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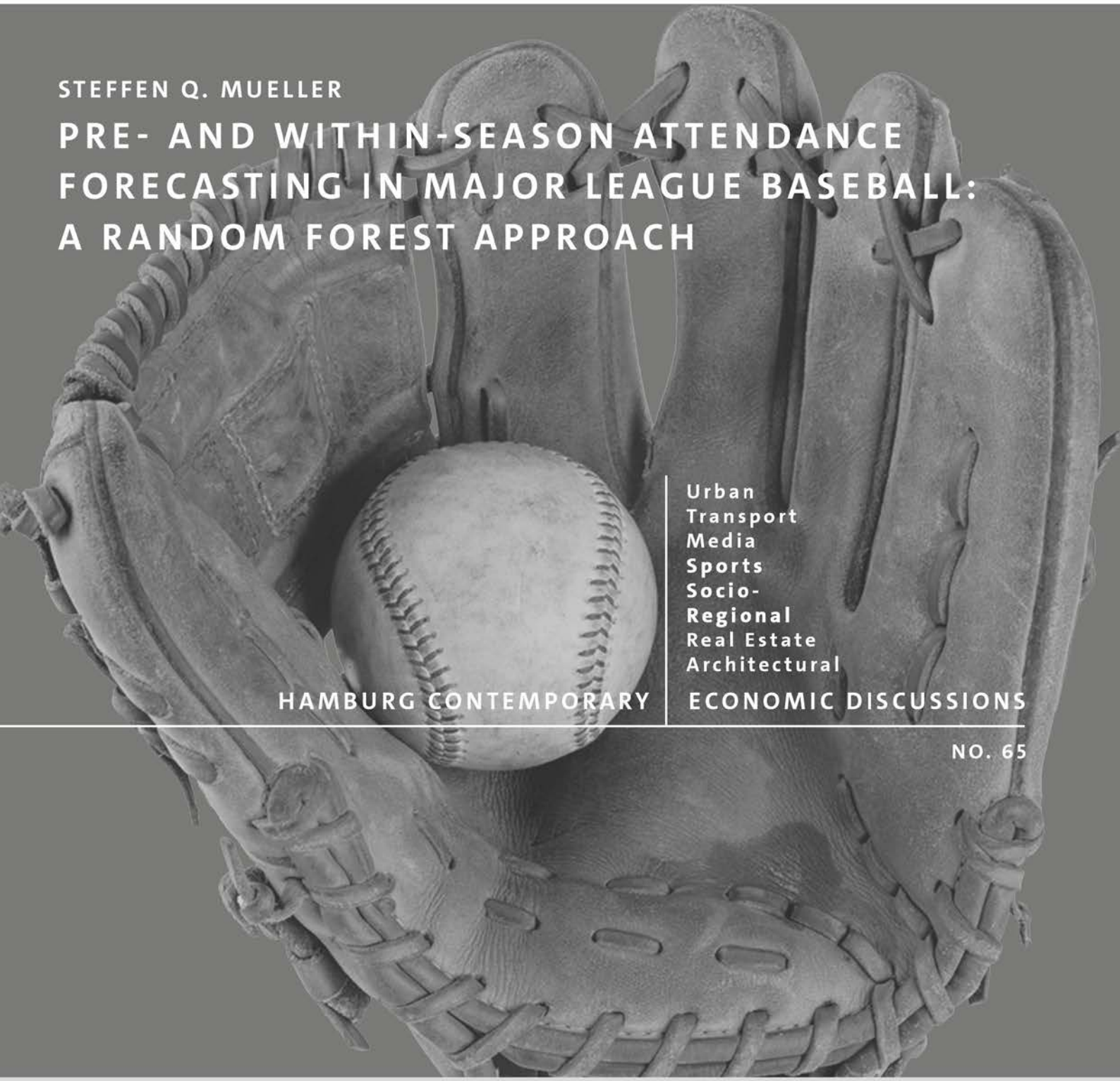

STEFFEN Q. MUELLER

# PRE- AND WITHIN-SEASON ATTENDANCE FORECASTING IN MAJOR LEAGUE BASEBALL: A RANDOM FOREST APPROACH

Urban
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# Pre- and within-season attendance forecasting in Major League Baseball: A random forest approach

**Abstract:** This study explores the forecasting of Major League Baseball game ticket sales and identifies important attendance predictors by means of random forests that are grown from classification and regression trees (CART) and conditional inference trees. Unlike previous studies that predict sport demand, I consider different forecasting horizons and only use information that is publicly accessible in advance of a game or season. Models are trained using data from 2013 to 2014 to make predictions for the 2015 regular season. The static within-season approach is complemented by a dynamic month-ahead forecasting strategy. Out-of-sample performance is evaluated for individual teams and tested against least-squares regression and a naive lagged attendance forecast. My empirical results show high variation in team-specific prediction accuracy with respect to both models and forecasting horizons. Linear and tree-ensemble models, on average, do not vary substantially in predictive accuracy; however, OLS regression fails to account for various team-specific peculiarities.

*Keywords*: Attendance, Major League Baseball, Random forest, Conditional forest, Sport demand, Sports forecasting, Ticket sales, Variable importance
*JEL:* C44, C53, Z2
*Version:* June 2018

## 1 Introduction

According to sport franchises, predicting sport demand in advance of a season is necessary for ticket pricing, and forecasting short-run fluctuations in attendance is important for staffing (Kleps, 2014). However, existent studies on predicting sport demand do not consider multiple forecasting horizons and mainly use linear and normal censored regression methods (e.g. Beckman et al., 2012; J. Borland & Macdonald, 2003; Denaux et

al., 2011; Lemke et al., 2010).[1] In contrast, this paper investigates tree-based ensemble methods for both pre- and within-season attendance forecasting.

In this study, I forecast ticket sales by means of random forest regressions for all 29 US Major League Baseball (MLB) teams for the regular 2015 season using data from 2013 to 2014 for model training. Precisely, I predict individual game attendance and identify important predictors by random forests that are grown from classification and regression trees (CART) (Breiman, 2001) and conditional inference trees (Strobl et al., 2007, 2008). To this extent, I distinguish between two sets of predictors. The first set includes variables that are known in advance of a season (e.g. game and promotion schedule), while the second set is extended to include variables that are observed as a season progresses (e.g. lagged attendance and team performance). Similar to McHale & Morton (2011), who forecast tennis match results, I complement my static predictions by introducing a dynamic month-ahead forecasting strategy in which the training data and models are iteratively updated on a monthly basis.

The random forest (RF) ensemble technique is a state-of-the-art machine learning algorithm that has been shown to yield accurate predictions in a wide range of regression and classification tasks (e.g. Lessmann et al., 2010; Lessmann & Voß, 2017; Nedellec et al., 2014; Swartz et al., 2017). RF automatically accounts for complex non-linear dependencies between considered predictors and the dependent variable (Hastie et al., 2009). This ability makes RF a promising tool in attendance forecasting, since there are many variables that are likely to impact fans' preferences in various and interdependent ways. As an example, fans want to experience an exciting game and, at the same time, want their home team to win, which is not necessarily the same objective and may interact

[1] It is common practice in the sport demand literature to use attendance and ticket sales as proxies for sport demand (J. Borland & Macdonald, 2003). Furthermore, the officially reported attendance figures are the total number of sold tickets per game, not the number of fans that were present at a game. In this paper, the terms sport demand, ticket sales, and attendance are used interchangeably.

with additional factors such as game importance, fan rivalries, and media coverage (Forrest et al., 2005).

This study makes several important contributions. First, it introduces a novel strategy for both pre- and within-season attendance forecasting by exploring the predictive capabilities of static and dynamic random forest approaches. Second, out-of-sample performance is evaluated for individual teams and tested against least-squares regression and a naive lagged attendance forecast. Third, I restrict the set of considered predictors exclusively to measures that are observable and publicly accessible before a season starts or a game is played. Fourth, I provide a robust assessment of variables' impact on predictive accuracy by comparing permutation importance measures that are derived from the random and conditional forest predictions.

The remainder of the paper is organized as follows: Section 2 discusses aspects in predicting attendance, and Section 3 describes the data that are employed in this study. Section 4 briefly reviews the methodologies of RF and CF regression. Section 5 shows the results for both the static pre- and within-season approach and the dynamic short-run forecasting strategy. Section 6 presents the conclusions of the paper.

