Running on Empty:
Examining the Effects of COVID-19 on the Behavior of MLB Umpires

From the benches, black with people, there went up a muffled roar,
Like the beating of the storm-waves on a stern and distant shore;
"Kill him! Kill the umpire!" shouted someone on the stand;
And it's likely they'd have killed him had not Casey raised his hand.

- Ernest Lawrence Thayer, *Casey at the Bat* (1888)
ABSTRACT

This paper provides an in-depth analysis of the behavior of MLB umpires, particularly their tendency to favor the home team with incorrect calls, and the effects of the COVID-19 pandemic on this phenomenon, as we saw empty stadiums in baseball for the first time. I begin by verifying that this umpire home-team bias exists. I then explore the effects of the pandemic, finding that umpire favor decreased as a result of COVID. Next, I analyze the relationship between umpire favor and stadium attendance, using attendance brackets to isolate the observed effect and more precisely determine the reasons for this umpire bias. I conclude with potential directions for future research.

Acknowledgments

I would like to thank my wonderful advisor, Professor Scott Ogawa, for his invaluable guidance throughout this process. I am also eternally grateful to the faculty of MMSS, Economics, and beyond for providing me with the tools to complete this project. Finally, an immense thank you to my family, friends, and my wonderful girlfriend for their support throughout the thesis-writing process and my broader undergraduate experience. I could not have made it through this without you.
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1. Introduction

Since its humble beginnings over a century ago, the game of baseball has always relied on umpires, who face countless difficult decisions that can change the course of a game. Inevitably, they will get many of these calls wrong. While history has seen countless arguments over questionable calls—whether from players, managers, or fans—umpires have never been as heavily scrutinized as they are in today’s game. The advent of new technologies and statistics makes their minute flaws more evident than ever before. With these technologies come new opportunities for analysis: now that the result of every pitch is recorded, we can explore umpires’ tendencies, such as whether they favor certain teams and whether this behavior is affected by external factors.

In addition to these opportunities presented by the introduction of pitch-tracking technology, there has recently been another major (albeit unplanned) change in Major League Baseball: the COVID-19 pandemic. As was the case with many sports leagues around the world, the 2020 MLB season was majorly affected by the pandemic: the regular season was shortened to 60 games, and more importantly, these games were played without a single fan in the stands. With the exception of one game in 2015, which was played behind closed doors due to civil unrest, not a single game in MLB history before 2020 had been played in an empty stadium (Fullmer and Daniel, 2021). While certainly not a welcome change for baseball fans, the abnormality of the 2020 season provided us with an unprecedented new set of data, so that for the first time in history, it has become possible to study the effects of an empty stadium on a Major League Baseball game.

In particular, in this paper, I have chosen to focus on what I will call “umpire home-team favor,” in order to distinguish it from home-field advantage in the traditional sense. Specifically,
the term “home-field advantage” refers to how a team, all else equal, is more likely to win a game when playing at home than when playing away. This is a well-documented phenomenon across all sports, and baseball is no exception: Swartz (2009) estimates that the home team in an MLB game between two evenly matched teams has roughly a 54% chance of victory. In contrast to this, I will take “umpire home-team favor” to mean the effect that a home-plate umpire’s missed calls have on the home team’s performance. Specifically, using data from 2015 to 2022, I look at whether or not these incorrect calls tend to favor the home team, thus contributing to the home team’s already-prominent advantage. I find that a statistically significant umpire home-team favor does exist during these eight seasons.

I then use these results to examine the effects of stadium attendance on umpire home-team favor. It seems logical that a stadium full of fans, whether cheering or jeering, might be able to influence an umpire into making a call in favor of the home team, especially in a high-leverage situation. As a result of the empty stadiums in 2020 and the limited-capacity stadiums at the start of 2021 (due to ongoing COVID-related safety restrictions), the dataset is richer and more diverse than ever before, making it ideal for the purposes of this paper.

