Is Covid-19 to Blame? Explaining Decreased Attendance in the 2021-22 NBA and NHL seasons.

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Abstract

This paper analyzes how the Covid-19 pandemic impacted sports attendance demand for the NBA and NHL 2021-22 seasons. The impact of new cases and deaths, as well as the implementation of different types of Covid-19 policies, are taken into consideration. Regression analysis generally finds that new cases and deaths did not impact attendance demand once controlling for other predictors and clustering standard errors. The impact of policy types, however, is more distinct, as vaccine and mask mandates appear to have decreased and increased attendance, respectively, in the NHL. An impact in the NBA, however, is not observed. Policy makers and team owners should be aware of these potential impacts in the case of a resurgence of Covid-19 in the future.

Acknowledgment

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Contents

1 Introduction

According to Our World in Data, March 17^{th} 2020 marked the highest reproduction rate of Covid-19 in the United states, reaching a value of 3.67.[1] Each case of Covid-19 was expected to lead to 3.67 additional new cases, creating a positive feedback loop that quickly began to infect the country. This period of intense disease spread was not unique to the United States either; the world as a whole faced its highest levels of Covid-19 growth around early to mid March.[2] As a result, many of the activities fundamental to contemporary life were abruptly halted - indefinitely suspended for the foreseeable future.

Professional sports matches are such examples of activities suspended due to the pandemic. The World Health Organization had recommended guidelines to severely limit large public gatherings on February 14^{th}, 2020, and although countries ignored these recommendations then, they were quick to adopt them in March when cases began to rise, and with their adoption came the mass shut down of professional sports. (WHO et al., 2020). The holistic nature of these shutdowns should not be understated. To give some perspective on the matter, Tovar (2021) compares the shutdown of European football during World War II to its shutdown during Covid-19, finding that "coronavirus has dwarfed [WWII's] effects on soccer." He continues, "For the first time in history, almost every soccer tournament in the world has stopped." Indeed, the world had collectively come together and agreed it was too risky to be hosting sports events while a perilous disease was running rampant, and as a result, nearly all professional sports leagues had been temporarily suspended by the end of March 2020 (Zucker, 2020).

These shutdowns garnered the criticism of many important people in the professional sports universe. For example, Italian Sports Minister Vincenzo Spadafora disagreed with the Italian government's decision to suspend Serie A matches, arguing to Prime Minister Giuseppe Conte that games should be allowed to continue provided no fans are in attendance (Zucker, 2020). To some, playing without live fans was a concession they were unwilling to make, as a number of NBA franchise owners staunchly opposed the idea, arguing games should continue until the government forcefully stops them (Golliver, 2020). Even some players got involved, most notably NBA superstar Lebron James, who initially told reporters, "I ain't playing if I ain't got the fans in the crowd. That's who I play for," before eventually going back on his statement four days later (Zucker, 2020). Clearly, the sports industry did not want to stop. Players wanted to play and they wanted their fans to be right there in the stadium watching. What is less clear is how the fans themselves felt about the situation. Faced with a growing public health concern in Covid-19, did fans still want to attend professional

[1] See their Covid-19 Data Explorer for full details: https://tinyurl.com/COVID-19-Reproduction

[2] This statement should not be predicated solely on reproduction rate, since growth and reproduction are two fundamentally different statistics (Julia Gog, 2020). See Perc et al. (2020) for information on some countries Covid-19 growth rates during March 2020

sports matches?

Although an interesting question, determining how Covid-19 impacted professional sports attendance *during the onset of the pandemic* is not what this paper seeks to explain. There are a few reasons for this. First, as was previously mentioned, a majority of the sports leagues shut down rapidly once the pandemic had begun. This severely limits the amount of data available to study, which in turn limits our ability to make accurate statistical inferences. Second, of the data that is available, sports economists have been quick to analyze it, limiting the amount of new and proprietary areas to explore. As a result, this paper instead chooses to analyze Covid-19's impact on the 2021-22 seasons of the NBA and NHL, roughly two years after the pandemic had begun. The decision to study sports attendance during this time frame is motivated beyond just the shortcomings of the onset data. Studying this time frame allows for inference on how people have adjusted their perceptions of Covid-19 since the beginning of the pandemic. This is especially topical given the surge of the Omicron variant in January 2022, which brought record new case numbers to the United States. Furthermore, the 2021-22 NBA and NHL seasons opened with no stadium capacity limits,[3] which in theory gave fans unbridled access to attend (or not to attend) sports matches as they please. The lack of capacity limits also meant that many stadiums had mask and or vaccine mandates active for at least part of the season, allowing for analysis of how these policies impacted attendance.

The goal of this paper is to determine how Covid-19 impacted attendance demand for the NBA and NHL during their respective 2021-22 seasons. This is accomplished via OLS regression analysis, where attendance per stadium capacity limit is the dependent variable. The main variables of interest are the weekly average count of new Covid-19 cases/deaths at a home team's Metropolitan Statistical Area, as well as the type of Covid-19 policy in place during the game. An additional hypothesis to explore is whether there is evidence of a rebound effect, that is, whether fans became less sensitive to the risks of Covid-19 as the 2021-22 season progressed. This paper therefore adds to the existing literature concerning sports attendance demand in the presence of risk by providing insight into the specific case of Covid-19 and the NBA and NHL, which, to the best of my knowledge, has not been covered before. An analysis of the impact of different Covid-19 policy types on attendance demand is also unique (in an empirical sense) in the field of sports economics, which further justifies this paper's subject matter.

The rest of paper is structured as the following: section 2 provides a review of the academic literature relevant to this paper, and then justifies this paper's motivation and contribution to the literature, section 3 introduces the data and key variables of the study, and then outlines the model specification used, section 4

[3] None in the United States. Many Canadian teams did start the season with a capacity limit. This paper, however, considers just the U.S. teams in its analysis.

provides the results of the regressions and discusses them, and finally, section 5 ends with some concluding remarks and policy implications.

2 Literature Review & Contribution

This section is divided into four subsections. The first three subsections present the relevant literature. Subsection 2.1 analyzes literature studying attendance demand in the presence of an exogenous public risk, subsection 2.2 analyzes literature studying professional sports' impact on spreading viral diseases, and subsection 2.3 analyzes all other potential variables which may impact attendance demand. Subsection 2.4 will then piece together the presented literature into a cohesive argument justifying this paper's relevance and uniqueness in the field of sports economics.

2.1 Attendance Demand in the Presence of Risk

Most relevant to this paper is the literature devoted to studying attendance demand given an exogenous public risk. Prior to the Covid-19 pandemic, a majority of papers studied the impact of other viral disease, such as influenza. An example of this is Gitter (2017), which studies how the 2009 outbreak of H1N1 affected Mexican triple A baseball attendance. Gitter finds that H1N1 cases, "reduced baseball game attendance by 15-30% with a greater reduction in attendance where there were more reports of influenza-like illness." Furthermore, when the Mexican government issued social distancing measures in public places, attendance dropped another 20%. Another type of risk studied in the literature, completely separate from disease, is the risk of terrorism. Kalist (2010) finds that MLB attendance "decreased by as much as 12%" following the United States' first ever increase in the national terror-alert level following 9/11. It is important to note that future increases in terror-alert levels did not have an impact on attendance, meaning consumers eventually adapted to the risk after an initial period of heightened salience. Performing a similar study is Frevel and Schreyer (2020), which examined the impact the 2015 Paris terrorist attacks had on German football attendance demand. They find that the number of no-shows, fans who had purchased a ticket but did not attend the match, increased from 3,262 to 6,409 following the day of the attack. Similar to the Kalist (2010) study, the effects diminished rapidly after a couple of days.

