4	249	251	2
Kingston Frontenacs	195	198	3	281	285	4
Niagara IceDogs	191	194	3	212	218	6
North Bay Battalion	189	189	0	264	267	3

3.3 Exploratory Data Analysis (EDA)

3.3.1 Preliminary Visualizations

The distribution of player performance is right-skewed, showing that most players do not generate many points per game. The preliminary hypothesis that not playing during the COVID season negatively impacted player performance is motivated by the plot of player performance distributions conditioned on treatment. It appears that players who played during the COVID season performed better in the post-COVID season, which motivated our analysis. Our models attempt to tease out if this difference is "real".

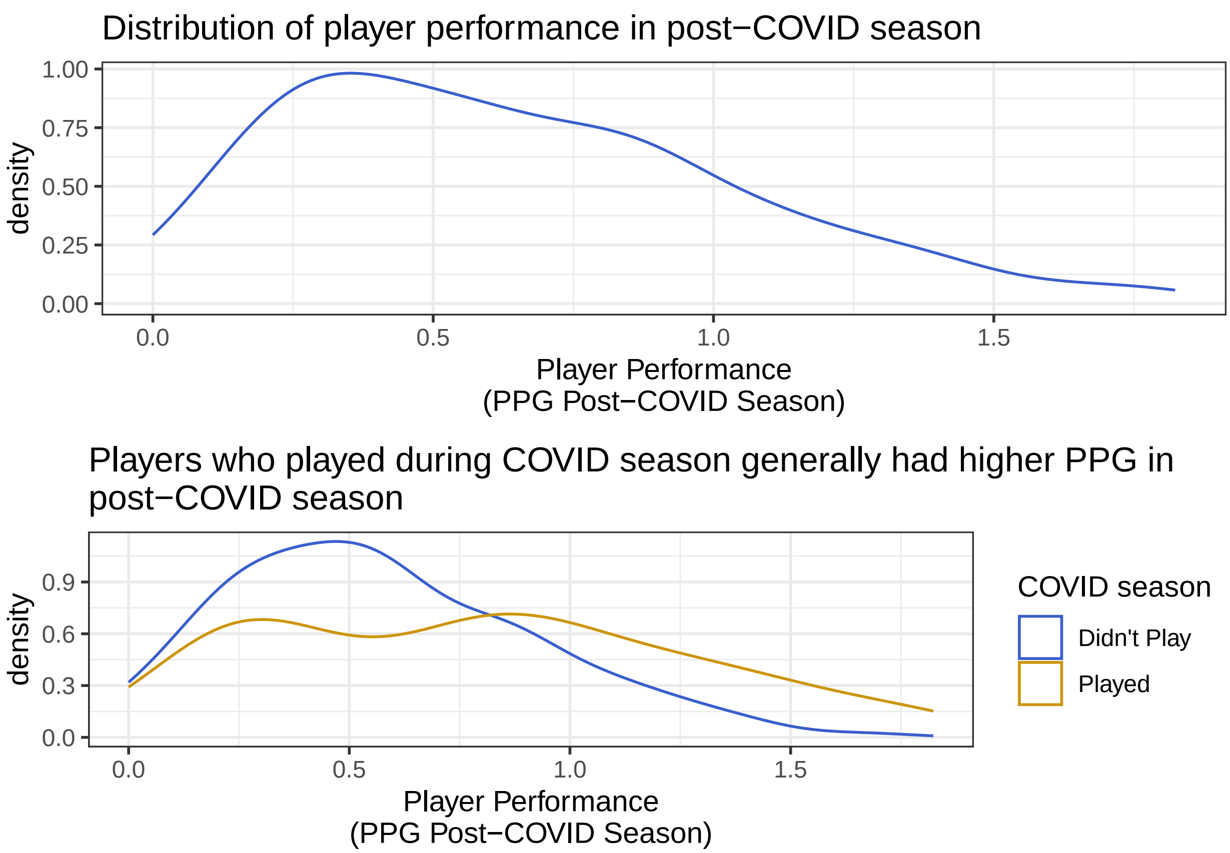


Figure 1. preliminary visualizations

We investigated relationships between potential confounders and our treatment and response to aid in variable selection. The variables we hypothesized as potential confounders are age, games played, drafted status, previous player performance, and position.

3.3.2 Age

We hypothesized that older players would be more likely to have better player performance, because they are further along in their development. Interestingly, the below plots do not support a strong relationship between age and player performance. We additionally hypothesized that older players would be more likely to be treated using the same logic as before. Better players are more likely to be selected to play in leagues, and older players tend to be better. However, the distributions do not differ significantly when conditioning on treatment.