I find a significant positive relationship between stadium attendance and umpire home-team favor, as well as a significant attendance effect on more general measures of home-field advantage. I also find that umpire favor dropped substantially during the pandemic, but that home-field advantage stayed roughly constant. Perhaps more importantly, I find a “big-crowd effect”: looking more closely at stadium attendance reveals that the most important driver behind umpire bias is whether a stadium is (close to) full. In other words, in relatively empty stadiums, changes in attendance have little effect on an umpire’s decisions, whereas the difference between a somewhat full stadium and a completely full one is substantial.
2. Literature

2.1 Home-Field Advantage

Unsurprisingly, there exists a rich body of work on home-field advantage in baseball. Swartz (2009) finds that a baseball team playing at home against a team of similar quality has about a 54% chance of winning. Attempting to find the source of the observed advantage, Smith and Groetzinger (2010) estimated the effects of attendance on overall home-field advantage using data from 1996-2005, concluding that high attendance had a strong positive effect: a one-standard-deviation increase in attendance resulted in a 4% increase in the likelihood of a home victory. Since the onset of the COVID-19 pandemic, some work has also been done regarding home-field advantage. Surprisingly, Fullmer and Daniel (2021) found no significant decrease in home-field advantage in 2020 relative to 2017-2019. In addition, for these four years of data, they found no evidence of an effect of stadium attendance on home-team win probability, a result that directly contradicts that of Smith and Groetzinger (2010). I am unsure as to the explanation for this discrepancy—it may simply be due to chance—but perhaps it suggests a fundamental change in fans’ contributions to their team’s performance. I have no explanation, however, for why this would be. This discrepancy between the two studies is nevertheless noteworthy, so I keep it in mind when doing my own analysis. Were the umpire data used in my study available for the years 1996-2005, it would have been interesting to see if my results were to change significantly.

2.2 Umpire Behavior

Relative to studies on general home-field advantage, most studies examining MLB umpire behavior are fairly new, owing to the greatly increased availability of umpire-specific
data in recent years. Many of these studies have shown that umpires are susceptible to behavioral changes in certain situations. For example, Kim and King (2014) find evidence of a significant effect of player status on home-plate umpire decisions: that is, a high-status pitcher is more likely to have a (borderline) true ball erroneously called a strike, while a high-status hitter is more likely to take a true strike and have it called a ball. Another study by Hamrick and Rasp (2015) finds limited evidence of racial discrimination by umpires against players when it comes to called balls and strikes. A third study by Brian M. Mills (2017) finds marked improvements in home-plate-umpire performance in response to increased levels of monitoring technology and improved training and feedback. In other words, in response to higher levels of scrutiny, umpires seem to have improved their overall accuracy behind the plate. All of these results suggest that MLB umpires (unconsciously) exhibit certain biases and respond to important changes. This gives validity to the theory that an umpire could, for instance, be swayed by a loud crowd into making a call in favor of the home team.

One relevant study specifically considering umpire home-team favor is a short paper by Jonathan Judge (2020). In this paper, Judge directly compares the 2019 and 2020 seasons, finding that the called strike zones in the two years were quite similar and that the (positive and significant) umpire home-team advantage, despite a small decrease, remained largely intact in 2020. Another study in the book Scorecasting by Tobias Moskowitz and L. Jon Wertheim (2011) examined in detail the nature of baseball’s home-field advantage, using detailed pitch-by-pitch analysis to find that the home-team bias of the home-plate umpire is not only significant, but accounts for over two-thirds of the home-field advantage in MLB. In this paper, I explore whether this conclusion still holds in today’s game or whether the way umpires behave has changed significantly in the last decade. I also more closely explore the relationship between
umpire bias and attendance: I split stadium attendance into brackets in order to isolate the attendance effect, finding that much of the positive effect comes from the fullest stadiums. It seems that when a stadium is nearly full, an umpire is far more susceptible to change his behavior in favor of the home fans.

3. Data

3.1 Umpire Favor Data

For this project, my primary data source was Umpire Scorecards (umpscorecards.com). The people behind this website create detailed reports of umpire performance in every single MLB game using Pitch f/x data, analyzing umpires’ accuracy, consistency, and bias. For my analysis, I focus on a specific metric: “favor.”