A majority of the contemporary attendance demand research, unsurprisingly, focuses on the impact of the Covid-19 pandemic. One such paper is Reade et al. (2020), which studies the peculiar case of the Belarusian Premier League. Unlike almost all other European football leagues, the BPL did not cease functioning because of the pandemic. This is particularly bizarre since a new season of the BPL started on March 19$^{\text{th}}$, meaning the decision was not even motivated by a desire to maintain an existing season's progress (Reuters, 2020). Taking advantage of the data opportunity generated by this outlier policy decision, Reade et al. (2020) finds that Covid-19 cases were significantly related, in a negative direction, to attendance. Furthermore, the effect was non-linear, as attendance increased after around 13,000 active cases and 190 deaths. Reade and Singleton extended the scope of their analysis in their 2021 paper which studied European football in the top English, Italian, French, Spanish, and German Leagues. Their analysis produced mixed results, finding that the day-to-day change in log stadium attendance in the English, German, and Italian football leagues decreased by 4.5, 10.8, and 13.2 percentage points per 100 new domestic cases, respectively, while there was no significant change in the French or Spanish leagues (Reade and Singleton, 2021). Furthermore, the global number of cases did not significantly impact any league, suggesting the domestic case count is much more salient to fans. Finally, Humphreys et al. (2021) studies sports fans' willingness to pay to attend U.S. professional sports matches under a variety of different social distancing policies. They find that fans had the highest willingness to pay for attending a game with a social distancing policy equivalent to 25% venue capacity. These findings are relevant as they showed that fans perceived Covid-19 as a serious risk, to the point where they were willing to pay extra for a stadium which mitigated these risks.

2.2 Professional Sports & Disease Spread

The logical analog to studying a virus' impact on attendance demand is to study how attendance impacts the spread of viruses. Gundlapalli et al. (2006) does just this, analyzing local influenza cases during the 2002 Salt Lake City Winter Olympics. Of the medical visits recorded during the Olympics, "Athletes comprised 36% of all influenza patients." This paper, then, suggests that a mechanism in which sports events transmit diseases is through the athletes themselves. Looking more generally to the impact sports events as a whole can have on disease spread is Stoecker et al. (2016), which studies the impact the Super Bowl had on local influenza rates. They find that having a local team in the Super Bowl "caused an 18 percent increase in influenza deaths for the population over age 65." Interestingly enough, they find this effect only for the local teams that host the Super Bowl contenders, and not for the city that hosts the Super Bowl itself. While this may suggest live fans do not contribute to disease spread, Cardazzi et al. (2020) provides evidence that they do. This paper, which also analyzed influenza mortality rates, finds that relative to U.S. cities with no professional sports teams, cities which gained one between 1962-2016 exhibited "increased local influenza mortality by between 4% and 24%." Furthermore, this increased rate vanished when games were temporarily halted due to work stoppages, and thus the effect could be directly attributed to the presence of games themselves.

As with the attendance demand literature, the disease spread literature picked up extensively after the onset of the Covid-19 pandemic. Although not directly about professional sports matches, Moritz et al. (2021), using a computer model, simulates the spread of Covid-19 at mass gathering events (MGEs). They find that depending on the hygiene-practices in place and the ventilation quality of the event space, an MGE can be expected to increase the number of new Covid-19 cases by 5 to 22 cases for a population of 1,000 people. New cases increased further when the simulation was run without masks. More directly related to sports, and serving as the analog study to Reade et al. (2020), Parshakov (2021) studies the effect the non-suspended Belarusian Premier League had on the spread of Covid-19. They find that a “1% growth in match attendance in a region increased the number of Covid-19 cases by 0.15%-0.48% percent.” This study is particularly interesting, since it uses attendance as the main predictor variable, as opposed to just match presence. A final paper of interest is Ahammer et al. (2020), which, like this paper, focuses on the NBA and NHL. They find “one additional mass gathering increased the cumulative number of Covid-19 deaths in affected counties by 9 percent,” where the mass gatherings here are NBA or NHL games.

2.3 Other Variables Impacting Sports Attendance.

The final area of literature relevant to this paper is the extensive research done on all other variables which impact a sports match’s attendance. This research is relevant since it is necessary to know what controls to include in our regressions so that they do not suffer from omitted variable bias. One variable extensively studied is match uncertainty, that is, whether a match is expected to be close or a blow out. Using evidence from the British Premier League, Cox (2018) finds that match uncertainty was negatively correlated with attendance. This result, however, could be biased by the fact that British Premier League matches can end in a draw, and draws are generally disliked by fans of both teams, since neither side is rewarded with many points.[4] Draws may also be associated with a dull, low scoring match, and in a sport where scoring is not that common, this may drive attendance down. Moreover, a preference for more certain games may simply reflect a desire for the home team to win, since home teams benefit from home court advantage. Touching on this last point is Forrest and Simmons (2002), which finds that an increase in either team’s quality raises attendance, even after holding match uncertainty constant. This article, however, contradicts Cox (2018), as it also finds that spectators preferred uncertain matches relative to certain ones. In the NHL, Coates and Humphreys (2012) finds that fans preferred more certain matches, and agreed with Forrest and Simmons (2002) in the finding that team quality is positively related to attendance. Studying the other three U.S. major sports leagues, Mills and Fort (2018) returns the inconclusive result that outcome uncertainty does not

[4]In the British Premier League, wins are three points, losses are zero, and draws are one. Less total points are awarded in a draw compared to a win, and this disparity may be telling of overall fan interest in the game.

affect attendance in the MLB, NFL, or NBA. A final variable to control for is the part of the season the game is being played in, as certain periods are correlated with higher/lower average attendance. For example, the first and last games of a season consistently draw higher attendance.

2.4 Motivation & Contribution

There are several reasons why this paper is important and relevant to the existing literature. First, to the best of my knowledge, this is the only paper studying attendance demand in the NBA and NHL since the Covid-19 pandemic. The results of this paper are therefore new and provide the first insight as to Covid-19's impact on the NBA and NHL. This fits into the literature concerned with how Covid-19 impacted attendance demand across different leagues, such as Reade et al. (2020) and Reade and Singleton (2021). Secondly, this paper is unique in that it uses empirical data to study how different Covid-19 policy types impacted attendance demand. Prior research has been conducted on how policies like social distancing have impacted attendance at sports games for different viral diseases, but no empirical studies have specifically looked at Covid-19 policies in the sports world. This paper therefore builds very directly on Humphreys et al. (2021), which studied Covid-19 policy impacts via consumer-reported willingness to pay. This can have policy implications regarding what policy measures teams should adopt in the future if another rise in cases occurs. A tertiary motivator is seeing whether the NBA and NHL exhibit the 'rebound' effect exhibited by other sports leagues during Covid-19. This, too, is important, as it informs policy makers as to whether they should expect fans to return to games over time, regardless of Covid-19 activity. Studies like Reade and Singleton (2021) have found a rebound effect during the onset of the pandemic, but none have studied the Omicron spike, since the data is so new.