## 2 Predicting game attendance and determinants of demand

Fans decide to attend a game based on not only economic variables of demand theory such as income and ticket price but also specific sport and game characteristics, e.g. competitive balance and outcome uncertainty (e.g. Dennis Coates et al., 2014; Forrest & Simmons, 2002). The list of potentially relevant predictors is extensive. Among others, additional attendance drivers are the day and time of a game, promotions, weather conditions, newly constructed stadiums, and city and population characteristics (e.g. Denaux et al., 2011; Feddersen et al., 2006; Winfree et al., 2004).

Studies on predicting season or game attendance usually focus on single sports, e.g. soccer (Villa et al., 2011), basketball (Zhang et al., 1995), ice hockey (D. Coates & Humphreys,

2012), Australian football (Jeff Borland & Lye, 1992), U.S. football (Welki & Zlatoper, 1999), and MLB (Lemke et al., 2010). However, most articles on sport demand attempt to explain in-sample attendance variation and use information on exogenous variables that is not strictly observable or publicly accessible in advance of a game (J. Borland & Macdonald, 2003). Examples include average season ticket prices, team payroll, game-day temperature, and macroeconomic variables on various geographical levels (e.g. Beckman et al., 2012; Lemke et al., 2010; Tainsky & Winfree, 2010; Villa et al., 2011; Winfree et al., 2004). I found only two studies that predict stadium attendance without relying on information that is not accessible before a game has started and both use artificial neural network models to forecast short-run soccer match attendance rates (Şahin & Erol, 2017; Strnad et al., 2017).

Frequently employed models in predicting attendance are linear regression methods such as OLS, and censored-normal regression models since stadium capacity limits game attendance (Beckman et al., 2012; Denaux et al., 2011; Lemke et al., 2010). A commonly applied variable transformation is the natural logarithm of game attendance, and some studies consider interaction terms between certain predictors, e.g. squared stadium age (Tainsky & Winfree, 2010). Conversely, RF is a data-driven method that accounts for the impact of higher-order interactions and non-linear dependencies without the need for pre-specification (Hastie et al., 2009).

To the best of my knowledge, only one article has been published in a peer-reviewed journal that also applies tree-based methods to analyze sport demand. King (2017) predicts individual NBA game attendance by CART RF. In contrast to my study, King (2017) employs a static forecast without considering multiple forecasting horizons and includes information on predictors that is not accessible at the time of model training and prediction. Furthermore, tree-based ensemble methods have already been applied in MLB research. Mills & Salaga (2011) and Freiman (2010) predict the election of hitters and pitchers into the National Hall of Fame by the Baseball Writers' Association by RF classification and Swartz et al. (2017) estimate pitch quality by RF regression.

## 3 Data description

The variables that are employed in this study are all publicly accessible in advance of a season or the night before game-day. My data sources are retrosheet.org (game-log data), MLB.com (promotions), seamheads.com (information on stadiums), covers.com (betting odds), darksky.net (weather API), and Beckman et al. (2012) and Lemke et al., (2010) (team rivalries).[2]

The original data sample covers all 7290 games that were played over the course of the 2013, 2014 and 2015 regular seasons. Since I include lagged attendance as a predictor in my analysis, I drop the corresponding 90 first home games. Furthermore, I only consider US teams in this study and, thus, drop the remaining 240 home games that were hosted by the Toronto Blue Jays. After additional minor adjustments that are common in the sport economics literature, the final data sample includes observations on 6852 games: 4571 records from the 2013 and 2014 seasons as a training set and 2281 records from the 2015 season as a hold-out test set. Concise descriptions of the data cleaning process, variable specifications, and descriptive statistics are provided in the Appendix. The 38 predictor variables that are employed in this study are summarized in Table 1.

[2] http://www.retrosheet.org, https://www.mlb.com, http://www.seamheads.com, https://www.covers.com, https://darksky.net.

**Table 1 Description of pre- and within-season predictor variables**

| Variables observed in advance of a season |
|---|
| 5 variables related to the date and time a game is scheduled |
| 6 variables related to stadium, city, and team characteristics |
| 5 variables related to team rivalries and specific match characteristics |
| 6 variables related to teams' former season success |
| 4 variables related to game promotions |
| **Variables observed as a season progresses** |
| Lagged home team game attendance |
| Home team's winning probability (calculated from betting odds) |
| 4 variables related to relative team performance |
| 5 variables related to weather conditions (day before game-day) |
| Season (only included in the dynamic forecast) |

Notes: This study includes 38 predictor variables: 12 numerical and 26 categorical variables with a total of 98 levels (see Section 2 in the Appendix).

Although weather conditions can be expected to have an impact on game attendance, they are often not considered in empirical research or only refer to the temperature that is measured at the beginning of a game (e.g. Kappe et al., 2014; Lemke et al., 2010). In contrast, I include several measures that account for the weather conditions of the day before a game is played. However, there are numerous potential attendance factors that are not considered in this study. For example, one may include information on fans' preferences that is derived from social-media activities.

## 4 Methodology

### 4.1 Random forest regression

The RF technique is an ensemble method that combines multiple de-correlated decision tree predictors on the basis of various sub-sets of a data sample (Hastie et al., 2009). The original RF approach averages the predictions that are generated from many unpruned single CART trees that are fitted to random draws of the training data with replacement, which is referred to as bootstrap aggregation ('bagging') (Breiman, 1994, 2001; Breiman et al., 1984). An RF is grown from $B$ bootstrap samples that each include individual observations multiples times, while some observations are not included (approximately

one third). The observations that are not included in the data that are used to fit a tree are called out-of-bag (OOB) observations. In contrast to bagging, the RF procedure imposes an additional form of randomness by only considering a random subset of $M$ predictors for the respective candidate variable any time a node is split in the tree building process. As a result, RF generates more diverse trees by allowing splitting rules on variables at early stages of a single tree that would otherwise be neglected (Breiman, 2001).

A convenient feature of bagged models is that they allow hyper-parameters to be determined in a way that is similar to cross-validation. Precisely, we can evaluate model performance by predicting the outcome for an observation $i$ using each of the single trees in which this observation was not included in the training process, i.e. in which this observation was OOB. This evaluation yields approximately $B/3$ predictions for the $i$th observation. The RF OOB prediction for the $i$th observation is simply the average of those $B/3$ predictions (or majority vote for classification). Using the OOB estimates for model tuning is less computationally demanding than cross-validation since no additional models (forests) must be trained to test a set of parameters (Lessmann et al., 2010).

The importance of each predictor in the RF tree building process can be assessed via different measures of variable importance. The arguably most-advanced RF measure is computed by calculating the difference in prediction accuracy that results from randomly permuting a predictor variable using the observations that are recorded in the OOB data (Strobl et al., 2007). The reasoning is intuitive: Let us assume that the difference in the prediction accuracy on the OOB records is substantially affected by whether we include a predictor $X_j$ or not, i.e. $X_j$ is a strong predictor. Then, it is reasonable to assume that assigning a different value to $X_j$ increases the resulting prediction error. Hence, permuting a variable over its values that were recorded in the OOB data enables one to mimic the exclusion of the predictor and calculate the resulting mean difference in MSE on the OOB data (Breiman, 2001; Strobl et al., 2007).

### 4.2 Conditional random forest regression

While the RF permutation importance measure covers both the individual impact of the assessed predictor and complex higher-order interactions with other predictors, it is biased in favor of numerical over categorical variables and similarly favors categorical variables with many levels (e.g. Archer & Kimes, 2008; Strobl et al., 2007). Precisely, Strobl et al. (2007) show that the RF inhibits a variable selection bias that emerges from CART and an additional bias that is induced by bootstrap sampling. As an alternative to CART, Strobl et al. (2007) propose using conditional inference trees as base learners. The main difference with RF is that the conditional forest (CF) aggregation scheme of the single-tree predictors within a forest involves averaging observation weights that are extracted from each of the trees, not simply averaging the predictions directly (Strobl et al., 2007, 2008).

In a later study, Strobl et al. (2008) find that the CF approach in Strobl et al. (2007) still favors correlated predictors in the tree building process; this bias is induced by the unconditional variable importance permutation scheme of CF. To account for this bias, Strobl et al. (2008) suggest conditionally permuting predictor variables to correlated ones, which they refer to as conditional permutation importance. However, there is no general consensus on how to interpret the importance measures when predictors are correlated and, more importantly, it is unclear how those correlations effectively impact CF importance measures (e.g. Nicodemus et al., 2010).