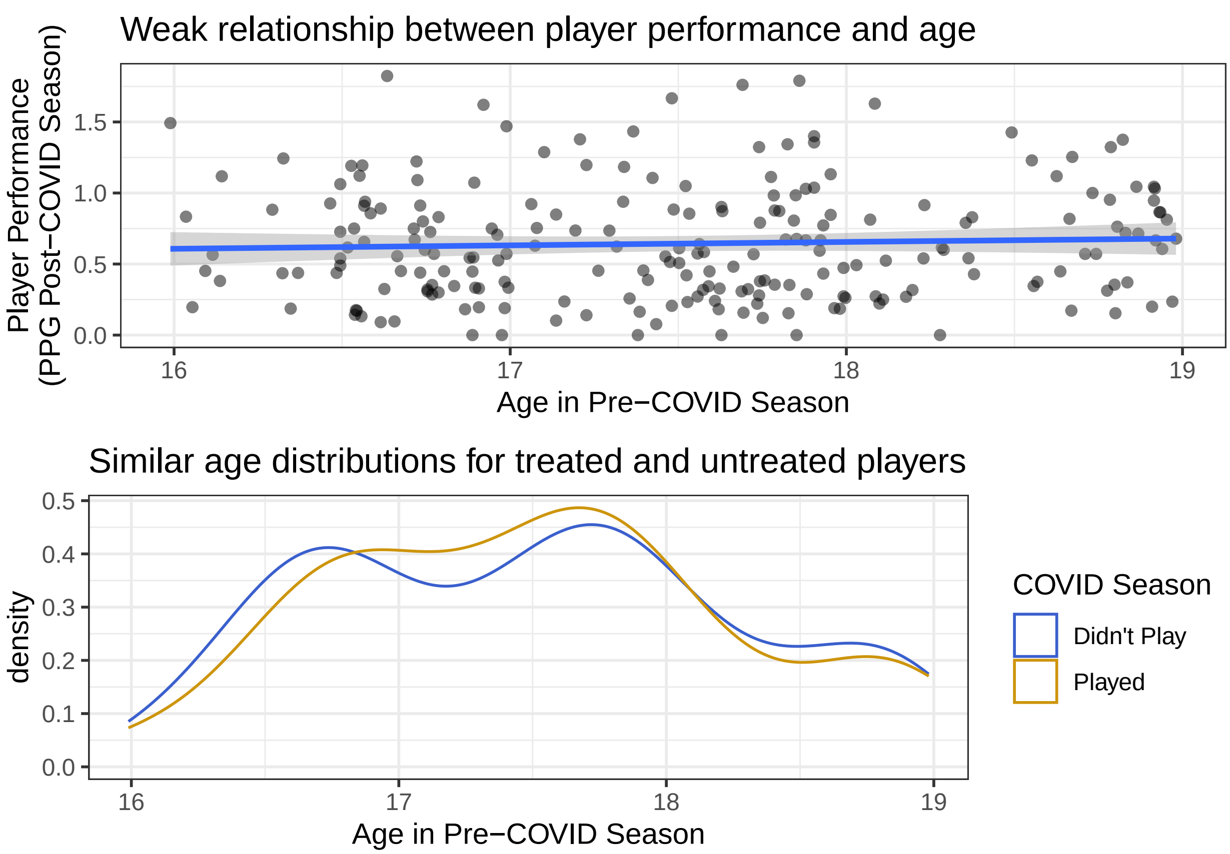


Figure 2. age vs. treatment and response

3.3.3 Games Played

The data supports that players who play more games are likely to be higher performing players. I.e. "good players don't get benched", as expected. However, there are no overwhelming differences in the distributions of player performance when conditioning on treatment, and the instability in the distribution of player performance for players who played during the COVID season is likely due to the smaller sample size.

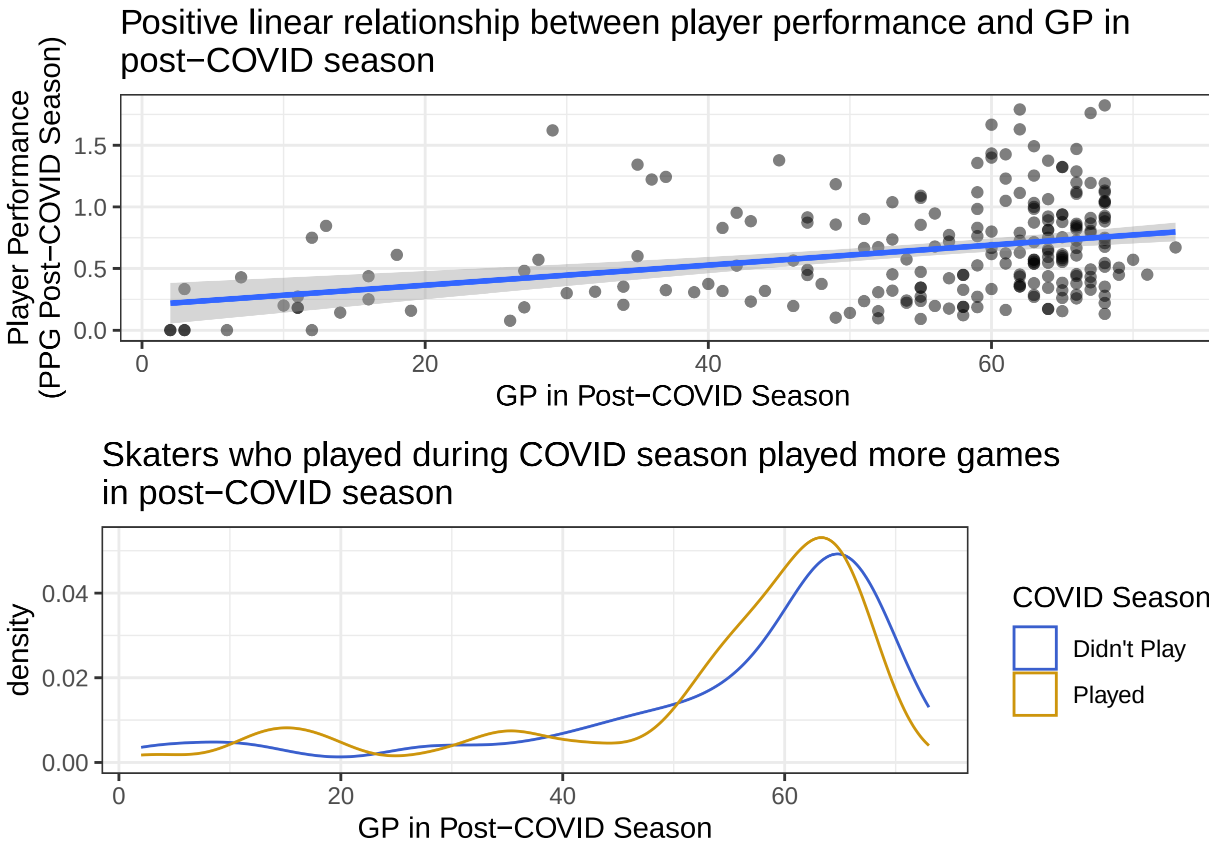


Figure 3. games played vs. treatment and response

3.3.4 Previous Player Performance

We hypothesized that higher performing players pre-COVID would likely be higher performing players post-COVID, because good players tend to keep being good. The data supports that there is a positive, moderate linear relationship between previous player performance and post-COVID player performance. We additionally thought that higher performing players pre-COVID would be more likely to be treated, because it would be easier to convince overseas leagues to take on better players, a notion that appears to be supported by the data.