3 Data Description & Empirical Strategy

3.1 Data, Graphs, Summary Statistics

A large number of sources were used to collect the necessary data. Covid-related data was collected from the New York Times's Covid-19 data repository hosted on github.com.[5] This is county level data that was aggregated to the metropolitan statistical area (MSA) level for the intents of this study. MSA code definitions followed the reference guide posted by the National Bureau of Economic Research (NBER, 2022). Since the

[5]https://github.com/nytimes/covid-19-data/blob/master/us-counties.csv

New York Times does not provide city-level measurements of Covid-19 cases in Canada, our data set had to be restricted to the sample of teams based in the United States. Figures 1 and 2 help visualize this data at the national and MSA level, respectively. Figure 1 graphs the number of new Covid-19 cases/deaths over the entire pandemic (up to 4/11/2021). Figure 2 graphs the weekly average number of new Covid-19 cases/deaths over the 2021-22 season time period (10/11/2021 - 4/11/2022) for a single MSA, Atlanta Georgia.

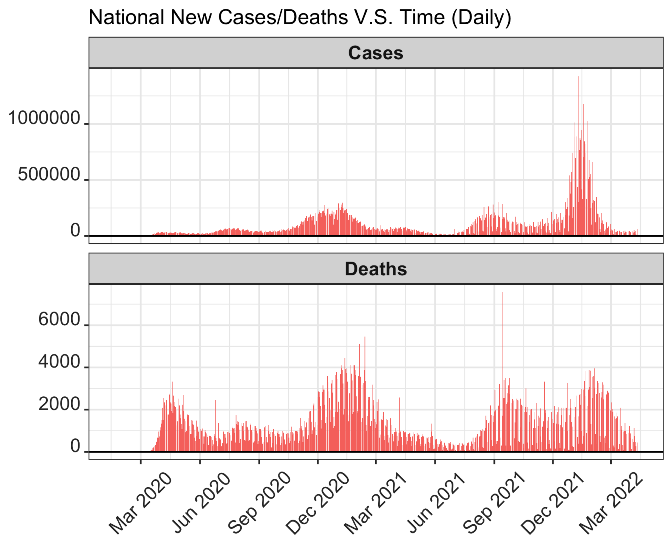

Figure 1: New Covid-19 cases and deaths over time.

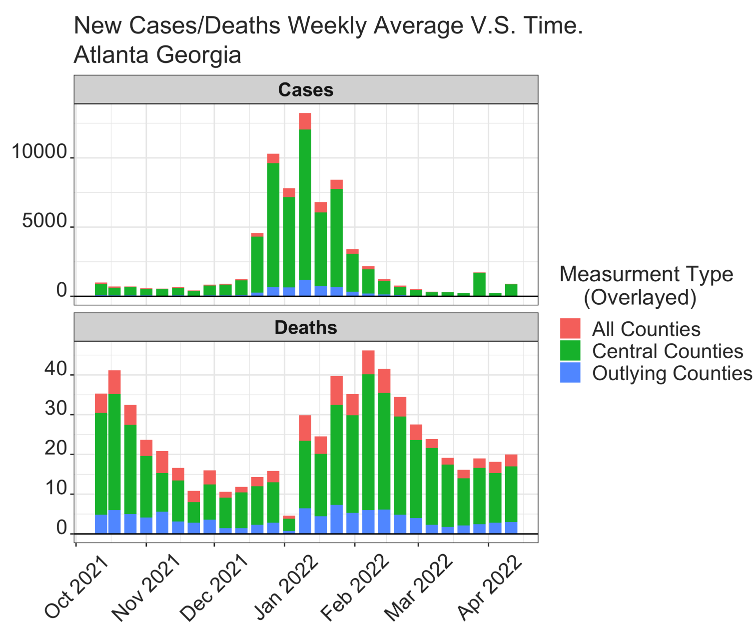

Figure 2: Weekly Average new cases and deaths in Atlanta, Georgia, over the 2021-22 sports season.

We can see in figure 1 that cases reached their peak values in the U.S. around January-February of 2022, right during the Omicron spike. We see this reflected in the individual MSA graph in figure 2. Deaths, however, did not rise to the same degree, likely because much of society had been vaccinated at this point. The reason why figure 2's observations are at the weekly level is because many U.S. counties stopped reporting daily case/death observations halfway through the pandemic. Instead, many counties reported a single figure, usually at the end of the week, that contained the weekly average cases/deaths in that county.[6] We can see this reflected in figure 1, as there is considerable jaggedness in the curve (white streaks) where daily observations are missing. Because of this, this study chose to work with the weekly average of cases/deaths as opposed to daily data. Consumers, most likely, responded to Covid-19 case/death information over longer, averaged-out periods of time anyway, so this likely will not affect results.

Although only Atlanta is displayed, the trends across all MSAs follow the basic structure shown in figure 2. The MSA level data has the advantage of dividing cases/deaths into those that are from 'central' and 'outlying' counties. The distinction between a central and outlying county is largely a factor of employment-commute statistics, and are ultimately defined by the Office of Management and Budget Standards[7]. Altering the composition of counties used to aggregate to the MSA level will be used as a robustness check later during the regression analysis.

There are 27 MSAs in the United States which host at least one NBA team, and 21 which host at least one NHL team. Altogether, this amount to 36 unique MSAs. Table 1 provides summary statistics about the Covid-19 data, averaged over time and across all MSAs.

Table 1: Covid-19 Summary Statistics Averaged Across All MSAs (10/12/2021 to 4/11/2021).

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Weekly Average New Cases	975	2465.588	5828.839	24.143	349.357	2390.786	83785.571
Weekly Average New Cases Central	975	2283.525	5651.385	19	299.929	2189.714	81337.857
Weekly Average New Cases Outlying	969	183.19	393.68	0	11.143	174.143	3195
Weekly Average New Deaths	975	15.548	19.841	0.143	4.857	19.214	257.571
Weekly Average New Deaths Central	975	13.844	19.165	0.143	3.786	17	251.571
Weekly Average New Deaths Outlying	964	1.723	2.315	0	0.214	2.429	30.286
Weekly Average New Cases Quartile 1	975	532.81	495.875	83	211.357	694.143	2644.286
Weekly Average New Cases Quartile 2	975	936.535	800.107	124.143	453	1206.643	4220.714
Weekly Average New Cases Quartile 3	975	2252.731	1924.935	533	974.143	2841.179	9762.179
Weekly Average New Deaths Quartile 1	975	7.928	5.846	0.786	4.357	10.786	26
Weekly Average New Deaths Quartile 2	975	12.507	8.302	1.071	6.857	16.857	34.714
Weekly Average New Deaths Quartile 3	975	20.956	16.092	2.714	10.429	26.393	76.571

[6] See https://github.com/nytimes/covid-19-data for the NYT's data methodology and definitions.
[7] For a full breakdown, refer to Census (2022)

Important to note is that the quartile variables are defined per MSA, and thus the variables above report the average quartile for cases/deaths across all MSAs. Note that the sample size N is reflecting the fact that there are approximately 27 weeks in the time period sampled above and 36 unique MSAs, giving around 972 observations. There are also some missing values for outlying cases/deaths, which is simply a characteristic of the underlying New York Times data. This paper does not use outlying cases/deaths in its regressions (it does implicitly when considering the full sample of counties, but it never considers just the sample of outlying counties) so this is not an issue. There were some additional missing data concerns in the data set that were imputed by the author's discretion.