## 5 Implementation and results

I use *R* (R Core Team, 2017) and the packages *randomForest* (Liaw & Wiener, 2002), *party* (Hothorn et al., 2015), and *lattice* (Sarkar, 2008) for the main computations and graphics in this paper.

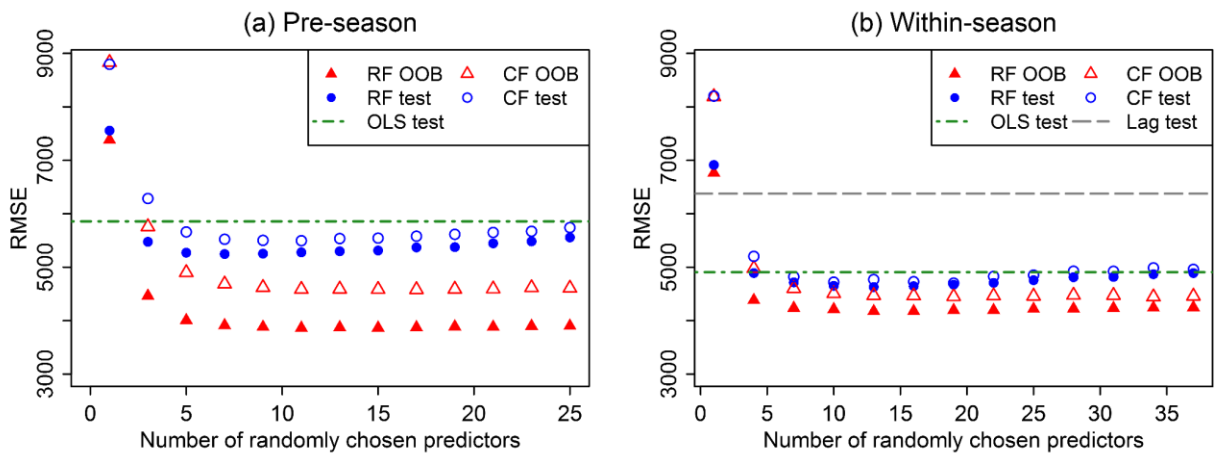
### 5.1 Static pre- and within-season forecasts

This study employs 37 within-season predictor variables, which are denoted as $X^{ws}$, in the static forecasting approach: 26 pre-season variables $X^{ps}$ and 11 short-run variables $X^{sr}$. I forecast individual game attendance $y_i$ by random forest regressions based on CART (RF) and conditional inference trees (CF), a standard OLS regression model, and a naive forecast that equals the lagged home-team game attendance (Lag).

#### 5.1.1 Model performance evaluation

In this paper, I follow the suggestion of Hastie et al. (2009) and exclusively grow trees to their maximal depths. This procedure simplifies parameter tuning and, with respect to this study, requires a justifiable increase in computational cost. Moreover, I quickly observed that the predictive performance for both pre- and within-season models is not very sensitive to the number of included trees per forest. For example, using the suggested default value (one third) for the number of randomly chosen predictors in the tree building process, the RMSE on the OOB and test data for both the RF and CF approaches stabilizes after averaging the prediction results of less than 100 trees (see Section 4 of the Appendix). However, in the further analyses, I train RF and CF models on the basis of $B = 500$ trees to ensure stable estimates of variable importance measures (Liaw & Wiener, 2002). Figure 1 shows the OOB and test set RMSEs for the pre-season [within-season] forecasts that are generated by the RF, CF, OLS, and lagged attendance models as functions of the number $M_{ps} = \{1, 3, \dots, 25\}$ $[M_{ws} = \{1, 4, \dots, 37\}]$ of randomly considered predictors at each split in the tree building process.

**Figure 1 Model performance evaluation: RMSE by number of randomly chosen predictors**




Notes: Out-of-sample (test) and out-of-bag (OOB) MLB game attendance RMSEs by random forest regressions based on CART (RF) and conditional inference trees (CF), OLS regression, and a simple lagged home-team attendance forecast (Lag). Maximal complex RF and CF are trained using $B = 500$ trees.

The RF yields the most accurate results but only slightly outperforms OLS and CF regressions for both the pre- (a) and within-season (b) forecasting horizons. The RF and CF performances on the OOB records appear to be relatively stable after the inclusion of 10 randomly chosen predictors at each split. However, the suggested default value of one third for the number of randomly considered predictors $M$ appears to approximately minimize RMSE for the RF and CF approaches for both the pre-season (a) and within-season (b) test data. For (a), the corresponding results for the RF [CF] model with $M_{ps} = 7$ yield minimum RMSEs of 3912 [4686] on the OOB data and 5241 [5522] on the test data. For (b), the corresponding results for RF [CF] with $M_{ws} = 12$ yield a minimal RMSE of 4205 [4478] on the OOB data and 4634 [4743] on the test data. The OLS model RMSEs are 5858 (a) and 4908 (b), while the simple home-team-specific lagged attendance forecast (Lag) achieves an RMSE of 6377 (b). Hence, the differences in prediction accuracy among RF, CF, and OLS are stronger for the pre-season forecast, but do not vary substantially when trained with the additional information that is provided by the within-season variables.

### 5.1.2 Team-specific results

Based on the performance evaluation in Section 5.1.1, I use $B = 500$ trees and set the number of randomly chosen predictors to $M_{ps} = 7$ and $M_{ws} = 12$ for all static pre- and

within-season RF and CF models. Table 2 shows the corresponding out-of-sample RMSEs for each home team for the static pre- and within-season predictions, together with the attendance summary statistics for the regular seasons from 2013 to 2015.

**Table 2 Out-of-sample MLB game attendance prediction accuracy by home team**

| | Seasons 2013 to 2015 | | | Out-of-sample RMSE for the 2015 season | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Attendance summary | | | Random forest | | | OLS | | | Lag att |
| Team name | Abr. | Mean | SD | Pre | Within | Diff | Pre | Within | Diff | Within |
| All | - | 30283 | 9609 | 5241 | 4634 | 607 | 5858 | 4908 | 950 | 6377 |
| Arizona Diamond Backs | ARI | 25639 | 7029 | 4959 | 4393 | 566 | 4820 | 4531 | 289 | 8737 |
| Atlanta Braves | ATL | 28313 | 8735 | 7063 | 6273 | 790 | 7465 | 5634 | 1831 | 8799 |
| Baltimore Orioles | BAL | 29671 | 9277 | 6861 | 6257 | 604 | 6421 | 6391 | 30 | 10230 |
| Boston Red Sox | BOS | 35694 | 2039 | 2048 | 1818 | 230 | 3381 | 3349 | 32 | 1532 |
| Chicago Cubs | CHC | 33869 | 4373 | 5023 | 4296 | 727 | 5657 | 3850 | 1807 | 3025 |
| Chicago White Sox | CHW | 21369 | 6265 | 4532 | 4300 | 232 | 4812 | 4275 | 537 | 6762 |
| Cincinnati Reds | CIN | 30366 | 7543 | 5047 | 4848 | 199 | 5886 | 5132 | 754 | 7797 |
| Cleveland Indians | CLE | 18386 | 6580 | 3850 | 3809 | 41 | 3815 | 3538 | 277 | 5702 |
| Colorado Rockies | COL | 32965 | 6746 | 5428 | 4572 | 856 | 4596 | 4035 | 561 | 6653 |
| Detroit Tigers | DET | 35781 | 5219 | 3430 | 3024 | 406 | 4868 | 3657 | 1211 | 4671 |
| Houston Astros | HOU | 22626 | 6579 | 6907 | 4833 | 2074 | 6805 | 3892 | 2913 | 6361 |
| Kansas City Royals | KCR | 26297 | 8176 | 5002 | 5280 | -278 | 10447 | 8510 | 1937 | 5298 |
| Los Angeles Angels | LAA | 37479 | 4053 | 4139 | 3949 | 190 | 3400 | 3285 | 115 | 5282 |
| Los Angeles Dodgers | LAD | 46377 | 5100 | 3789 | 3905 | -116 | 4023 | 4237 | -214 | 5215 |
| Miami Marlins | MIA | 20676 | 4200 | 3880 | 3871 | 9 | 4684 | 4373 | 311 | 5349 |
| Milwaukee Brewers | MIL | 32223 | 6316 | 4794 | 4328 | 466 | 4403 | 4164 | 239 | 6700 |
| Minnesota Twins | MIN | 28560 | 5231 | 4652 | 4272 | 380 | 5020 | 4123 | 897 | 5641 |
| New York Mets | NYM | 28208 | 6260 | 7262 | 6562 | 700 | 6905 | 5418 | 1487 | 7341 |
| New York Yankees | NYY | 40892 | 4723 | 4748 | 4368 | 380 | 4737 | 4696 | 41 | 5193 |
| Oakland Athletics | OAK | 22944 | 7516 | 4851 | 4805 | 46 | 5089 | 4914 | 175 | 7779 |
| Philadelphia Phillies | PHI | 30047 | 7172 | 8955 | 6358 | 2597 | 9622 | 6531 | 3091 | 5148 |
| Pittsburgh Pirates | PIT | 29614 | 7926 | 4369 | 3900 | 469 | 5199 | 4463 | 736 | 6470 |
| San Diego Padres | SDP | 27886 | 8042 | 6121 | 5790 | 331 | 8077 | 6780 | 1297 | 8881 |
| Seattle Mariners | SEA | 24522 | 8773 | 7061 | 6345 | 716 | 7683 | 6650 | 1033 | 8717 |
| San Francisco Giants | SFG | 41583 | 618 | 427 | 410 | 17 | 3960 | 3685 | 275 | 406 |
| St. Louis Cardinals | STL | 42851 | 2464 | 2069 | 1874 | 195 | 3589 | 3193 | 396 | 2223 |
| Tampa Bay Rays | TBR | 17069 | 5895 | 4746 | 4283 | 463 | 4400 | 3696 | 704 | 5214 |
| Texas Rangers | TEX | 34169 | 6701 | 7355 | 5728 | 1627 | 7717 | 6554 | 1163 | 7002 |
| Washington Nationals | WAS | 32254 | 5339 | 3939 | 3848 | 91 | 4338 | 3930 | 408 | 5827 |
| R2 | - | - | - | 0.697 | 0.763 | 0.066 | 0.630 | 0.737 | 0.107 | 0.551 |