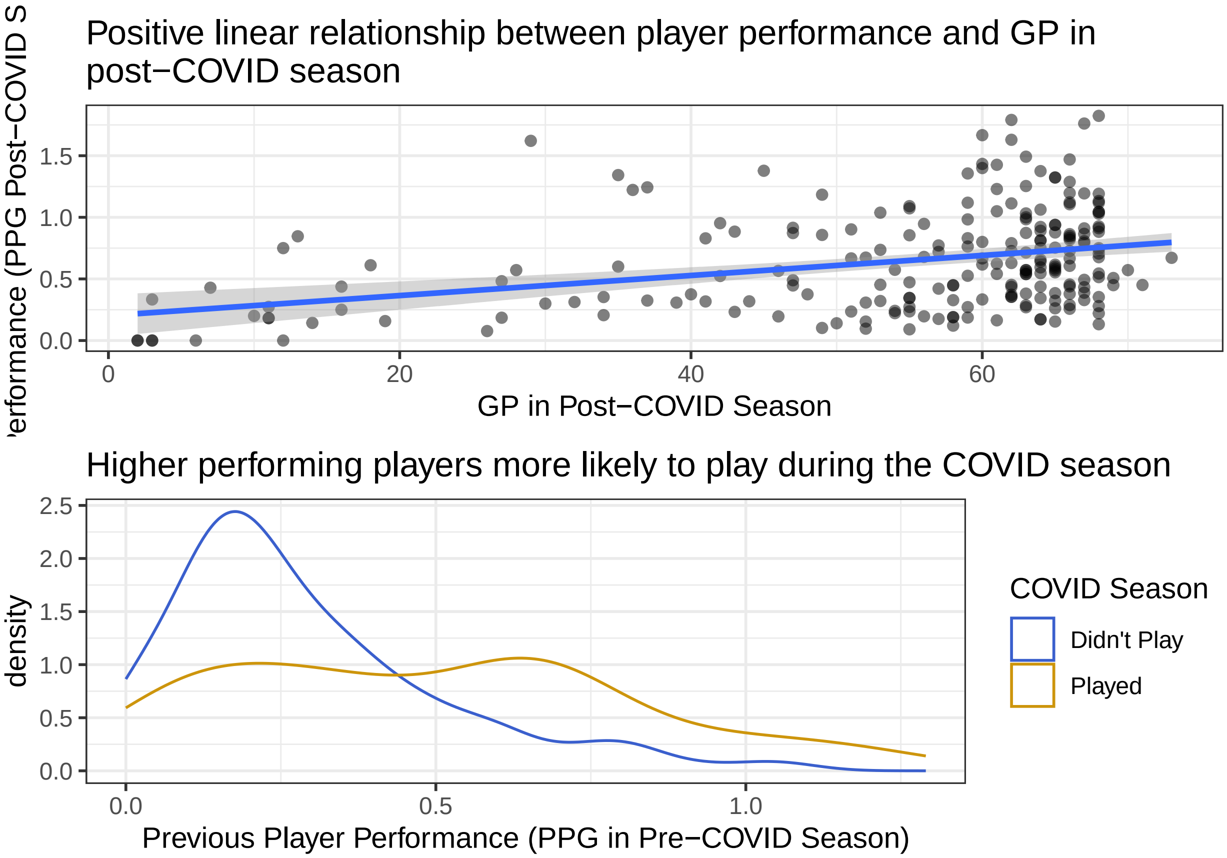


Figure 4. previous player performance vs. treatment and response

3.3.5 Position

Lastly, we know that defensemen will be lower performing players because of the way we have defined player performance and because of the nature of the position, a notion that is supported by the data. However, there is no reason to believe that position would influence probability of treatment, which is again supported by the data.