Figures 3 and 4 illustrate the distribution of the weekly average of cases/deaths for all U.S. counties and a single MSA (Atlanta), respectively. The 25^{th}, 50^{th}, and 75^{th} percentiles for each distribution are overlayed on the distributions. We see that the new case count distribution is heavily skewed to the right. The deaths distribution is also right skewed, but is much more normal. The distributions in figure 4 are again representative, generally, for all MSAs, not just Atlanta.

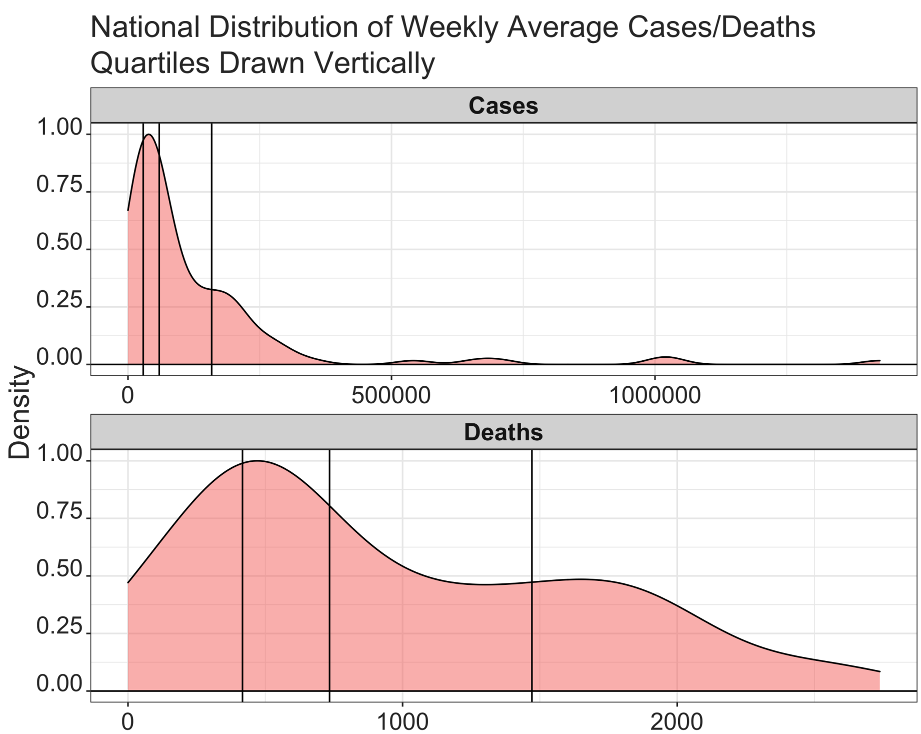

Figure 3: National Distribution of the weekly average new cases and deaths.

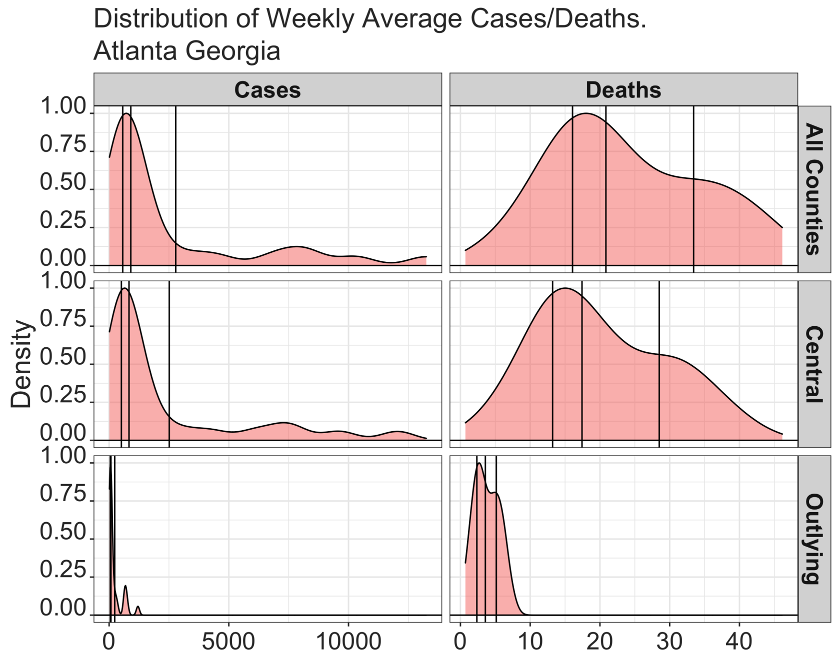

Figure 4: Distribution of weekly average new cases and deaths in Atlanta, Georgia.

The other important data sources used in this paper are basketball-reference.com and hockey-reference.com. Using the `Rvest` package in `R`, attendance data was scraped for the 2015 to 2018 and 2021-2022 NBA and NHL seasons, that is, four pre-Covid-19 seasons and one season during Covid-19. The 2019-20 and 2020-21 seasons are not included in the sample. As noted in the introduction, there were many capacity restrictions and generally many changing variables that make it difficult to compare the 2020-21 season to any others, and thus it was dropped. Because of this, the 2021-22 season is our Covid-19 season of interest. The 2019-20 season was excluded since part of the season was abruptly cut off when Covid-19 first began. Furthermore, only regular season games are analyzed.

The distribution of attendance for the averaged pre-Covid-19 and Covid-19 seasons are graphed below in figure 5. Summary statistics are provided in tables 2 and 3. We see that the pre-Covid-19 seasons were distributed very heavily around 100% capacity, with a long tail extending into the 60-50 percents. The pandemic flattened these curves considerably, increasing the number of 80-90 percent observations. Note that many observations fall above 100%. This is ‘normal.’ These attendance figures come directly from the teams themselves, and are based on tickets sold rather than turnstile clicks. The inflated figures are mostly a function of some venues selling floor/stand tickets as opposed to just seat tickets. There is also a history of sports teams being dishonest in their attendance figures for market prestige (Brown, 2011). Whatever the reason is, it is normal, recognized by sports journals, and as long as it is not correlated to this paper’s Covid-19 predictor variables, should not influence the results of this paper.