Broadly speaking, favor measures how heavily the home-plate umpire aided the home team with his incorrect calls – a positive value indicates that the home team benefited from the umpire’s imprecision, while a negative value means the away team benefited more. This favor value is measured in units of expected runs. The term “expected runs” refers to how many runs a team can expect to score between the present situation (considering the number of runners on base, the count, and the number of outs) and the end of an inning. For example, according to umpscorecards.com, a team can expect to score roughly 0.5 runs in an inning when it begins (no runners, 0-0 count, 0 outs); however, a team with the bases loaded, 0 outs, and a 3-0 count can expect to score 2.75 runs before the inning ends.

The calculation of favor, then, is simple: every time the home-plate umpire gets a call wrong (a true ball is called a strike or vice versa), the favor is the difference in expected runs between the incorrect and correct calls. Once again, the website provides a clear example:
imagine the home team is hitting and has the bases loaded, 2 outs, and a 3-2 count. The pitcher throws a true strike. If the umpire gets the call correct, the inning ends (0 expected runs).

However, if the umpire misses the call, a run scores, the count is reset, and the inning continues. From that point on, the home team would still be expected to score another 0.74 runs in the inning. Thus, the overall favor would be 1.74 expected runs for the home team. Note that if the same events had occurred with the away team batting, the number would be recorded as \(-1.74\).

An umpire’s overall favor for a game, then—the number ultimately recorded in the data—is the sum of the individual favors from each of his missed calls.

Very importantly, this measure takes leverage into account: it gives greater weight to missed calls in high-pressure situations, rather than simply measuring the quantity of missed calls. In the presence of an umpire home-field advantage, we would see positive average favor and might, as hypothesized, see an increase in favor as a function of stadium attendance.

3.2 Foul Territory Data

Next, I collected data on the size of foul territory behind home plate in each of the 30 MLB stadiums. One would expect that the closer fans are to an umpire, the louder they would sound to him, thus increasing their influence over his decisions. To do this, for 24 of the 30 stadiums, I used Google Earth to measure the distance (in feet) from home plate to the wall in front of the nearest fans. The distances ranged from 42 to 60 feet; pictures of the most extreme distances are shown in figure 2. The remaining six stadiums (Toronto, Arizona, Tampa Bay, Miami, Texas, and Houston), however, had satellite imagery with closed roofs, making such measurements impossible. To get around this issue, I used Wikipedia’s values for home-plate-to-backstop distance for these final six stadiums. I found that these values were consistent enough
with my aforementioned measurements to suggest that they were still appropriate to include in my dataset.

The histogram in figure 1 shows the distribution of home-plate-to-backstop distance for the 30 Major League stadiums. Across the range of 42 to 60 feet (pictures of the extreme values are shown in Figure 2), we see a slightly right-skewed distribution, with 18 of the 30 distances being below the average distance of 50.17 feet. There are several data points at the extremes, however, so if this variable impacts umpires significantly, we would expect to see a clear negative relationship between the size of foul territory behind home plate and an umpire’s bias towards the home team.

**Figure 1: Histogram of Home-Plate-to-Backstop Distances for 30 MLB Stadiums**

**Figure 2: Longest and shortest foul distances**

2.1 Angel Stadium, Anaheim, CA (60 ft)

2.2 Wrigley Field, Chicago, IL (42 ft)
Note: For the purposes of simpler analysis, I standardized the foul territory variable by subtracting the mean home-to-backstop distance from each value, thus making the new mean value equal to zero.

3.3 Attendance and Other Data

In addition to favor data for nearly every game from the 2015-2022 seasons (with 2022 data going up to July 26) and foul territory data, I also collected data on general home-field advantage: using the same data from Umpire Scorecards, I measured home-team run differential and home-team wins, in order to compare changes in umpire behavior with changes in general home-field advantage. In addition, I got attendance data for each game from Baseball Reference (baseball-reference.com). These eight seasons provide a diverse range of attendances: all 2020 games were played in empty stadiums and attendance in many stadiums was limited for parts of the 2021 season. Thus, these data should provide a great look at the relationship between attendance, umpire home-team favor, and general home-field advantage, as well as insight into the broad effects of COVID on umpires and baseball more broadly (thanks to many thousands of data points both pre- and post-pandemic).