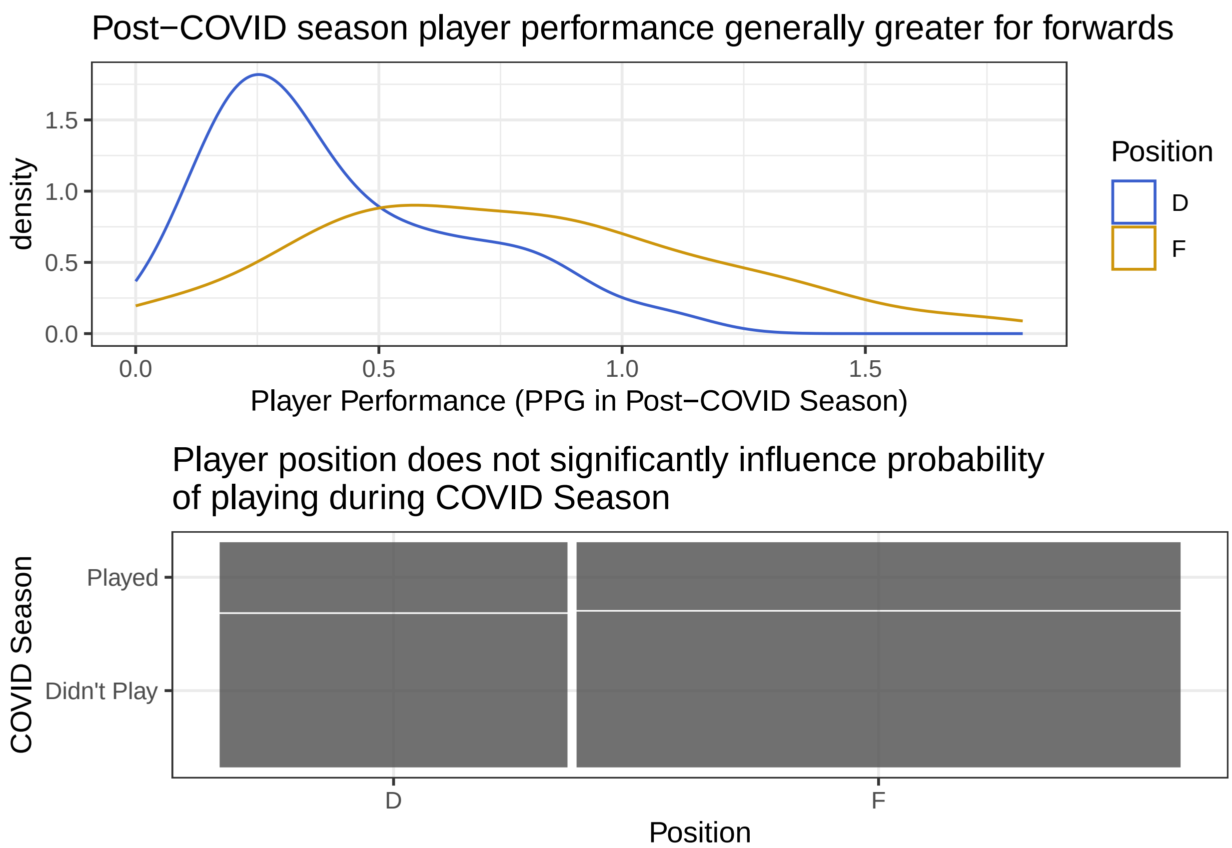


Figure 5. position vs. treatment and response

4 Methods

Before performing causal analysis, we used traditional statistical inference methods to determine whether playing during the COVID season had a significant effect on post-COVID player performance while controlling for variables (and interactions between variables) suspected to be associated with the response through EDA. When possible, we attempted a few different measures of player performance, including PPG z-scores (to control for differences in overall scoring across seasons) and relative plus-minus scores. All code is available in the supplementary code document (CITE).

For all methods $\epsilon \sim N(0, \sigma^2)$

4.1 Regression

4.1.1 Ordinary Least Squares (OLS)

We fit an OLS regression model without interaction, because it is the simplest and most interpretable model to assess the significance of playing during COVID, while still controlling for variables that could be confounding our analysis.

$$\text{Player Performance} = \beta_0 + \beta_1\text{Treatment} + \beta_2\text{Forward} + \beta_3\text{Previous Performance} +$$

$$\beta_4\text{Games Played Post-COVID} + \beta_5\text{Age} + \epsilon$$

4.1.2 Interaction OLS

We fit an OLS model with interaction to account for relationships observed between explanatory variables during the EDA process. We also tested whether the additional complexity of this full model significantly increased predictive power over the nested model.

$$\text{Player Performance} = \beta_0 + \beta_1\text{Treatment} + \beta_2\text{Forward} + \beta_3\text{Previous Performance} +$$

$$\beta_4\text{Games Played Post-COVID} + \beta_5\text{Age} + \beta_6\text{Position*Previous Performance} +$$

$$\beta_7\text{Age*Previous Performance} + \beta_8\text{Previous Performance*Treatment} + \beta_9\text{Games Played} + \epsilon$$

4.1.3 Gamma

PPG is right skewed and bounded between 0 and some positive number, so we believed PPG may be Gamma-distributed. We performed simple and interaction Gamma regression with the log link function in an attempt to more accurately model the relationship between our response and explanatory variables.

- Player Performance $\sim$ Gamma(α, λ)
- for the i^{th}player, $i = 1, ..., 219$,

$$E[\text{Player Performance}_i] = e^{\beta_0}\text{Treatment}^{\beta_1}\text{Forward}^{\beta_2}\text{Previous Performance}^{\beta_3}$$

$$\text{Games Played Post-COVID}^{\beta_3}\text{Age}^{\beta_5}$$

4.1.4 Mixed-effects Model

Lastly, we fit a mixed-effects model to determine if the effect of playing during the COVID season was significantly different across leagues. The slope and intercept of the regression line varied according to the league. Players who did not participate during the COVID season were grouped into a "league" called "NONE".

Level One:

- for the i^{th}player, $i = 1, ..., 219$,

$$Y_i = a_i + b_i \text{Treatment} + \epsilon_i$$

- $\epsilon_i \sim N(0, \sigma^2)$

Level Two:

- $a_i = \alpha_0 + \alpha_1 \text{Forward} + \alpha_2 \text{Previous Performance} + \alpha_3 \text{Games Played Post-COVID} + \alpha_4 \text{Age} + u_i$
- $b_i = \beta_0 + \beta_1 \text{Forward} + \beta_1 \text{Previous Performance} + \beta_3 \text{Games Played Post-COVID} + \beta_4 \text{Age} + v_i$

$$\begin{bmatrix} u_i \\ v_i \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_u^2 & \\ \rho\sigma_u\sigma_v & \sigma_v^2 \end{bmatrix} \right)$$

4.2 Causal Methods

4.2.1 Matching

Matching on covariates allowed us to better control for confounding variables and more accurately estimate the true impact of the treatment. The results fit on matched data were compared to the results of the model fit on unmatched data. Control and treatment observations were matched on games played post-COVID, position, points pre-COVID, previous player performance, age, and ranked PM pre-COVID. Optimal matching method and GAM measure of distance were used, and a 1-to-1 matching ratio was used due to the small sample size. The model is the same as the OLS model, but fit with matched data.