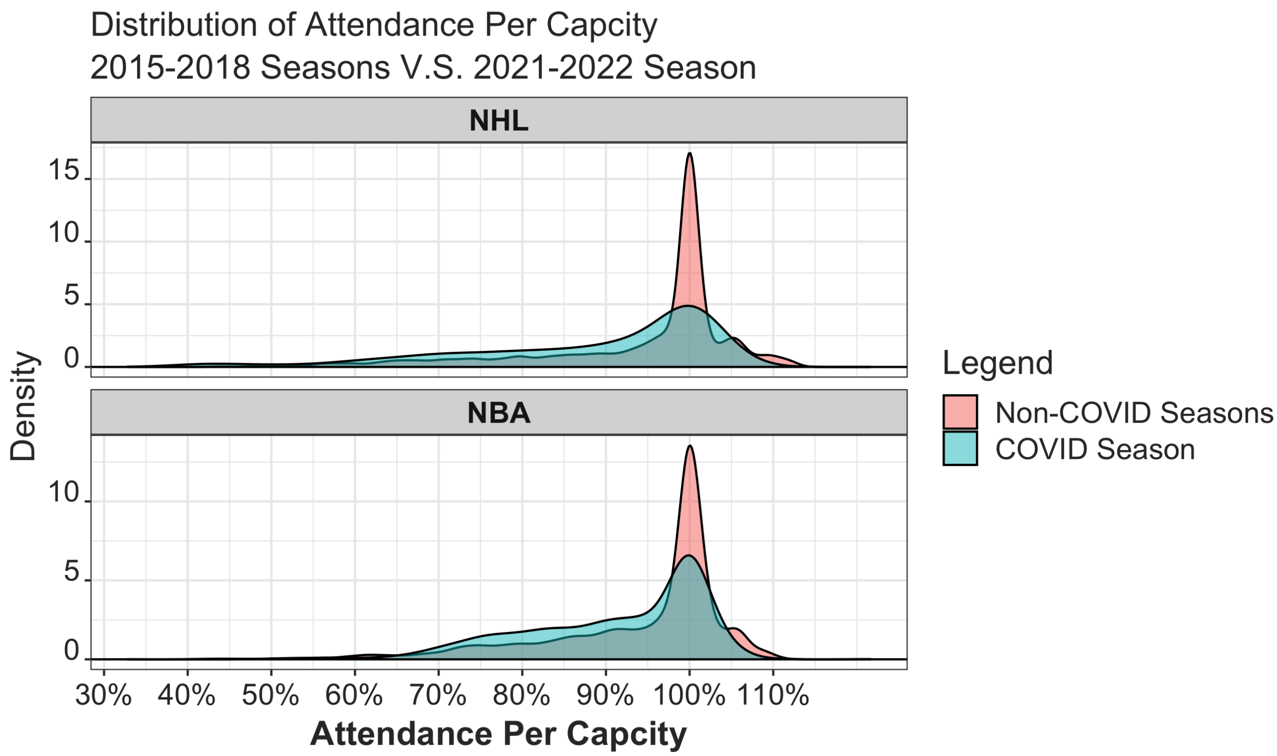

Figure 5: Attendance Distribution for the NHL and NBA.

Table 2: Non-Covid-19 Seasons (2015 - 2018) Summary

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
			League: NBA				
Attendance	4745	17828.4	2170.63	7244	16647	19473	23152
Attendance per Capacity	4745	0.94	0.11	0.33	0.9	1	1.11
Home Win Probability	4745	0.6	0.21	0.05	0.43	0.77	0.99
			League: NHL				
Attendance	3842	17204.23	2546.2	7892	16403.5	18680	22247
Attendance per Capacity	3842	0.95	0.12	0.43	0.92	1	1.13
Home Win Probability	3842	0.57	0.09	0.24	0.51	0.63	0.85

Table 3: Covid-19-season (2021) Summary

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
League: NBA							
Attendance	1206	17163.42	2306.73	8702	15573.25	19068	24760
Attendance per Capacity	1206	0.91	0.11	0.43	0.84	1	1.22
Home Win Probability	1206	0.59	0.21	0.08	0.42	0.74	0.98
Covid-19 Policy	1206						
... Mask Mandate	147	12%					
... No Policy	582	48%					
... Vaccine and Mask Mandate	366	30%					
... Vaccine Mandate	111	9%					
League: NHL							
Attendance	884	16076.62	2842.26	7026	14476	18096	20490
Attendance per Capacity	884	0.88	0.15	0.37	0.79	1	1.07
Home Win Probability	884	0.55	0.13	0.22	0.45	0.65	0.88
Covid-19 Policy	884						
... Mask Mandate	123	14%					
... No Policy	453	51%					
... Vaccine and Mask Mandate	191	22%					
... Vaccine Mandate	117	13%					

We see that the average attendance decreased from 94% to 91% from the pre-Covid-19 seasons to the Covid-19 season in the NBA, and decreased from 95% to 88% for the NHL. Again, it is important to note that the time period observed ends on April 11th, 2022. At this point, the NBA regular season had completely finished, but the NHL season was still ongoing. The 91% metric for the NBA closely matches what was reported by sports journals (Broughton, 2022). Note that figures for both leagues will not be 100% accurate as they exclude teams from Canada in the calculation. It appears, generally, that the NHL was hit harder by Covid-19 in the 2021-22 season than the NBA. This corroborates the fact that many games had to be canceled or postponed in the NHL in December and January due to Covid-19 (Relations, 2022).

Table 3 also reports statistics about the proportion of games played under certain different Covid-19 policies. There are four policy levels this paper chose to study: no policy, a mask mandate (everyone), a vaccine or negative test requirement (everyone), and both a mask mandate and vaccine or negative test requirement. **These policy categories may not perfectly reflect the true policy in place at each stadium, or its enforcement**. This policy data was meticulously collected by scouring official NBA/NHL reports and (mostly) online local news articles which detailed when policies were lifted/put in place across different stadiums. This was a long, arduous process that lacked a reliable way to check whether a source was valid. There also exists much variation in each stadium's specific policy details, such as what type of negative test was allowed (pcr vs. rapid), if a booster shot was required, etc. Policy types were boiled down to these four levels since they were the most consistently reported in the news. There could, however, be some errors.

With that out of the way, figure 6 plots how the proportion of policy types changed in the NBA and NHL during the 2021-22 season. We see that the NBA had more stringent policy overall. We also see a surge in the strictest type of policy around January in response to the Omicron variant. A majority of the policy decisions were made by the state government or local city government, so there should not be much of an issue of team's self-selecting into certain policy types that they perceived would boost their attendance (or self-selection for any other reason). Individual stadiums did have some agency in the choice, however, so it may still be a concern.