Notes: Summary statistics and static pre-and within-season forecasts for US home-team game attendance.

With respect to average team results, the RF model performs only slightly better than the OLS model for both pre-season (PS) and within-season (WS) predictions. For the pre-season (PS), the RF model yields an RMSE of 5241 and within-season (WS) an RMSE of 4634. The naive home-team-specific lagged attendance (LAG) model performs worst, with an average RMSE of 6377. The CF results do not differ substantially from the RF results and, therefore, are included in the

Appendix. The RMSEs for the OLS regression are 5858 (PS) and 4908 (WS), and 6377 (WS) for the LAG predictions.

Most importantly, the results in Table 2 reveal the high variation in prediction accuracy within and across teams, models, and forecasting horizon. A good example for team-specific peculiarities are the San Francisco Giants (SFG). With respect to team-specific differences in the PS and WS results for the RF approach, the corresponding RMSEs are only 427 (PS) and 410 (WS) sold tickets per game. In contrast, with RMSEs of 3960 (PS) and 3685 (WS), the OLS model is not able to account for the unique peculiarities that are associated with SFG. Precisely, SFG's standard deviation in ticket sales per game across the 2013, 2014 and 2015 seasons is as low as 618 and the average game attendance is 41583. SFG's stadium capacity is reported as 41915 over all seasons, which implies that practically every game was almost sold out. As a result, the lagged attendance model (LAG) achieves a corresponding RMSE of 406 sold tickets per game. Similarly, the LAG is also more accurate than RF and OLS are for BOS, CHC, and PHI, and more accurate than OLS is for STL and KCR.

There are also instances in which the OLS model performs best with respect to the PS forecasting horizon (ARI, BAL, CLE, COL, HOU, LAA, MIL, NYM, NYY, and TBR) and the WS predictions (ATL, CHW, CLE, COL, HOU, LAA, MIL, NYM, MIN, and TBR). However, the corresponding differences between OLS and RF are small for the teams for which the OLS performs better, e.g. the maximal difference for PS is 832 (COL) and for WS 1144 (NYM). In contrast, the maximal difference in RMSEs for the teams for which the RF outperforms the OLS model are 5445 for PS (KCR) and 3275 for WS (KCR). Moreover, there are substantial differences with respect to the improvement in prediction accuracy that is obtained by including short-run information in the WS framework. For the RF approach, the difference between the PS and WS RMSEs is negative for KCR and LAD, and for the OLS model for LAD. Lastly, the highest RMSEs for the RF model are 8955 for PS (PHI) and 6562 for WS (NYM), and for the PS and WS OLS model 10447 (KCR) and 8510 (KCR), respectively. However, I train and evaluate the RF and CF approaches over all teams. To improve prediction accuracy, we may simply train and optimize models with respect to each team individually.

### 5.1.3 Variable importance analysis

Table 3 shows the ranking of predictors according to their impact on the forest building process in terms of the permutation importance measures of the RF (scaled mean decrease in MSE) (Breiman, 2001), the unconditional CF (Strobl et al., 2007), and the conditional CF (CCF) (Strobl et al., 2008) approaches. Precisely, I present the RF, CF, and CCF rankings for the ten most important predictors of the RF pre-season and within-season models (lowest rank corresponds to highest impact).

**Table 3 Comparison of random and conditional forest variable importance rankings**

| | Pre-season | | | Within-season | | |
|---|---|---|---|---|---|---|
| Variable | RF | CF | CCF | RF | CF | CCF |
| *Variables observed before a season starts* | | | | | | |
| Weekday | 1 | 3 | 1 | 1 | 3 | 1 |
| Home team (HT) indicator | 2 | 1 | 2 | 2 | 1 | 15 |
| HT season game number | 3 | 9 | 10 | 4 | 14 | 30 |
| Distance between stadiums | 4 | 14 | 5 | 10 | 23 | 34 |
| Month | 5 | 7 | 4 | 13 | 9 | 36 |
| Visiting team (VT) indicator | 6 | 13 | 3 | 16 | 16 | 18 |
| Fireworks promotion | 7 | 12 | 16 | 7 | 7 | 17 |
| Stadium capacity | 8 | 2 | 6 | 8 | 4 | 23 |
| Day or night game | 9 | 15 | 17 | 14 | 13 | 16 |
| VT is Division Series Winner | 10 | 18 | 13 | 22 | 22 | 32 |
| *Variables observed before a game starts* | | | | | | |
| HT lagged attendance | | | | 3 | 2 | 2 |
| Maximum temperature | | | | 5 | 20 | 11 |
| HT games behind | | | | 6 | 17 | 10 |
| Minimum temperature | | | | 9 | 18 | 21 |
| HT winning percentage | | | | 12 | 10 | 6 |
| VT winning percentage | | | | 15 | 19 | 3 |
| VT games behind | | | | 17 | 26 | 7 |
| HT implied winning probability | | | | 20 | 24 | 5 |
| Relative humidity | | | | 21 | 27 | 8 |
| Weather conditions | | | | 30 | 33 | 26 |

Notes: Permutation importance rankings (lowest rank corresponds to highest impact) are derived from the OOB estimates for the 2013 and 2014 regular seasons from the random and conditional forest regressions for US home-team-specific MLB game attendance (see Section 5.1.2). $P_{ps} = 26$ [$P_{ws} = 37$] included predictors for the pre-season [within-season] forecast. Ranking of predictor relevance in the forest building process according to permutation variable importance is performed using the (scaled) CART random forest (RF) and conditional forest (CF) measures and the conditional permutation importance CF measure (CCF).

For the pre-season forecast, the rankings in terms of RF, CF, and CCF largely appear to identify the same predictors as being of relatively high importance in the tree and forest building process. Weekday and home team (HT) effects are consistently ranked among

the three most important predictors. However, there are differences among the considered ranking approaches: The CF measure ranks ballpark capacity as the second most important variable, and the third rank in the CCF approach is assigned to the dummy variable that indicates whether a game is played against BOS, CHC, or NYY (VT).

The largest differences in rankings are observed for the distance between stadiums, VT, and fireworks promotions. Conversely, an HT's season game number is a numeric variable that seems to be artificially preferred in the RF. With respect to highly correlated variables, in contrast to the RF and CCF, the CF assigns the first and second ranks to stadium capacity and the HT indicator.