4.2.2 Bayesian Additive Regression Trees (BART)

An appeal of the BART model is that it controls overfitting, which is one issue with normal additive regression trees. Each tree tries to account for something new in the model. Once all added, accurate estimates are produced. This allows for causal inferences to be drawn. The workflow used is taken from Joshua Bon's vignette on using the tidytreatment package with BART.

A variable selection model was used to find important variables for obtaining propensity scores. The variable selection model was a continuous BART model regressing all covariates except for the treatment against post-COVID player performance. The burn-in period was set to 2000 iterations, with posterior draws set to 5000. Variables were deemed important if their average inclusion in the model was equal to or greater than 50%. The most important variables were used to produce propensity scores using a probit BART model, with a burn-in of 2000 draws and 5000 posterior draws. Finally, all covariates, including treatment, and propensity scores were used in the final BART model to predict post-COVID player performance. The final model produced a posterior distribution of estimated post-COVID player performance for each player, with a burn-in of 10,000 draws and 200 posterior draws per player. The method of obtaining the posterior is outlined by Chipman et al. (CITE)

For all models "let T denote a binary tree consisting of a set of interior node decision rules and a set of terminal nodes, and let $M = \{\mu_1, \mu_2, ..., \mu_b\}$ denote a set of parameter values associated with each of the b terminal nodes of T" (CITE).

Variable selection model:

$$\text{Player Performance} = \sum_{j=1}^{25} g(x; T_j, M_j) + \epsilon$$

- $x = \{\text{Games Played Pre-COVID}, \text{Games Played Post-COVID}, \text{Points Pre-COVID}, \text{Age}, \text{Ranked PM Pre-COVID}, \text{Relative PM Pre-COVID}, \text{PM Pre-COVID}, \text{Position}, \text{Previous Player Performance}\}$

- $x_{important}$ are the most variables in this model, deemed important if average inclusion was greater than or equal to 50%.

Propensity score model:

Table 3: RMSE values for all models

model	RMSE
BART	0.2254971
mixed effects	0.2386779
OLS interaction	0.2548995
OLS	0.2553530
intercept-only	0.2662603
matched	0.4018033
gamma simple	1.1395561
gamma interaction	1.2248592

$$\text{Propensity Score} = P(\text{Treatment} = \text{played} \mid x_{important}) = \Phi(\sum_{j=1}^{200} g(x_{important}; T_j, M_j) + \epsilon)$$

- Φ is the cumulative distribution function of the standard normal distribution.

Final Predictive Model:

$$\text{Player Performance} = \sum_{j=1}^{200} g(x, \text{Treatment}, \text{Propensity Score}; T_j, M_j) + \epsilon$$

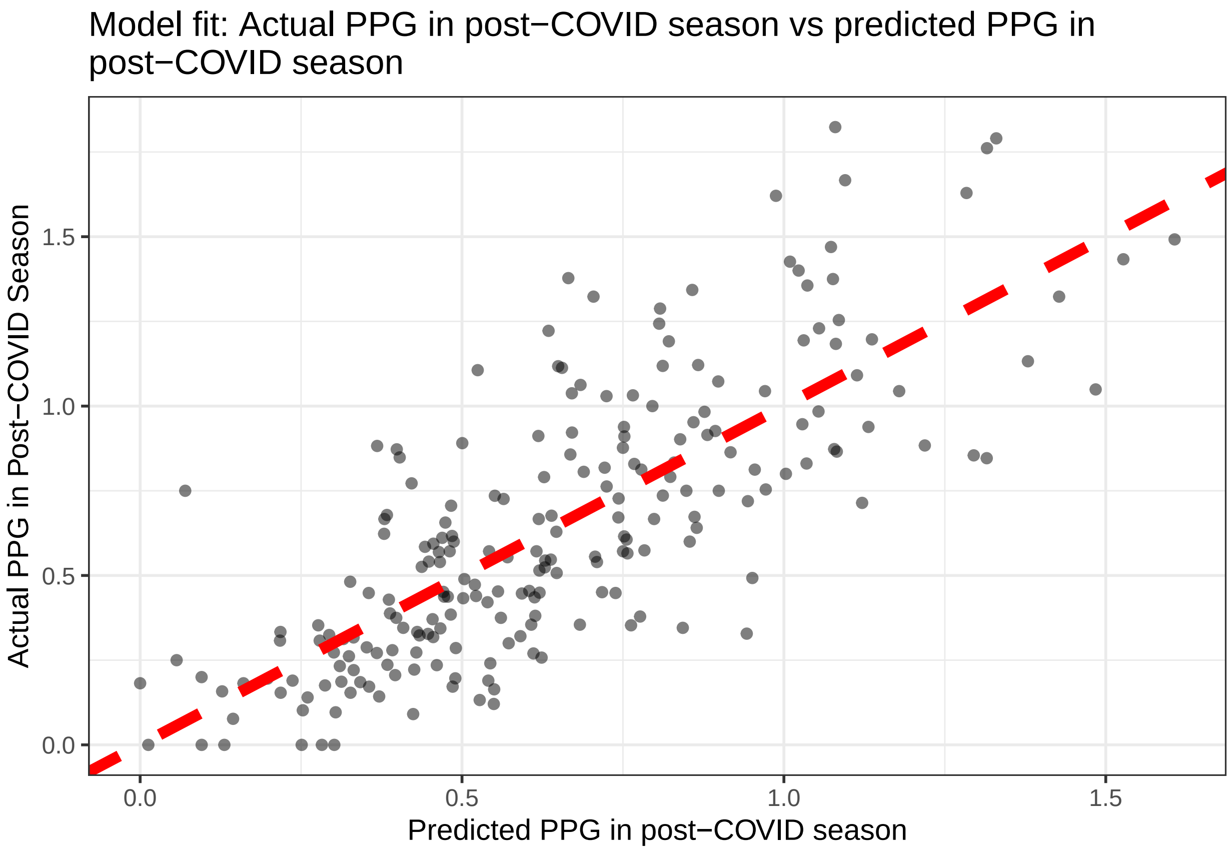
5 Results

Across all models there was no evidence of a treatment effect given the observed data, regardless of the measure of player performance chosen (PPG, PPG z-scores, ranked PM, relative PM). PPG was ultimately chosen as the response measure because of its interpretability. The RMSE values for each of the models according to ascending error is summarized in Table 3.