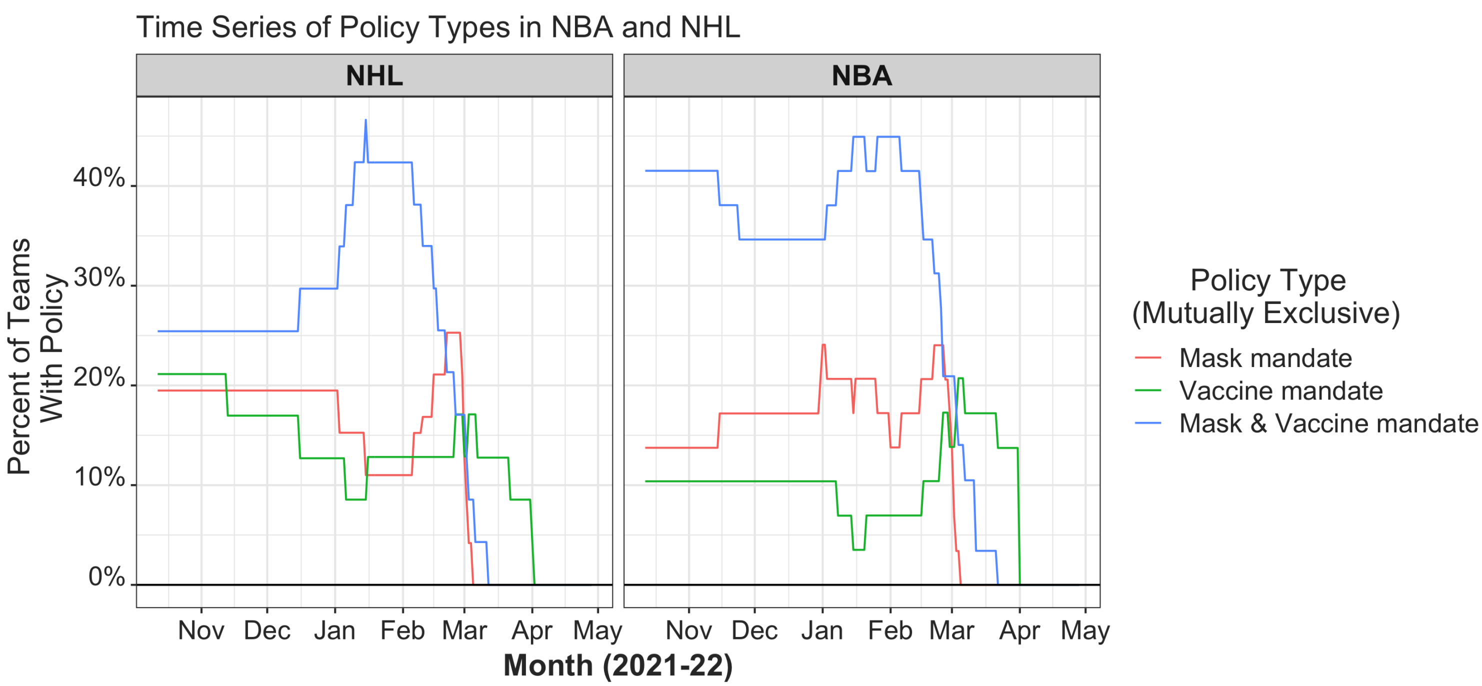

Figure 6: Proportion of policy types during the 2021-22 season.

The Covid-19 case/death data, the attendance data, and the policy data comprise the largest and most important data sets used in the paper. There are a variety of other smaller data sets used. Following Coates and Humphreys (2012) and Forrest and Simmons (2002), season-level data on team quality (a ranking) is collected from NBA.com's "Advanced Stats" page, and from NHL.com's "Team Stats" page. Following Cox (2018), betting line data is collected from sportsbookreviewsonline.com for both the NBA and NHL in order to create a variable measuring match uncertainty. At the time of the data's collection, this source did not have betting line data for the last five days of the NBA season, and thus scoresandodds.com was used instead. MSA-level data on vaccination rates and population density was collected from the CDC.[8] Finally, data on gubernatorial and legislative party control of state government was collected from ballotopedia.org.[9]. We will use this data to control for any political fixed effects. The data consists of a single variable for each state that signifies whether the state in a given year is primarily controlled by democrats, republicans, or is not controlled by either in majority.

For the sake of brevity, this paper only includes the output for the quartile specification of the model. Furthermore, all standard errors are clustered at the home team level (which follows papers like Gitter (2017), Reade and Singleton (2021), Reade and Singleton (2021)). The inclusion of clustered standard errors, in theory, helps control for temporal serial correlation in the error terms within groups. Essentially, it allows each home teams to have their own smaller error terms (clustered), which controls for noise across different home teams. This best addresses heteroskedacity.

3.2 Regression Design

The regression model of this paper sets attendance per capacity as the dependent variable and regresses it against a variety of independent variables. The model scales attendance per capacity by one hundred so that the coefficient estimates on the right hand side are all in terms of their percent change on attendance. The basic model is comprised of four levels. The first controls for the home team, away team, season, day of the week, and the month of the season. It also controls for home rank, away rank, and home odds of winning. The main independent variable is then the Covid-19 season dummy. This dummy provides us the extensive margin - how much worse attendance was during the Covid-19 season relative to the reference season, which is 2015-16. The following levels provide us with our intensive margin - the magnitude of each variables' effect on attendance during the Covid-19 season. Level two adds a measure for Covid-19 activity. This is either a dummy indicating which quartile that home team's case/death measurement was (quartile defined at the MSA level) when the game was played, or the hyperbolic sine transformed measure of weekly average cases/deaths per population. The motivation behind using the hyperbolic sine transformation is that the cases per population observations are extremely close to 0, and thus the hyperbolic sine transformation will better treat the data as a log transformation as opposed to log itself (Bellemare and Wichman, 2020). The

[8]See this link for the data set: https://tinyurl.com/CDC-Vaccine

[9]Special thanks to my friend and fellow economics student Anthony Palazzola for providing me with the cleaned data!

third level adds three variables - two dummies indicating whether the game had a mask or vaccine mandate, respectively, and the dummies' interaction. The final level includes the interaction between the month of the season and the Covid-19 season. The model uses the subscript i to denote variation at the home team level, j for variation at the away team level, t for time variation, and g for game-level variation. The full regression is shown in the equation below:

$$
\begin{aligned}
\text{Attendance}_{ijtg} = \beta_0 &+ \sum_{i=1}^{\hat{i}-1} \beta_{1,i}\text{Home Team} + \sum_{j=1}^{\hat{j}-1} \beta_{2,j}\text{Away Team} + \sum_{s=1}^{3} \beta_{3,s}\text{Season} \\
&+ \sum_{w=1}^{6} \beta_{4,w}\text{day of week} + \sum_{m=1}^{6} \beta_{5,m}\text{Month of Season} \\
&+ \beta_6\text{Home Rank}_{it} + \beta_7\text{Away Rank}_{jt} + \beta_8\text{Home Odds}_g \\
&+ \beta_9\text{Covid-19 Season} \qquad (1) \\
+ \sum_{q=1}^{3} \beta_{10,q}\text{Lag Cases/Deaths Quartile}_{itg} \quad OR \quad &+ \beta_{10}\text{arcsin(Lag Cases/Deaths)}_{itg} \qquad (2) \\
&+ \beta_{11}\text{Mask}_{itg} + \beta_{12}\text{Vaccine}_{itg} + \beta_{13}(\text{Mask} \times \text{Vaccine})_{itg} \qquad (3) \\
&+ \sum_{m=1}^{6} \beta_{14,m}(\text{Month of Season} \times \text{Covid-19 Season}) \qquad (4) \\
&+ \epsilon_{ijtg}
\end{aligned}
$$

Where, $\hat{i}$ and $\hat{j}$ are the number of home and away teams in each league. Level (1) is intended to provide insight as to Covid-19's average effect on attendance. Level (2) then tests if the case/death count itself plays a role in determining attendance output. Both the log and quartiles are used to test for non-linear effects, although, the quartile regression follows more closely the relevant literature examples, and is thus the preferred specification. Level (3) allows for inference on the effect of the policy measures. Level (4) tests for the rebound effect evident in the relevant literature.

This model above is subject to variation via the type of case/death measurement used. The standard measures that will be reported in the results section are the one week lag weekly average cases and deaths.

One final structural change is made to model level (4). It involves swapping home fixed effects for political party effects. We add the following state-level variables:

$$
\begin{aligned}
&\alpha_1 \text{Democratic}_{it} + \alpha_2 \text{Republican}_{it} \\
&+ \alpha_3 \left(\text{Democratic} \times \text{Covid-19 Season}_{it}\right) + \alpha_4 \left(\text{Republican} \times \text{Covid-19 Season}_{it}\right)
\end{aligned}
$$

Where the baseline reference category is a divided political state. This cannot simply be added to model level (4) since a state's political control varies very little over the span of five years, and thus is nearly perfectly collinear with state identifiers.