The differences among the RF, CF, and CCF rankings appear to be more severe for the within-season forecast. First, the rank for lagged HT attendance is between two and three for RF, CF, and CCF. However, CCF results in a vastly different ranking compared to all other PS and WS rankings for an HT's indicator and the number of games, distance, and month. This result is unexpected and seems unreasonable since the WS forecast is not substantially better than the PS forecast is for the RF or the CF model (see Table 2). Although the RF and CF results suggest that the additional WS information (e.g. relative team rankings) has no substantial impact on the predictive accuracy, CCF still ranks many of the additional WS variables among the ten most important predictors. Lastly, the differences between the RF and CF ranking are small. However, similar to the PS rankings, the RF appears to rank specific numeric and continuous variables relatively higher. However, one should be careful when interpreting these results since the stadium capacities and distances between competing teams' ballparks do not vary substantially within seasons, and there is high correlation between current- and previous-season success and individual teams (Tainsky & Winfree, 2010).

Lastly, similar to Lessmann et al. (2010), I assess the observed significance in the differences among the variable importance rankings that are produced by CF, RF, and CCF by computing the corresponding ranking correlation coefficients by means of Kendall's tau. The WS CCF ranking is reported to be statistically significantly different from all other

PS and WS rankings at a minimum $p$-value of 0.311. All other combinations of differences in importance rankings across models for both PS and WS are similar. The precise results are included in the Appendix.

### 5.2 Dynamic within-season forecast

In the dynamic within-season forecast, I iteratively update the training data after each month. The models are trained using the updated training set to make predictions for the games of the next consecutive month. Then, I repeat this procedure for all months of the 2015 regular season. Moreover, in contrast to the static within-season approach, I include an additional categorical variable that indexes the corresponding season, which results in $X^{dyn} = 38$ predictors for the dynamic forecasting strategy. Unlike the static predictions, this approach allows one to account for seasonal differences in preferences for game attendance. Table 4 shows the out-of-sample results for the dynamic RF, CF, OLS, and lagged attendance month-ahead predictions. As in the static forecasting approach, I train the RF and CF models using $B = 500$ trees and $M_{ws} = 12$ randomly chosen predictors.

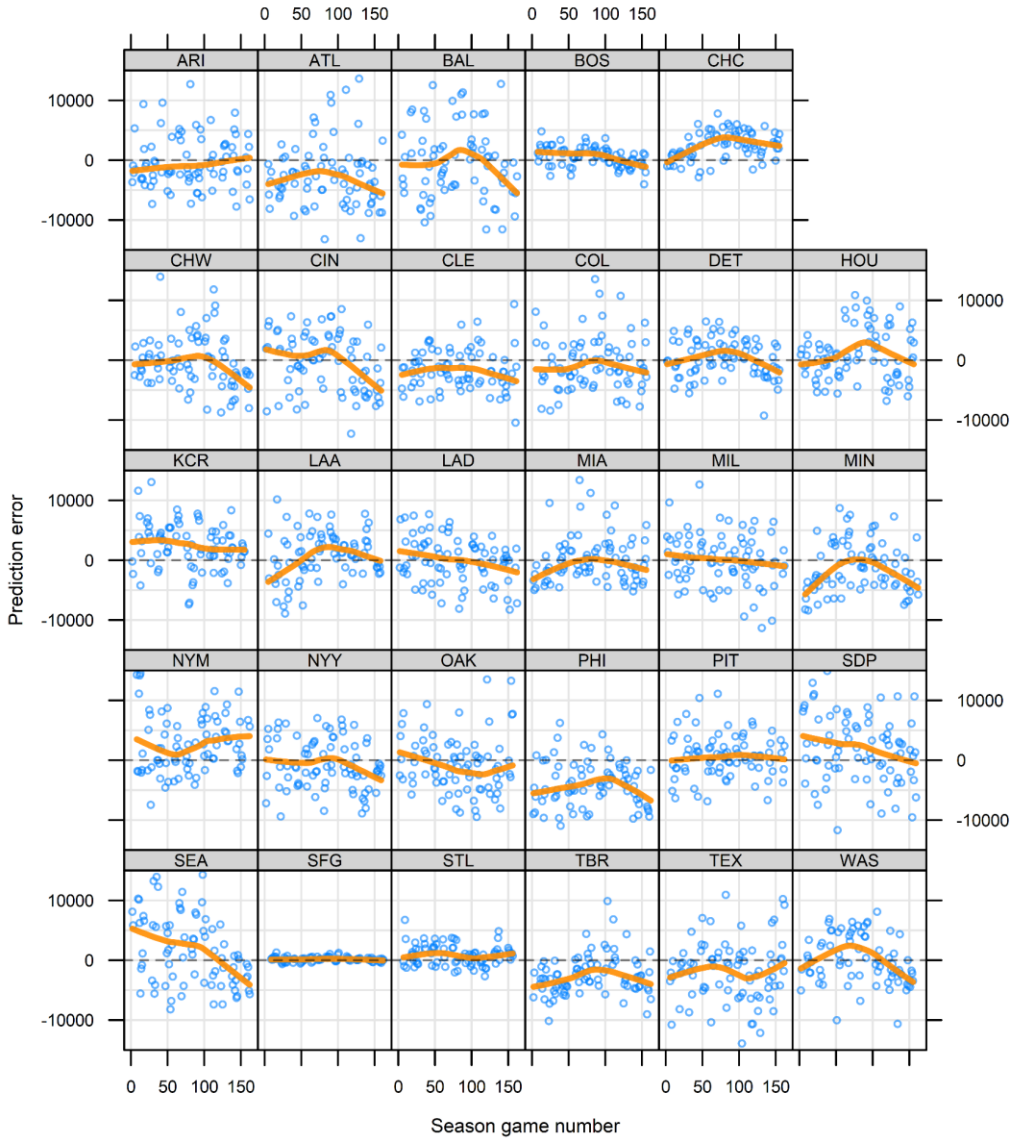
**Table 4 Dynamic within-season attendance forecasts**

| | | Out-of-sample month-ahead prediction accuracy | | | | | |
|---|---|---|---|---|---|---|---|
| Model | | Apr | May | Jun | Jul | Aug | Sep |
| Random forest | RMSE | 4608 | 4481 | 3994 | 4373 | 4424 | 4405 |
| | R2 | 0.79 | 0.78 | 0.80 | 0.76 | 0.76 | 0.80 |
| Conditional forest | RMSE | 4780 | 4655 | 4198 | 4589 | 4523 | 4519 |
| | R2 | 0.77 | 0.76 | 0.78 | 0.73 | 0.75 | 0.80 |
| OLS | RMSE | 4540 | 4481 | 4411 | 4432 | 4419 | 4427 |
| | R2 | 0.74 | 0.75 | 0.78 | 0.78 | 0.79 | 0.78 |
| Lagged attendance | RMSE | 7863 | 6587 | 5846 | 5983 | 6505 | 5694 |
| | R2 | 0.39 | 0.52 | 0.57 | 0.54 | 0.48 | 0.67 |

Notes: Training data and models are iteratively updated after each month of the MLB 2015 season.

The dynamic forecasting approach produces only slightly more accurate predictions than those of the static approach. For example, the difference between the RMSE of the static WS RF approach and the average monthly RMSE of the dynamic WS RF approach is only 299 tickets per game. The RF model performs only marginally better than the OLS model does, and both explain, on average, 78% of the variation in attendance, while the monthly average for the CF model is 76%. For the July and August game attendance predictions, the OLS model is even more accurate than the RF and CF models are. Furthermore, the lagged attendance prediction results indicate that variation in game-to-game attendance at the beginning of the 2015 season is relatively high (April), but relatively low during the end (September). Instead of the team-specific RMSE, I show the aggregated monthly prediction errors by season game number and team for the dynamic RF model in Figure 2.