5.1 Regression

The regression model that best balances accuracy and parsimony is the OLS model.

Player $\widehat{\text{Performance}} = 1.14 + 0.05 * \text{Treatment} + 0.18 * \text{Forward} + 0.89 * \text{Previous Performance} + .006 * \text{Games Played Post-COVID} - .07 * \text{Age}$



- Coefficients for position, games played in post-COVID season, age, and previous player performance were all found to be statistically significant from 0 at the $\alpha = 0.01$ level.

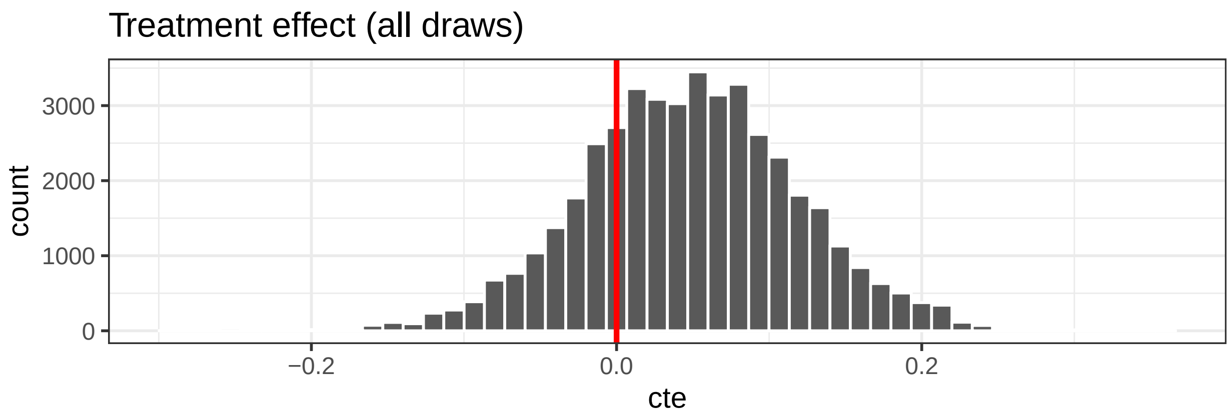
- The model explains approximately 59% of the variation in player performance in the post-COVID season, which is a statistically significant amount at the $\alpha = .001$ level $F(5, 213) = 62.88, p < .001$.

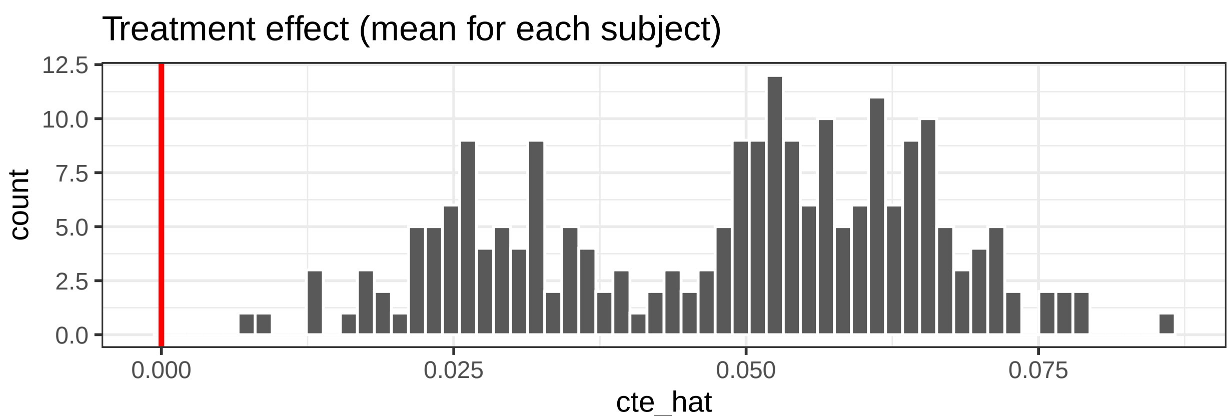
5.2 BART

The variables deemed important in the variable selection model were games played post-COVID, points pre-COVID, relative PM pre-COVID, position, and previous player performance.

$$x_{important} = \{\text{Games Played Post-COVID}, \text{Points Pre-COVID}, \text{Age},$$
$$\text{Relative PM Pre-COVID}, \text{Position}, \text{Previous Player Performance}\}$$

The estimated effects do not differ significantly from the line at 0, which indicates that there is not sufficient evidence of a treatment effect. Figure 1 is bell-shaped and fairly symmetric. At first Figure NUM appears to be alluding to a treatment effect. The range of the x-axis in Figure 2 is much smaller than in Figure NUM. This graph is suggesting that if there is a treatment effect, it is very small.





The confidence intervals for Conditional Average Treatment Effect support the same conclusions. Similar to Figure 2., most of the point estimates in Figure 3. are positive. But since all of the confidence intervals contain 0, this visualization is compatible with no treatment effect.