Though it happened rarely, there were a few games for which data were missing: some games lacked values for favor or attendance. I decided to simply omit these games from the dataset, as there is no reason to believe they would have influenced the results in any particular way. I also omitted playoff games from the dataset due to the unusual nature of the 2020 playoffs (which were played at neutral locations, sometimes with limited attendances).
4. Methodology

I begin with the simplest possible model:

$$Favor_i = \beta_0 + \beta_1 Attendance_i$$

where Attendance is the game’s paid attendance divided by 10,000 and Favor is the number of expected runs a home-plate umpire gives to the home team in a given game. This regression is the simplest way to ask the question, “does the number of fans in the stands affect the umpire’s decisions?” If it did, we would expect a positive value for $\beta_1$, as favor would increase with attendance.

I then consider the model with the foul-territory variable added:

$$Favor_i = \beta_0 + \beta_1 Attendance_i + \beta_2 Foul_i$$

where Foul, for a given stadium, is the distance in feet from home plate to the nearest fans in the stands subtracted by the average distance of 50.17 feet. For example, a stadium with 60 feet of foul territory would have a value of 9.83 for Foul, while 50 feet would return a value of -0.17. Not only does this model enhance the previous one by adding a new an interesting variable, but it also allows us to control for foul-territory size, meaning the coefficient $\beta_1$ represents the increase (or decrease) in favor in response an increase of 10,000 fans holding foul territory constant, i.e., in the same stadium. In other words, this coefficient more directly captures the effects of additional fans. One would expect $\beta_2$ in this model to be negative, as smaller foul territory would result in a greater fan-driven influence on the home-plate umpire, and vice versa.

Finally, I consider the full model:

$$Favor_i = \beta_0 + \beta_1 Attendance_i + \beta_2 Foul_i + \beta_3 (Attendance_i \times Foul_i)$$

where the $\beta_3$ term is an interaction between the Attendance and Foul variables. I include this interaction term because of a potential relationship between the two variables. For example, the
effects of foul territory size depend greatly on attendance: in an empty stadium, foul territory is irrelevant, as no fans are there to heckle the umpire from any distance. The interaction term in this model aims to capture this relationship.

I then repeat this analysis using two different dependent variables: *Rundiff* (calculated as Home Team Runs – Away Team Runs in a given game, a measure of home-field advantage) and *Win* (an indicator variable equal to 1 if the home team won a game and 0 otherwise, a more traditional measure of home-field advantage). The purpose of these models is to examine the effects of the same variables on home-field advantage overall and compare the results with the umpire favor analysis. The models provide insight into how much of the overall home-field advantage is due to the home-plate umpire.

Next, I investigate the hypothesis that favor is not a linear function of attendance, but rather depends solely on the presence of any fans. In other words, I test the hypothesis that there is something special about the number zero. One could imagine that umpires, simply knowing that there are fans around to critique them (regardless of how many), change their behavior to favor the home team. In the complete absence of fans, however (i.e., the 2020 season), we might see a substantial drop in home-team favor, since the umpires don’t feel they’re being watched as closely. To test this theory, I use the following model:

\[ Favor_i = \beta_0 + \beta_1 Fans_i \]

where *Fans* is an indicator variable equal to 1 if a game was played fans in the stands (i.e., all games outside of 2020) and 0 if the game was played in an empty stadium. A positive and statistically significant value for \( \beta_1 \) would suggest that the simple presence of fans is the primary driver behind the changes in the behaviors of home-plate umpires.
Finally, I break attendance down into several “brackets” in order to more accurately capture the effects of varying numbers of fans. For this, I use the following model:

\[ \text{Favor}_i = \beta_0 + \beta_1 U10K_i + \beta_2 U20K_i + \beta_3 U30K_i + \beta_4 U40K_i + \beta_5 40K_i \]

where \( U10K \) is an indicator variable equal to 1 if the number of fans is between 1 and 10,000 (inclusive) and 0 otherwise, \( U20K \) indicates if the number of fans is between 10,001 and 20,000, and so on. The variable \( 40K \) is equal to 1 only if attendance for a given game was at least 40,000.