4 Results & Discussion

Tables 4 and 5 present lag weekly average cases and deaths quartile models for the NBA. Column 1 essentially states that the 2021-22 season exhibited 2.67% less attendance relative to the non-Covid-19 seasons. Column 2 examines the non-linear effects of new cases and deaths. We can see that relative to the 1$^{\text{st}}$ quartile, the other three quartiles all have negative coefficients, implying that fans reacted more intensely to new cases/deaths when the count was high. The -2.09 coefficient in column 2 of table 4, for example, reveals that attendance decreased by 2.09% when the weekly average new case count was in the 4$^{\text{th}}$ quartile relative to the first. We only, however, find significant results for these non-linear effects for new cases, and, surprisingly, only for the 2$^{\text{nd}}$ and 4$^{\text{th}}$ quartiles. In column 3, we include the three policy variables. We see the coefficients for mask and vaccine mandates are positive, but their interaction is negative. The standard error for these coefficients are large, and are thus statistically insignificant. Column 4, which includes month fixed effects, reveals that February, March, and April appear to raise attendance in a statistically significant manner, which corroborates a rebound affect. Here, the baseline month is October, when the season began. The inclusion of the month fixed effects, however, wipe out the significance of the non-linear effects observed in columns 2 and 3 for new cases. The results largely remain the same when changing from home team fixed effects to political party fixed effects, however, we see that the policy variables gain significance, suggesting mask and vaccine mandates attracted fans, although their interaction limits the overall affect.

Tables 6 and 7 present the same regressions for the NHL. Column 1 shows that NHL, on average, experienced 5.51% less attendance during the 2021-22 season, a much greater decrease than in the NBA. Column 2 again shows some evidence of non-linear affects for both weekly new cases and deaths, but they are not significant. Unlike the NBA, however, the coefficient for the policy variables show some significance in column (3). in table 6, for example, the vaccine coefficient is -14.09, suggesting games that just had a vaccine mandate experienced a hefty decrease in attendance. A mask mandate, however, had the opposite affect, as did the interaction of mask and vaccine, although statistically insignificant. Column 4 reveals no evidence of a rebound effect, as none of the month-Covid-19 interaction terms are significant. The coefficients for the other variables remain largely the same, although the mask mandate variable is not only significant at the 10% level. Switching to political fixed effects wipes out the significance of the vaccine variable, and shows some evidence of a rebound effect in March. Similar to the NBA, being a democratic or republican state does not seem to make much of a difference.

Striking is that there is not much of a difference between the weekly average new cases and weekly average new deaths. The results, in fact, suggest fans reacted more non-linearly to new cases rather than new deaths. This seems counterintuitive, since deaths appear more salient than cases. Perhaps this is the case because cases are reported more actively in the media, or simply because the number is cases is much larger in a nominal sense.

These four regressions tables below were repeated for a variety of different model specifications. They include changing the lag from one to two weeks, including only central or only outlying county observations, and using the arcsin specification instead of the quartile specification. These are not reported in the paper for succinctness, but their results largely agree with the tables below, and thus the models appear rather robust to slight modeling changes.

Table 4: NBA Lag Weekly Average Cases, SEs Clustered at Home Team Level

	Dependent variable:				
	Attendance Per Capacity				
	(1)	(2)	(3)	(4)	(5)
Covid Season	−2.67* (1.56)	−1.30 (1.66)	−1.40 (1.83)	−5.02** (2.36)	−5.51 (3.77)
Weekly Average New Cases Quart 2		−2.42*** (0.83)	−2.55** (1.00)	−1.40 (0.92)	−1.34 (0.87)
Weekly Average New Cases Quart 3		−1.06 (0.88)	−1.05 (0.94)	−0.11 (0.99)	−0.32 (1.11)
Weekly Average New Cases Quart 4		−2.09*** (0.64)	−2.10*** (0.76)	−0.20 (0.97)	0.10 (1.03)
Masks			1.74 (2.01)	2.84 (2.16)	6.09** (2.68)
Vaccines			1.80 (2.72)	2.48 (2.89)	7.41** (2.92)
Masks × Vaccines			−4.34 (3.41)	−5.00 (3.48)	−7.38** (3.61)
November × Covid Season				1.06 (1.28)	1.42 (1.54)
December × Covid Season				1.66 (1.19)	2.47* (1.34)
January × Covid Season				0.18 (1.60)	−0.23 (1.66)
February × Covid Season				2.66* (1.38)	2.88* (1.52)
March × Covid Season				4.01*** (1.42)	5.90*** (1.63)
April × Covid Season				5.80** (2.27)	8.40*** (2.21)
Democratic × Covid Season					−5.74 (3.57)
Republican × Covid Season					−3.13 (3.36)
Constant	93.00*** (1.23)	93.07*** (1.22)	93.03*** (1.20)	93.61*** (1.19)	95.96*** (3.12)
Home, away, day of week FE	Yes	Yes	Yes	Yes	No home FE
Season, month of season FE	Yes	Yes	Yes	Yes	Yes
Political Party FE	no	no	no	no	yes
Observations	5,951	5,951	5,951	5,951	5,951
Adjusted R^2	0.53	0.53	0.53	0.54	0.23
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5: NBA Lag Weekly Average Deaths, SEs Clustered at Home Team Level

	Dependent variable:				
	Attendance Per Capacity				
	(1)	(2)	(3)	(4)	(5)
Covid Season	−2.67* (1.56)	−1.89 (1.82)	−1.84 (1.99)	−5.59** (2.52)	−5.81 (3.72)
Lag Weekly Average Deaths 2		−1.16 (1.05)	−1.24 (1.11)	−0.43 (0.94)	−0.04 (0.96)
Lag Weekly Average Deaths 3		−1.08 (0.78)	−1.10 (0.84)	−0.33 (0.66)	−0.71 (0.83)
Lag Weekly Average Deaths 4		−1.05 (1.06)	−1.02 (1.11)	−0.37 (1.14)	−1.38 (1.37)
Masks			1.28 (1.88)	2.73 (2.13)	5.90** (2.72)
Vaccines			1.68 (2.87)	2.42 (2.94)	7.32** (3.02)
Masks × Vaccines			−4.10 (3.46)	−4.84 (3.52)	−7.13* (3.67)
November × Covid Season				1.36 (1.10)	1.48 (1.36)
December × Covid Season				1.99* (1.16)	2.77** (1.29)
January × Covid Season				0.88 (1.56)	1.06 (1.63)
February × Covid Season				3.24** (1.59)	4.16** (1.67)
March × Covid Season				4.60*** (1.51)	6.41*** (1.52)
April × Covid Season				6.16*** (2.22)	8.51*** (1.99)
Democratic × Covid Season					−5.83 (3.60)
Republican × Covid Season					−3.25 (3.37)
Constant	93.00*** (1.23)	93.07*** (1.22)	93.03*** (1.19)	93.62*** (1.19)	95.96*** (3.12)
Home, away, day of week FE	Yes	Yes	Yes	Yes	No home FE
Season, month of season FE	Yes	Yes	Yes	Yes	Yes
Political Party FE	no	no	no	no	yes
Observations	5,951	5,951	5,951	5,951	5,951
Adjusted R^2	0.53	0.53	0.53	0.54	0.23
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: NHL Lag Weekly Average Cases, SEs Clustered at Home Team Level