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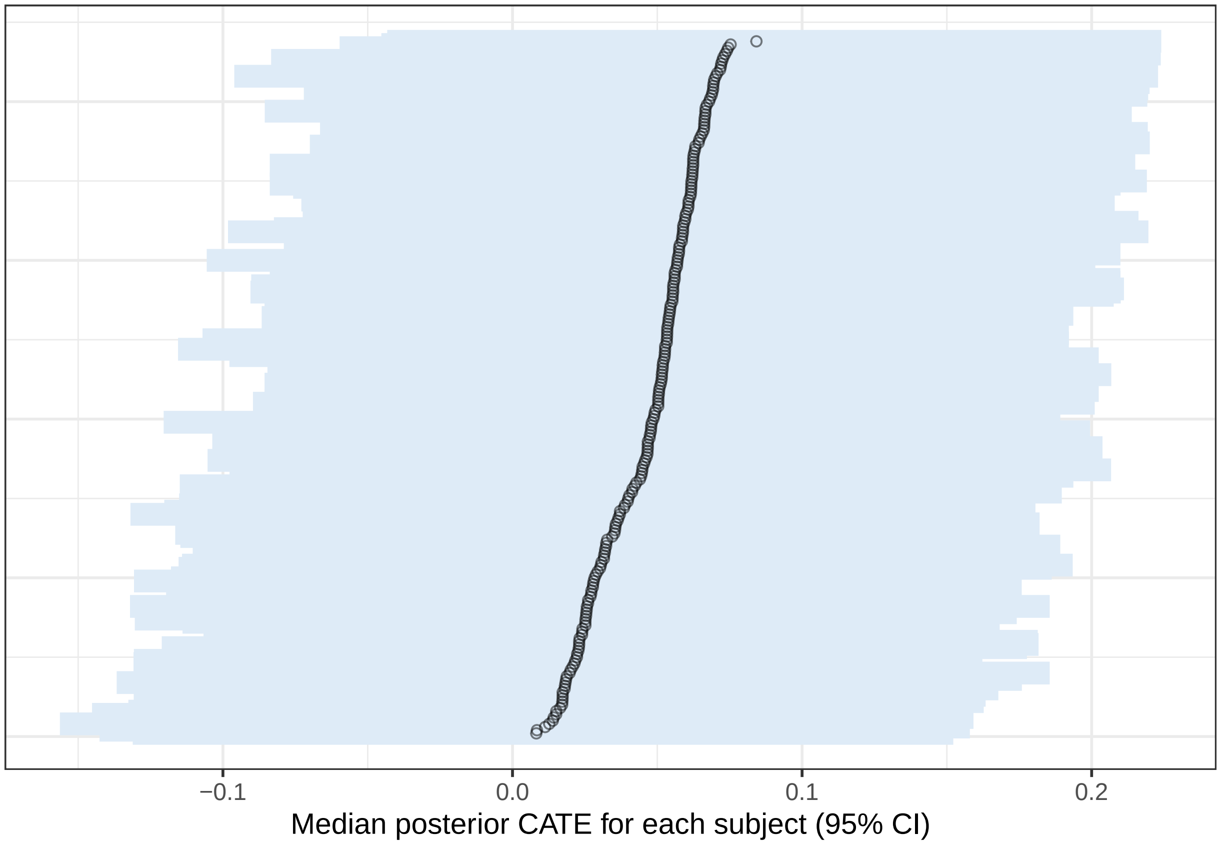


6 Discussion

6.1 Interpretations of Models

6.1.1 OLS Regression Model

Player performance in the post-COVID season is expected to increase by 0.05 PPG on average for skaters who played during COVID, when holding constant position, previous player performance, games played in the post-COVID season, points scored in the pre-COVID season, and age. Over the course of a 68 game season in the OHL, the treatment effect would result in only approximately 3 extra points. In this model, the coefficient for whether someone played during the COVID-season was not statistically significantly different from zero. There is no evidence that playing during the COVID season impacted player performance in the post-COVID season for players who played in both the pre- and post-COVID seasons in the OHL.

Table 4: Shane Wright stats

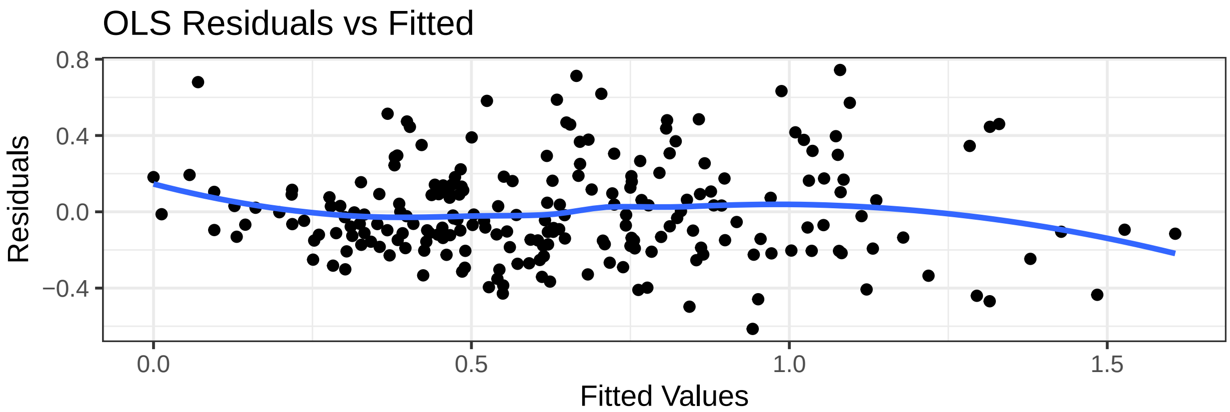
treatment	position	ppg_19	gp_21	age_continuous	ppg_21	ols_pred
Played	F	1.137931	63	15.98904	1.492063	1.606924