**Figure 2 Dynamic random forest attendance forecast**



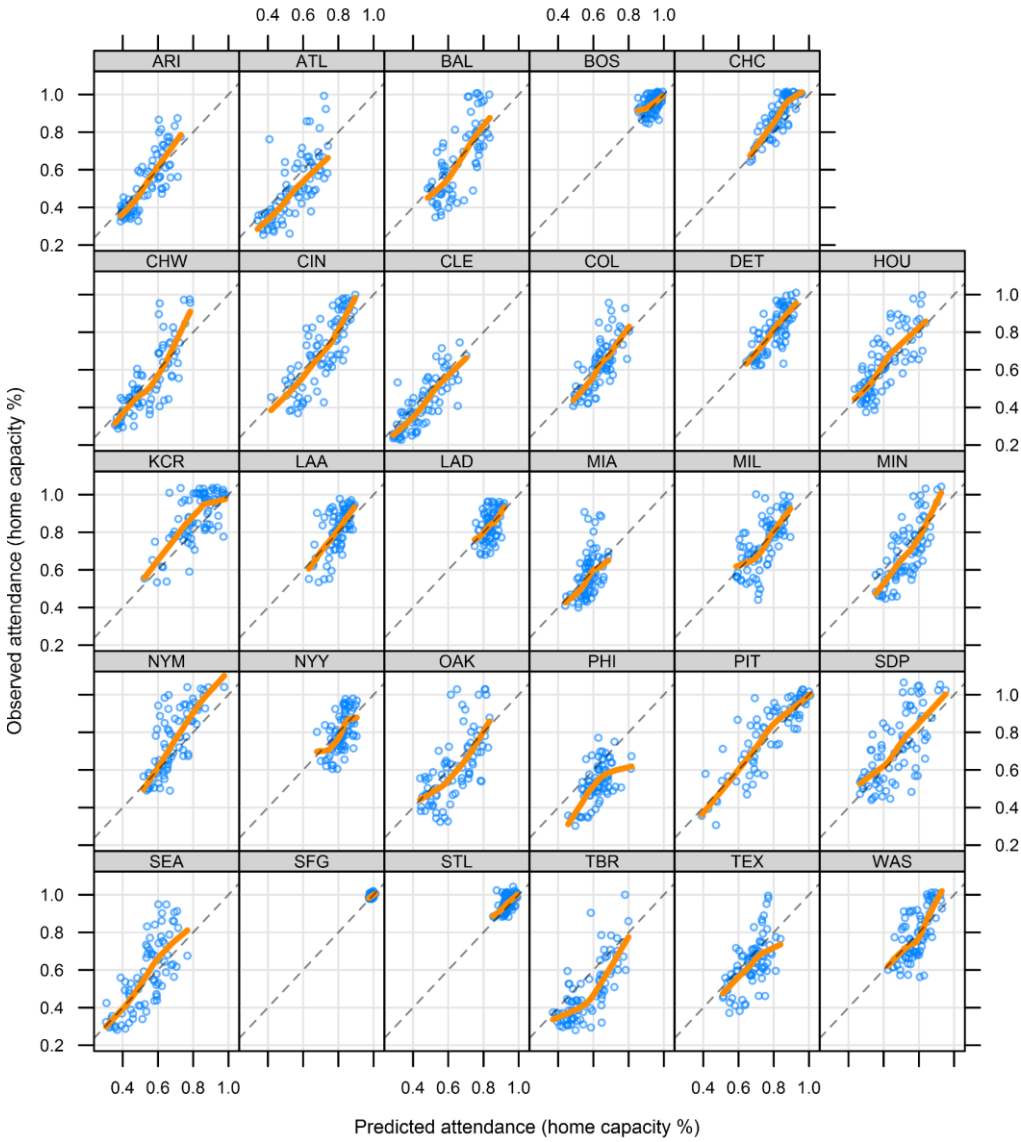

Notes: Dynamic random forest attendance forecasts for the 2015 MLB regular season by aggregated out-of-sample month-ahead prediction error for US home-team-specific game attendance. Orange lines correspond to LOESS smoothing curves.

As in the static pre- and within-season forecasts, the dynamic approach shows high heterogeneity in the predictive accuracy for game attendance across home teams. In contrast to the team-specific results that are presented in Section 4.1, Figure 1 shows for which games the RF forecasts over- and underestimate attendance. A casual inspection reveals a bell-shaped LOESS curve, especially for BAL, HOU, LAA, MIN, PHI, and WAS. However, there are also teams that show more linear and approximately unbiased curves, e.g. MIL, PIT, and SFG. Furthermore, SEA appears to be an interesting case in

which the variance of prediction accuracy decreases as the season progresses. The lowest prediction errors are obtained for BOS, SFG, and STL. Examples of high variation in predictive accuracy in terms of magnitude and direction are produced for ATL, BAL, SDP, and SEA.

However, Figure 1 does not account for the large differences in team-specific attendance rates. To complete my analysis, I show the differences in observed and predicted game attendance relative to stadium capacity in Figure 2.

**Figure 3 Dynamic random forest attendance rate forecast**




Notes: Dynamic random forest attendance forecast for the MLB 2015 regular season by aggregated out-of-sample month-ahead prediction error for US home-team-specific game attendance rates and stadium capacities. Orange lines correspond to LOESS smoothing curves. Dashed lines indicate a perfect attendance rate forecast.

The results in Figure 3 reveal that there is high variation not only in team-specific prediction accuracy of absolute attendance but also in attendance relative to stadium capacity. The general pattern seems reasonable since the games of teams with consistently high attendance rates throughout the season are well predicted, e.g. the games of BOS, SFG, and STL. In contrast, ticket sales for teams that face a greater variation in game attendance are predicted less well, e.g. ATL, SDP, and SEA. Moreover, with respect to

teams with low attendance rates throughout the season, RF appears to overestimate attendance for TBR and PHI and underestimate attendance for, e.g. CIN, KCR, and NYM.

## 6 Conclusions

The vast majority of studies that predict stadium attendance have employed linear and censored regression models, do not consider multiple forecasting horizons, and use information on variables that is nonexistent or not publicly accessible in advance of a game or season. In contrast, this study explores the predictive capabilities of RF and CF regressions for pre- and within-season attendance forecasting without relying on such information. In addition to static predictions, I propose a dynamic month-ahead forecasting strategy in which the training data are iteratively updated on a monthly basis. In an example of forecasting game ticket sales and identifying important attendance predictors in MLB, I find that prediction accuracy and within-season information gain can highly depend on team-specific characteristics. My empirical results show that OLS regression, on average, performs only slightly worse than RF does. However, OLS fails to account for the peculiarities of a small number of teams. Consequently, this study shows that data-driven methods are promising tools in sports demand forecasting since relevant attendance factors are likely to impact fans' preferences across teams in different and interdependent ways.

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# Appendix

## 1 Introduction

This Appendix provides additional information on the data that are used in this study, empirical specifications, and descriptive statistics, complementing the main analysis by providing robustness verification and detailed results for variable importance rankings and the dynamic within-season forecasting approach. Although this Appendix includes text and results from the main paper for clarity, it is not meant to stand alone.

## 2 Data and context

Major League Baseball (MLB) is divided into the American League and the National League, which are each divided into three divisions: East, Central, and West. Since 2013, each League has consisted of fifteen teams. There are 29 US teams and one Canadian team, which are equally distributed among the six divisions. The regular season is played from April to September and includes 2430 officially scheduled games in total.[3] In this study, the corresponding 162 games per team and season include 20 inter-league games, 66 inter-division games, and 76 intra-division games.

### 2.1 Sources and empirical specifications

The data that are used in this study are collected from various sources and only cover variables that are observed and publicly accessible before a season starts (pre-season) and before a game is played (within-season). Most of the variables are obtained from retrosheet.org[4] (game-log data), MLB.com[5] (promotions), seamheads.com[6] (information

[3] There are a few games that are scheduled at the end of March or at the beginning of October. In addition, very few games are usually cancelled at the end of a season, e.g. due to bad weather conditions. However, games are only cancelled if the game does not affect team rankings.

[4] http://www.retrosheet.org

[5] https://www.mlb.com

[6] http://www.seamheads.com

on stadiums), covers.com[7] (betting odds), and Lemke et al. (2010) and Beckman et al. (2012) (team rivalries). The geographical regions of the historic weather data are specified with respect to a ballparks' longitude and latitude coordinates. The precise measurements refer to the day before a game is played and are obtained using Dark Sky's weather API[8].

The data sample covers all 7290 games that were played over the course of the 2013, 2014 and 2015 regular seasons. Since lagged attendance is included as a predictor in this analysis, I drop the corresponding 90 first home games. Furthermore, I only consider US teams in this study and, thus, drop the remaining 240 home games that were hosted by the Toronto Blue Jays. In addition to those adjustments, I follow a standard practice in the sport economics literature and discard all 106 rescheduled games from the data sample.[9] Those games are usually rescheduled due to bad weather conditions or other extreme events and sometimes the same games are rescheduled more than once. Lastly, there are two observations with missing attendance numbers for unknown reasons, which are dropped as well. However, I calculate all relevant variables using the whole data sample before I discard any observations, e.g. I include all observations in calculating a team's winning percentage and games behind. In this context, in 2015, three home-team games of the Baltimore Orioles against the Texas Rangers were rescheduled to be played in Arlington. I defined those games as home-team games that were played by the Rangers. As a matter of course, I exclude the two observations with missing attendance data before computing the lagged home-team-specific game attendance. The final data sample includes observations on 6852 games: 4571 records for the training set (2013 and 2014 seasons) and 2281 records for the hold-out test set (2015 season).