	Dependent variable:				
	Attendance Per Capacity				
	(1)	(2)	(3)	(4)	(5)
Covid Season	−5.51** (2.72)	−4.51* (2.64)	−3.68* (2.17)	−5.67** (2.82)	−8.05** (3.25)
Weekly Average New Cases Quart 2		−1.54* (0.91)	−1.51 (1.29)	−0.46 (1.15)	−0.43 (1.45)
Weekly Average New Cases Quart 3		−1.55 (1.02)	−1.74 (1.55)	−0.49 (1.37)	−1.03 (1.42)
Weekly Average New Cases Quart 4		−1.16 (0.80)	−2.07 (1.45)	0.38 (1.68)	1.01 (1.87)
Masks			7.85** (3.79)	8.19* (4.30)	9.74*** (3.63)
Vaccines			−14.09** (6.27)	−14.28** (6.24)	−5.92 (5.65)
Masks × Vaccines			7.20 (8.01)	7.26 (8.04)	3.58 (6.85)
November × Covid Season				1.95 (1.73)	3.09* (1.86)
December × Covid Season				0.29 (2.19)	0.37 (1.95)
January × Covid Season				−0.91 (2.38)	−2.04 (2.37)
February × Covid Season				−0.21 (2.27)	0.69 (2.35)
March × Covid Season				3.86 (2.89)	6.44*** (2.48)
April × Covid Season				−1.58 (2.51)	3.51 (3.00)
Democratic × Covid Season					−4.12 (3.49)
Republican × Covid Season					3.93 (4.06)
Constant	94.78*** (1.90)	94.79*** (1.87)	96.84*** (1.90)	97.05*** (1.86)	100.55*** (3.12)
Home, away, day of week FE	Yes	Yes	Yes	Yes	No home FE
Season, month of season FE	Yes	Yes	Yes	Yes	Yes
Political Party FE	no	no	no	no	yes
Observations	4,726	4,726	4,726	4,726	4,726
Adjusted R^2	0.60	0.60	0.63	0.63	0.27
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: NHL Lag Weekly Average Deaths, SEs Clustered at Home Team Level

	Dependent variable:				
	Attendance Per Capacity				
	(1)	(2)	(3)	(4)	(5)
Covid Season	−5.51** (2.72)	−5.17** (2.42)	−5.30** (2.24)	−6.92** (3.18)	−8.45** (3.30)
Lag Weekly Average Deaths 2		−0.66 (1.45)	1.12 (1.32)	1.07 (1.52)	−0.45 (1.13)
Lag Weekly Average Deaths 3		−0.66 (0.83)	0.80 (1.37)	1.14 (1.56)	0.61 (1.31)
Lag Weekly Average Deaths 4		−0.10 (1.27)	1.55 (1.88)	3.10 (2.25)	1.54 (1.74)
Masks			7.17** (3.54)	8.17* (4.25)	9.62*** (3.64)
Vaccines			−14.83** (6.46)	−14.76** (6.37)	−6.16 (5.77)
Masks × Vaccines			7.49 (8.04)	7.40 (8.03)	3.76 (6.89)
November × Covid Season				2.28 (1.72)	3.01 (1.83)
December × Covid Season				0.36 (1.89)	0.15 (1.64)
January × Covid Season				−1.19 (1.71)	−1.52 (1.93)
February × Covid Season				−1.27 (1.90)	−0.13 (2.18)
March × Covid Season				4.30 (2.90)	6.61*** (2.33)
April × Covid Season				−0.64 (3.09)	3.58 (3.48)
Democratic × Covid Season					−4.11 (3.48)
Republican × Covid Season					4.00 (4.05)
Constant	94.78*** (1.90)	94.83*** (1.91)	96.95*** (1.95)	97.09*** (1.87)	100.57*** (3.14)
Home, away, day of week FE	Yes	Yes	Yes	Yes	No home FE
Season, month of season FE	Yes	Yes	Yes	Yes	Yes
Political Party FE	no	no	no	no	yes
Observations	4,726	4,726	4,726	4,726	4,726
Adjusted R^2	0.60	0.60	0.63	0.63	0.27
Note:					*p<0.1; **p<0.05; ***p<0.01

5 Conclusion

Altogether, these results fail to find that Covid-19 activity (weekly average cases or deaths) significantly impacted attendance demand in both the NBA and NHL. Lag weekly average case/death counts are initially significant in early levels of the regression, but almost always lose significance once we control for month interactions with the Covid-19 season dummy variable. Mask and vaccine mandates were significantly related to increased attendance in the NBA, but their interaction was negative. In the NHL, mask mandates increased attendance, but vaccine mandates severely decreased attendance. The NBA shows evidence of rebound effects starting in February, while the NHL does not. The most significant effects are those of the vaccine mandate (and mask mandate, at the 10% level) in the NHL, and the rebound effects of the NBA. Political interaction with the Covid-19 season dummy variable also did not yield significant results. In both leagues, however, the coefficient estimate for teams in Democratic states was more negative than that of teams in Republican states. This was most pronounced in the NHL, where the Democratic coefficient was -4.12 (SE 3.49) and the Republican coefficient was 3.93(SE 4.06), which are more likely to be statistically different from each other than from 0.

The finding that Covid-19 cases/deaths numbers did not seem to have an impact on attendance demand is not necessarily unexpected. As mentioned in the literature review, some leagues were not affected, and others were. The most striking result of this paper, then, is the impact vaccine mandates seemed to have on NHL attendance. This is most likely a result of the difference in demographics between NHL and NBA fans. NHL fans, on average, are more politically conservative than NBA fans. The Morning Consult estimates that 33% of NHL fans identify as Republican, as opposed to 26% in the NBA (Dem, 2020). Academic literature also suggests there is a link between lower vaccination rates and identifying politically as Republican. (Kirzinger, 2021). Thus, it makes sense that policies which restrict entry to only fans who are vaccinated leads to a larger decrease in attendance in leagues where more fans are conservative, such as the NHL.

The results of this paper have various implications for both sports franchises and city/state legislative bodies. Governing bodies should be aware that fans did not seem to treat Covid-19 as a serious risk when deciding to attend sports matches during the 2021-22 season. They should also be aware of potential rebound effects, as evidenced by this paper's analysis of the NBA. These two factors could potentially lead to large attendance figures even during periods where Covid-19 is most active, which could consequently further help spread the virus. This helps justify the decision to implement state-wide Covid-19 policies for large gather events, as precautions will be necessary to deal with continuous, unresponsive attendance demand. Franchise owners should be aware of fans' unresponsive behavior too, since it means potentially more demand than one may expect. Furthermore, franchises should be aware of the finding that mask mandates were generally well received by fans. Although this study only finds significant results linking vaccine mandates in the NHL to a decrease in attendance, the coefficients for mask mandates in both leagues were positive, and significant at the 10% level in the NHL. Mask mandates, therefore, may be the best Covid-19 policy to employ, since it both makes the games safer, and potentially even draws in fans. While this study doesn't analyze the effectiveness of each policy in regard to their ability to diminish the spread of Covid-19, it perhaps makes sense to maintain mask policies for longer periods of time until case counts necessitate a vaccine mandate. Future research should seek to analyze the effectiveness of each policy type at diminishing disease spread so as to help aid in determining the optimal Covid-19 policy for both franchises and governing bodies.

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