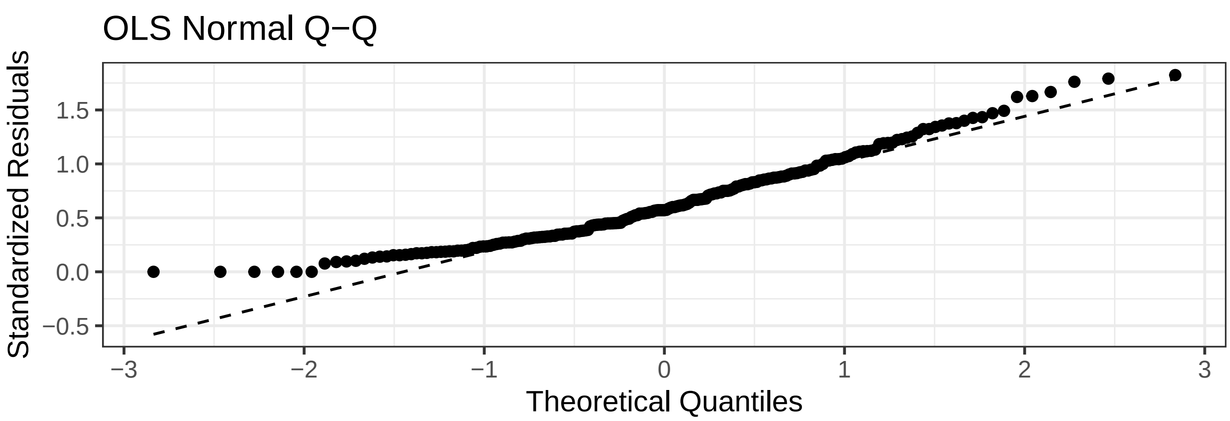
We are 95% confident that the change in player performance in the post-COVID for players who played during the COVID season is between -0.0185 and 0.149 PPG, holding constant position, previous player performance, games played in the post-COVID season, points scored in the pre-COVID season, and continuous age. This model can be used to predict player performance in the post-COVID season based on a variety of factors in the pre-, COVID, and post-COVID seasons among skaters who played in the OHL in both the pre- and post-COVID seasons. For example, using Shane Wright as our observation, the model predicts his post-COVID player performance to be 1.61 points per game, while his actual points per game was slightly lower at 1.49.

6.2 Limitations

6.2.1 Model Limitations

OLS The model conditions for inference were not all met. The relationship between our explanatory variables and post-COVID season PPG looks roughly linear, so the linearity condition of OLS is met. However, the skaters in the dataset are playing together on the same teams in the same league and influencing each other's player performance. Because we were using player level data, and not play level data, we could not attempt to account for this non-independence. Therefore, this condition is not met. The residuals seem roughly normally distributed, as shown in the normal QQ plot, so this condition is met. There seems to be roughly constant variance in residuals across all levels of our explanatory variables, so the error homogeneity condition is met.





Mixed Effects Though the mixed effects model shows a significant positive effect for some teams, the confidence intervals were generated using as few as one observation in many cases. Teams where a significant positive effect is shown had at most eight observations. Because of these small sample sizes, we did not believe that our confidence intervals nor our league effect size estimates were credible. Additionally, the model did not converge.

Matched regression Though the the regression model fit on matched data did not support a significant treatment effect, the matching was not ideal. There were not enough observations in the dataset to support extremely precise matching between treatment and control units.

6.2.2 Variable and Data Limitations

Though we hypothesized that drafted status would have a significant effect on treatment status, unfortunately not enough players in our dataset were drafted prior to the COVID season for this variable to be meaningful (only three players were drafted pre-COVID). We hypothesized that if a player was drafted, it is more likely that they would be able to play during the COVID season, because their NHL team would have the resources to convince a league or team to take the player on for that year. Additionally, we do not have any record of players who left the OHL post-COVID. It is possible that there are a significant number of players who played during the COVID season and became too advanced to continue playing in the OHL, resulting in them leaving to play in other leagues. This missing data could be confounding our analysis, because if these hypotheticals were true, then including these players would likely result in the treatment effect being significantly positive.

Our estimates of player performance were biased towards offensive production. Variables such as time on ice, line number, shots blocked, successful passes, and battles won, among other measures could be combined to create a more comprehensive metric to approximate player performance, which may show a different treatment effect. In general there are many confounding variables that were either not present in our dataset or cannot be easily measured. For example, possible confounders that were not measured in our dataset are time spent practicing per week (on ice, off ice, etc), coaching support, diet, etc.

7 Future Work

Future models could utilize weighting and account for dependence of observations. If models were weighted so that players who played more games contributed more to the overall outcome of the model and significance of the treatment, this would likely result in more robust estimates of the treatment effect. Player performance for players who only played a small number of games may not be as accurate as player performance for players with more games. Additionally, robust variances could be used when performing inference for models because of the dependence of our residuals. Play-level data could also be used to address the dependence of residuals in the dataset.

Ideally, we would like to study the effects of the COVID-19 pandemic restrictions and prolonged periods without play on other populations. For example, we would like to investigate if our results generalize to goalies, other major junior leagues, and the NHL/NHL taxi squad. There are other scenarios where players experienced prolonged periods without play. Players may be forced to take time off due to injury, personal reasons, or scenarios like the NHL lockouts.

We would also like to facilitate a comparison of typical hockey player development curves compared to COVID-impacted development curves, and investigate the impact of our treatment on long-term development. Even if not playing during the COVID season negatively impacted the development of any population of players, would this impact last forever? Or is it the case that these players would catch up to their counterparts who played during the COVID season in the long-term? As time passes and more data is collected post-COVID, future work could focus on assessing the long-term impact of playing or not playing during the COVID season or not playing during other seasons.

8 Conclusion

When studying the effects of the pandemic hockey restrictions on OHL hockey player performance, no significant effect was found between those who played during the pandemic and those who didn't. Both statistical and causal inference methods showed no significant evidence of a treatment effect when controlling for relevant confounding variables, though model and data limitations may have contributed to this null effect. Further research could investigate other populations and variable definitions to determine if our results generalize beyond the population studied.

9 Acknowledgments

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