In an empty stadium, all variables in the model are equal to 0, providing a reference point for analysis of the various coefficients. I then repeat this model using brackets of size 20,000 to check for any change in the results. The results of these various regressions are discussed in section 5.2.

5. Results and Analysis

5.1 Testing for Umpire Home-Field Advantage

Before moving on to further analysis, it is important to check whether an umpire home-team bias exists at all. Judge (2020) found strong evidence of an umpire home-team favor in both 2019 and 2020. My results differ slightly: for the 2020, 2021, and 2022 seasons, using simple t-tests, I find that mean umpire home-team favor was positive, but not statistically significant. In other words, at the 5% level, I find no evidence of an umpire home-team advantage for any of the three post-pandemic seasons. However, I find a positive and significant value for each year from 2015-2019, as well as for all of the combined data (see Appendix, Table A1). Thus, at the 5% level, I do find evidence that umpire home-team favor is nonzero and positive, with a mean of 0.0356 expected runs per game. In other words, a team playing at home can expect, on average, to receive about 0.0356 expected runs per game as a result of the home-plate umpire’s
missed calls. The pattern here is unsurprising: if an attendance effect did exist, it makes sense that we should see a substantial decrease in favor for the two years when attendance was down.

Figure 3 visually demonstrates these results. There is a clear drop in favor during the 2020 and 2021 seasons, suggesting that the empty and low-attendance stadiums did affect how umpires called games. The 2022 season, which is still in progress at the time of writing, is showing signs of returning to the pre-pandemic levels of home-team favor, but still has an average value below any individual year from 2015 to 2019. Based on the results of Moskowitz and Wertheim (2011), who posit that umpire favor is by far the greatest driver of home-field advantage, we would expect home-field advantage to have sharply declined in 2020. However, Fullmer and Daniel (2021) found no such decline, noting that home-field advantage stayed completely intact. I also found this to be the case, and it also holds true in terms of run difference: home teams did not score fewer runs relative to their opponents in 2020, either. This begs the question: why didn’t the home-field advantage disappear? I discuss possible alternative explanations in section 6.

Figure 3: Bar Chart of Average Home-Team Favor by Year
5.2 Regression results

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Umpire Home-Team Favor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Stadium Attendance (10,000s of fans)</td>
<td>0.018***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Size of Foul Territory (ft above average)</td>
<td>0.002**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Attendance x Foul Territory</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.012</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
</tr>
<tr>
<td>Observations</td>
<td>16,515</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.001</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.001</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.642 (df = 16513)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>21.058*** (df = 1; 16513)</td>
</tr>
</tbody>
</table>

*Note:* $p<0.1; **p<0.05; ***p<0.01$

Table 1: Regression Results with Favor as Dependent Variable

Table 1 demonstrates the results from the three primary models discussed in section 4. In all three models, the attendance coefficient $\beta_1$ is highly significant: in response to an increase of 10,000 fans in the stands for a given game, we expect the umpire to gift 0.018 more expected runs to the home team. While this sounds like a small amount, even a slight increase in the probability of a missed call in a high-leverage situation has the potential to completely change the outcome of a game. Counterintuitively, the coefficient for foul territory, $\beta_2$, is positive: it seems that holding all else equal, umpires give a slightly higher advantage to teams with larger areas behind home plate. However, the values for $\beta_2$ are small and, in the full model with the interaction term, not statistically significant.
Table 2: Regression Results with Run Difference as Dependent Variable