Moreover, there are 11 games in the data sample that were not finished during their officially scheduled day. Instead, they were extended and finished one or two days after the scheduled game day. Unfortunately, no attendance numbers are available for the

[7] https://www.covers.com

[8] https://darksky.net.

[9] The average model accuracy only decreases marginally when rescheduled games are included. The main reason I discard rescheduled games is to provide an approach that does not rely on data that are not observable or publicly accessible in advance of a season.

games that were extended and finished on another day or the second game day of a double-header. As is common practice by the MLB Association and in the sports economics literature, I treat the outcomes of extended games as if they had been realized during the first official game day and set the second-day game attendance equal to the first-day game attendance for double-headers, instead of discarding those observations (e.g. Lemke et al., 2010). In the remaining sample, there are two games that were played in March and 53 games that were played in October. I specify those games as if they had been played in April and September, respectively. The predictor variables that are employed in this study are described in Table A.1.

**Table A.1 Pre- and within-season predictor variable descriptions**

| Predictor | Description | Levels |
|---|---|---|
| *Variables observed before a season starts (#26)* | | |
| HT.id | Home-team identification number: ARI, ATL, BAL, BOS, CHC, … , WAS | 29 |
| HT.NoG[a] | HT's number of games within seasons | Numeric |
| WDay[a] | Weekday: Mon, Tue, Wed, Thu, Fri, Sat, Sun | 7 |
| Month[a] | Month: Apr., May, Jun., Jul., Aug, Sep. | 6 |
| Night[a] | Night: No, Yes | 2 |
| PHoliday | Public holiday: No, Yes (Labor Day, 4th, or Memorial Day) | 2 |
| CTeams | Number of teams in HT's city or county: One, two | 2 |
| Capacity[b] | Stadium capacity | Numeric |
| SType[b] | Stadium type: Open, retractable roof, dome | 3 |
| SBuild[b] | Stadium age: 1-5 years, 6-10 years, +10 years | 3 |
| ILGame[c] | Interleague game: No, Yes | 2 |
| DivGame[c] | Division game: No, Yes | 2 |
| DRgame[d] | Division rivalry game: No, Yes | 2 |
| ILRGame[d] | Interleague rivalry game: No, Yes | 2 |
| VTeam | Visiting team (VT): Other, BOS, CHC, NYY | 4 |
| HT.WSW[c] | HT is last season's World Series winner: No, Yes | 2 |
| VT.WSW[c] | VT is last season's World Series winner: No, Yes | 2 |
| HT.LCSW[c] | HT is last season's league championship series winner: No, Yes | 2 |
| VT.LCSW[c] | VT is last season's league championship series winner: No, Yes | 2 |
| HT.DSW[c] | HT is last season's league division series winner: No, Yes | 2 |
| VT.DSW[c] | VT is last season's league division series winner: No, Yes | 2 |
| Distance[b] | Distance between HT's and VT's stadiums (in miles) | Numeric |
| FWorks[c] | Fireworks promotion: No, Yes | 2 |
| BHeads[c] | Bobblehead promotion: No, Yes | 2 |
| OPromo[c] | Other promotion or giveaway: No, Yes | 2 |
| DHeader[a] | Game is played as a double-header: No, first game, second game | 3 |
| *Variables observed as a season progresses (#12)* | | |
| Lag.GAttend[a] | Lagged HT-specific game attendance | Numeric |
| HT.Wprob[e] | HT's winning probability (calculated from betting odds) | Numeric |
| HT.GB | Games behind between HT and its division-leading team | Numeric |
| VT.GB | Games behind between VT and its division-leading team | Numeric |
| HT.Wper | HT's winning percentage (within-season) | Numeric |
| VT.Wper | VT's winning percentage (within-season) | Numeric |
| Humidity[f] | Relative humidity during the game before game day (day before) | Numeric |
| TempMax[f] | Maximum temperature (day before) | Numeric |
| TempMin[f] | Minimum temperature (day before) | Numeric |
| Weather[f] | Clear, partly cloudy, cloudy, wind, fog, rain, snow (day before) | 6 |
| Precip[f] | Precipitation: No, Yes (day before) | 2 |
| Season | Season year: 2013, 2014, 2015 (only included in the dynamic forecast) | 3 |

Notes: The data sample covers 6852 games from the 2013, 2014, and 2015 MLB regular seasons for all 29 US teams. Each HT's first game of the season and rescheduled games are not included. The HT's winning probability is calculated from betting odds. Game log data are obtained from [a] Retrosheet.com. Additional data sources: [b] Seamheads.com, [c] MBL.com, [d] Lemke et al. (2010), Beckman et al. (2012), [e] covers.com [f] and dark-sky.net (API).

While most variable descriptions are self-explanatory, in the following, I discuss further details with respect to their empirical specifications and corresponding implications. The categorical variable that accounts for home-team-specific effects also captures dependencies with respect to city characteristics such as market size, income, and demographic structure variables (Tainsky & Winfree, 2010). Similarly, team-specific ticket prices do not vary substantially from season to season and home-team effects also account for differences in ticket prices across teams (Beckman et al., 2012). The distance between ball parks is defined with respect to their longitude and latitude coordinates as the geodetic ellipsoidal distance using Vincenty's (1975) equations. In addition to a dummy variable for fireworks during a game, I include two additional distinctive but not mutually exclusive promotion categories: Bobblehead promotions are found to have a significant effect on attendance in MLB (Kappe et al., 2014; Siegfried & Eisenberg, 1980); therefore, I include a dummy variable to account for their impact. An additional dummy variable captures all other promotions, e.g. kids' days, autograph signing events, and free T-shirts or other giveaways.

A home team's implied winning probability is calculated from the historic betting odds (money line) that are taken from covers.com. A negative money line ($Ml < -100$) results in an implied winning probability ($WP$) of greater 50%, which is calculated as $WP = (Ml/(M - 100))$. A positive money line ($Ml > 100$) results in a $WP$ that is smaller 50%, which is calculated as $WP = (Ml/(Ml + 100))$. However, although betting odds are commonly used to approximate a home team's winning probability, they are not equivalent to the winning probability and betting odds may inhibit several biases (Coates & Humphreys, 2012; Forrest & Simmons, 2002; Tainsky & Winfree, 2010). Moreover, I assign the same home-team winning probabilities for second games of included double-headers as were retrieved and computed for the corresponding first games. However, the vast majority of double-headers in the data are the result of rescheduled games, which I do not include in this analysis.

All variables that account for relative within-season team performance are computed such that they include the outcome of the last game that was scheduled on the day before game day, e.g. games behind (GB). GB is a popular measure that accounts for the differences in relative team success between a leading team $L$ and another team $i$ at

time $t$. I define games behind with respect to a team's assigned division $d$ and compute it as $B_{i,t,d} = \left(\left(\sum_{t=1}^{t} Win_{L,t,d} - \sum_{t=1}^{t} Win_{i,t,d}\right) + \left(\sum_{t=1}^{t} Loss_{i,t,d} - \sum_{t=1}^{t} Loss_{L,t,d}\right)\right)/2$. It follows that a leading team's GB equals zero. However, the leading team is defined in terms of the highest (positive) difference between wins ($\sum_{t=1}^{t} Win_{L,t}$) and losses ($\sum_{t=1}^{t} Loss_{L,t}$) at time $t$. Hence, GB does not take into account the number of remaining games in the season and several teams of the same division can show a GB of zero at the same time.

Home-team division and interleague rivalry data are taken from Beckman et al. (2012) and Lemke et al. (2010). Assignment of division rivals is not constrained to be symmetric and, furthermore, I make two adjustments due to changes in teams' assigned divisions over time. CIN changed their division in 2008 and HOU their league and division in 2013. Both teams have no assigned division rivals in Lemke et al. (2010) and HOU and TEX are still interleague rivals in 2012. Therefore, I define HOU's former interleague rival TEX as their division rival and vice versa. Following the MLB attendance literature, I also include a categorical variable that accounts for games against BOS, CHC, or NYY (e.g. Beckman et al., 2012; Lemke et al., 2010). The precise division and interleague rivalry mapping is presented in Table A.2.