In Table 2, we see the results of the regressions with home-team run difference as the dependent variable. Many of the results are similar to those in Table 1. $\beta_1$ tells us that for an increase of 10,000 fans, on average, we would expect the home team to score roughly 0.14 more runs relative to the away team. The significance of this is more apparent: for a stadium of 40,000 fans, there is a difference of nearly 0.6 runs for a full stadium compared to an empty one. This clearly demonstrates that home-field advantage in baseball is strongly tied to attendance (keeping in mind, of course, that a substantial part of this attendance effect exists as a result of umpire favor). Once again, we see positive coefficients for foul territory, but neither is statistically significant. The interaction coefficient $\beta_3$ is quite small in magnitude and also not significant.
Table 3: Regression Results with Win Dummy as Dependent Variable

In table 3, we once again see results that mirror those of tables 1 and 2. The values for $\beta_1$ indicate a clear positive relationship between attendance and home-field advantage (a 1.5% increase in win probability for each additional 10,000 fans). The foul territory and interaction coefficients are small and insignificant.
<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Umpire Home-Team Favor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fans in the stands (=1)</td>
<td>0.024 (0.022)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.013 (0.022)</td>
</tr>
<tr>
<td>Observations</td>
<td>16,515</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.0001</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.00001</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.642 (df = 16513)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>1.157 (df = 1; 16513)</td>
</tr>
</tbody>
</table>

*Note:* *p*<0.1; **p**<0.05; ***p***<0.01

Table 4: Testing the Importance of Having Zero Fans

Table 4 shows the results of the penultimate regression discussed in section 4. The aim of this model was to test whether rather than a linear relationship between attendance and umpire favor, umpires simply behaved very differently when stadiums were empty and similarly when any number of fans was present. However, I find no evidence that simply having fans in the stands increases umpire home-team favor. While the previous models make it clear that fans affect favor positively, it does not appear to be the case that the jump from no fans to some fans is the main driver of this effect.
Owing to the surprising results of the previous table, I ran this model in an attempt to isolate the attendance effect on favor. I found that the effect steadily rose as attendance increased, and that it was most significant for attendances higher than 40,000. Thus, I conclude that it is not the difference between an empty stadium and a moderately full one that sways home-plate umpires the most, but rather the difference between a moderately full stadium and a

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Umpire Home-Team Favor</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 &lt; # Fans ≤ 10,000 (=1)</td>
<td>-0.009 (0.030)</td>
</tr>
<tr>
<td>10,000 &lt; # Fans ≤ 20,000 (=1)</td>
<td>-0.008 (0.024)</td>
</tr>
<tr>
<td>20,000 &lt; # Fans ≤ 30,000 (=1)</td>
<td>0.018 (0.024)</td>
</tr>
<tr>
<td>30,000 &lt; # Fans ≤ 40,000 (=1)</td>
<td>0.045* (0.024)</td>
</tr>
<tr>
<td># Fans &gt; 40,000 (=1)</td>
<td>0.051** (0.025)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.013 (0.022)</td>
</tr>
</tbody>
</table>

| Observations | 16,515 |
| R² | 0.001 |
| Adjusted R² | 0.001 |
| Residual Std. Error | 0.642 (df = 16509) |
| F Statistic | 4.347*** (df = 5; 16509) |

*Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Testing Attendance Intervals
completely full one. It seems that when a stadium is completely packed, with noise coming from all directions, a home-plate umpire is substantially more likely to favor the home team. Figure 4 visually illustrates the results of this regression.
Finally, I ran one more model testing wider attendance intervals, the results of which are shown in table 6. My findings here are similar: for lower attendance intervals, I see no significant attendance effect, but for completely full stadiums, there is a clear positive effect. A stadium packed with fans does indeed seem to be the most influential environment for a home-plate umpire.
6. Discussion and Conclusion

Throughout this paper, I have investigated in detail the effects of varying levels of attendance on MLB umpire behavior. I first demonstrated that home-plate umpires tend to favor the home team with their incorrect calls, a phenomenon that contributes significantly to baseball’s well-documented home-field advantage. This home-team bias, however, dropped sharply in the 2020 and 2021 seasons, when the league was most heavily affected by the COVID-19 pandemic, suggesting that this home-team favor might be positively correlated with stadium attendance. I then confirmed this hypothesis using several regression models, showing that increased attendance is associated with higher levels of umpire home-team bias. I found similar results when examining general home-field advantage, finding a similarly strong attendance effect. Next, I found that the emptiness of a stadium is not a significant driver behind this effect, but rather that favor increases more gradually with attendance. Finally, delving further into the details of stadium attendance, I found that instead of empty stadiums, it is full stadiums that matter: in a stadium packed with over 40,000 people, an umpire is substantially more likely to give favorable calls to the home team than in a less full stadium.

The most obvious remaining question, then, is this: why didn’t home-field advantage go away in 2020? In Scorecasting, Moskowitz and Wertheim (2011) found that home-plate umpire bias was by far the most important driver of home-field advantage. If this were still the case, we would surely have seen a drop in home-team win rate and run differential in 2020 and 2021, but we did not. It is then likely that the nature of home-field advantage has fundamentally changed in the last decade; the mechanics of this, however, are unclear. Mills (2017) found that umpires improved markedly in response to increased levels of monitoring, which I suspect is an important factor: over the last decade, umpires’ overall accuracy has increased, so even if the
majority of their missed calls favor the home team, the magnitude of this favor has most likely gone down. However, the Umpire Scorecards favor data only goes back as far as 2015, so I was not able to investigate this issue here. But even if umpires’ contribution to the home-field advantage has decreased, there is still no obvious explanation for why the advantage itself remains completely intact, perpetually hovering around 54%. Especially during the pandemic, when favor was clearly down, it is remarkable that nothing seemed to change. A future paper might investigate more closely the other conventional explanations for the home-field advantage and examine how they changed in 2020. I believe the inner workings of the home-field advantage, especially during the pandemic, have yet to be completely deciphered.
Works Cited


### Appendix

**Table A1: t-tests for Favor in various years**

<table>
<thead>
<tr>
<th>Year(s)</th>
<th>Mean Favor</th>
<th>t</th>
<th>P-value</th>
<th>95% CI Lower Bound</th>
<th>95% CI Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>0.0485</td>
<td>3.4157***</td>
<td>0.0006</td>
<td>0.0206</td>
<td>0.0763</td>
</tr>
<tr>
<td>2016</td>
<td>0.0303</td>
<td>2.1017**</td>
<td>0.0357</td>
<td>0.002</td>
<td>0.0586</td>
</tr>
<tr>
<td>2017</td>
<td>0.0524</td>
<td>3.8155***</td>
<td>0.0001</td>
<td>0.0255</td>
<td>0.0794</td>
</tr>
<tr>
<td>2018</td>
<td>0.0539</td>
<td>4.3258***</td>
<td>0+</td>
<td>0.0295</td>
<td>0.0784</td>
</tr>
<tr>
<td>2019</td>
<td>0.0334</td>
<td>2.5168**</td>
<td>0.0119</td>
<td>0.0074</td>
<td>0.0593</td>
</tr>
<tr>
<td>2020</td>
<td>0.0131</td>
<td>0.6191</td>
<td>0.536</td>
<td>-0.0285</td>
<td>0.0547</td>
</tr>
<tr>
<td>2021</td>
<td>0.0083</td>
<td>0.7104</td>
<td>0.4775</td>
<td>-0.0146</td>
<td>0.0312</td>
</tr>
<tr>
<td>2022</td>
<td>0.0281</td>
<td>1.82*</td>
<td>0.069</td>
<td>-0.0022</td>
<td>0.0584</td>
</tr>
<tr>
<td>Pre-COVID (2015-19)</td>
<td>0.0438</td>
<td>7.1751***</td>
<td>0+</td>
<td>0.0318</td>
<td>0.0558</td>
</tr>
<tr>
<td>Post-COVID (2020-22)</td>
<td>0.0153</td>
<td>1.7845*</td>
<td>0.0744</td>
<td>-0.0015</td>
<td>0.032</td>
</tr>
<tr>
<td>All (2015-22)</td>
<td>0.0356</td>
<td>7.1296***</td>
<td>0+</td>
<td>0.0258</td>
<td>0.0454</td>
</tr>
</tbody>
</table>

*** P < 0.01; ** P < 0.05; * P < 0.1