**Table A.2 MLB home-team names and team rivalries**

| Team | Home-team name | Division rivals | Interleague rival |
|---|---|---|---|
| ARI | Arizona Diamond Backs | COL | - |
| ATL | Atlanta Braves | NYM, MIA | - |
| BAL | Baltimore Orioles | NYY, BOS | WAS |
| BOS | Boston Red Sox | NYY | - |
| CHC | Chicago Cubs | MIL, STL | CHW |
| CHW | Chicago White Sox | CLE, DET | CHC |
| CIN | Cincinnati Reds | - | CLE |
| CLE | Cleveland Indians | DET | CIN |
| COL | Colorado Rockies | ARI | - |
| DET | Detroit Tigers | CLE | - |
| HOU | Houston Astros | TEX | - |
| KCR | Kansas City Royals | - | STL |
| LAA | Los Angeles Angels | OAK | LAD |
| LAD | Los Angeles Dodgers | SFG | LAA |
| MIA | Miami Marlins | ATL | TBR |
| MIL | Milwaukee Brewers | CHC | MIN |
| MIN | Minnesota Twins | CLE | MIL |
| NYM | New York Mets | ATL, PHI | NYY |
| NYY | New York Yankees | BOS | NYM |
| OAK | Oakland Athletics | LAA | SFG |
| PHI | Philadelphia Phillies | NYM | - |
| PIT | Pittsburgh Pirates | - | - |
| SDP | San Diego Padres | - | - |
| SEA | Seattle Mariners | - | - |
| SFG | San Francisco Giants | LAD | OAK |
| STL | St. Louis Cardinals | CHC | KCR |
| TBR | Tampa Bay Rays | - | MIA |
| TEX | Texas Rangers | HOU | - |
| WAS | Washington Nationals | - | BAL |

Notes: The home-team division and interleague rivalry data are obtained from Lemke et al. (2010) and Beckman et al. (2012). Assignment of division rivals is not constrained to be symmetric and I made two adjustments due to changes in teams' assigned divisions over time. CIN changed their division in 2008 and HOU their league and division in 2013. Both teams have no assigned division rivals in Lemke et al. (2010). HOU and TEX are still interleague rivals in 2012. Therefore, I define HOU's former interleague rival TEX as their division rival and vice versa.

## 2.2 Descriptive statistics

This section shows a list of the included predictor variables, their precise encodings, and the corresponding summary statistics in Table A.3.

**Table A.3 Variable specifications and descriptive statistics**

| Variable | Value | Description | Mean | St. Dev | Min | Max |
|---|---|---|---|---|---|---|
| *Dependent variable* | | | | | | |
| GAttend[a] | - | Game attendance (as ticket sales) | 30283 | 9609 | 8701 | 53509 |
| *Variables observed before a season starts* | | | | | | |
| HT.NoG | - | HT's number of games (within season) | 82 | 46 | 2 | 163 |
| Weekday[a] | 1 | Monday | 0.10 | 0.30 | 0 | 1 |
| | 2 | Tuesday | 0.15 | 0.36 | 0 | 1 |
| | 3 | Wednesday | 0.16 | 0.36 | 0 | 1 |
| | 4 | Thursday | 0.11 | 0.31 | 0 | 1 |
| | 5 | Friday | 0.16 | 0.37 | 0 | 1 |
| | 6 | Saturday | 0.16 | 0.37 | 0 | 1 |
| | 7 | Sunday | 0.16 | 0.37 | 0 | 1 |
| Month[a] | 1 | March / April | 0.14 | 0.35 | 0 | 1 |
| | 2 | May | 0.18 | 0.38 | 0 | 1 |
| | 3 | June | 0.17 | 0.38 | 0 | 1 |
| | 4 | July | 0.16 | 0.37 | 0 | 1 |
| | 5 | August | 0.18 | 0.38 | 0 | 1 |
| | 6 | September / October | 0.17 | 0.38 | 0 | 1 |
| Night[a] | 1 | During the night | 0.68 | 0.47 | 0 | 1 |
| Pholiday | 1 | Labor Day / 4th of July / Memorial Day | 0.02 | 0.13 | 0 | 1 |
| CTeams | 1 | 1 Team in HT's City/County | 0.86 | 0.34 | 0 | 1 |
| | 2 | 2+ Teams in HT's City/County | 0.14 | 0.34 | 0 | 1 |
| Capacity[b] | - | Stadium capacity | 42980 | 5037 | 31042 | 55500 |
| SType[b] | 1 | Open stadium | 0.79 | 0.41 | 0 | 1 |
| | 2 | Dome | 0.04 | 0.18 | 0 | 1 |
| | 3 | Retractable roof | 0.18 | 0.38 | 0 | 1 |
| SBuild[b] | 1 | Stadium is 0-5 years old | 0.15 | 0.36 | 0 | 1 |
| | 2 | Stadium is 6-10 years old | 0.77 | 0.42 | 0 | 1 |
| | 3 | Stadium is 10+ years old | 0.08 | 0.27 | 0 | 1 |
| ILGame[c] | 1 | Interleague game | 0.12 | 0.33 | 0 | 1 |
| DivGame[c] | 1 | Division game | 0.47 | 0.50 | 0 | 1 |
| DRgame[d] | 1 | Division rival game | 0.11 | 0.31 | 0 | 1 |
| ILRGame[d] | 1 | Interleague rival game | 0.02 | 0.13 | 0 | 1 |
| VTeam | 0 | Other VT | 0.91 | 0.29 | 0 | 1 |
| | 1 | VT is BOS | 0.03 | 0.17 | 0 | 1 |
| | 2 | VT is CHC | 0.03 | 0.18 | 0 | 1 |
| | 3 | VT is NYY | 0.03 | 0.17 | 0 | 1 |
| HT.WSW[c] | 1 | HT is last season's WS winner | 0.03 | 0.18 | 0 | 1 |
| VT.WSW[c] | 1 | VT is last season's WS winner | 0.03 | 0.18 | 0 | 1 |
| HT.LCSW[c] | 1 | HT is last season's LCS winner | 0.07 | 0.25 | 0 | 1 |
| VT.LCSW[c] | 1 | VT is last season's LCS winner | 0.07 | 0.25 | 0 | 1 |

| Variable | Value | Description | Mean | St. Dev | Min | Max |
|---|---|---|---|---|---|---|
| HT.DSW[c] | 1 | HT is last season's DS winner | 0.14 | 0.34 | 0 | 1 |
| VT.DSW[c] | 1 | VT is last season's DS winner | 0.13 | 0.34 | 0 | 1 |
| Distance[b] | - | Between stadiums (in miles) | 995 | 698 | 7 | 2732 |
| FWorks[c] | 1 | Fireworks promotion | 0.08 | 0.27 | 0 | 1 |
| BHeads[c] | 1 | Bobblehead promotion | 0.05 | 0.22 | 0 | 1 |
| OPromo[c] | 1 | Other promotion | 0.66 | 0.47 | 0 | 1 |
| DHeader[a] | 0 | Regular game | 0.01 | 0.11 | 0 | 1 |
| | 1 | First game of a double-header | 0.01 | 0.11 | 0 | 1 |
| | 2 | Second game of a double-header | 0.00 | 0.01 | 0 | 1 |
| *Variables observed as a season progresses* | | | | | | |
| Lag.GAttend[a] | - | Lagged HT's game attendance | 30405 | 9672 | 8701 | 53518 |
| HT.Wprob[e] | - | HT's winning probability | 0.55 | 0.08 | 0.252 | 0.780 |
| HT.GB | - | HT games behind | 6.91 | 7.16 | 0 | 44 |
| VT.GB | - | VT games behind | 6.85 | 7.14 | 0 | 43 |
| HT.Wper | - | HT's winning percentage | 0.50 | 0.09 | 0 | 1 |
| VT.Wper | - | VT's winning percentage | 0.50 | 0.09 | 0 | 1 |
| Humidity[f] | - | Humidity | 0.67 | 0.14 | 0.07 | 0.95 |
| TempMax[f] | - | Maximal measured temperature | 24.782 | 6.523 | -1.867 | 44.439 |
| TempMin[f] | - | Minimal measured temperature | 16.501 | 6.130 | -11.000 | 32.711 |
| Weather[f] | 1 | Clear day | 0.46 | 0.50 | 0 | 1 |
| | 2 | Cloudy day | 0.31 | 0.46 | 0 | 1 |
| | 3 | Snowy day | 0.00 | 0.04 | 0 | 1 |
| | 4 | Rainy day | 0.16 | 0.37 | 0 | 1 |
| | 5 | Windy day | 0.06 | 0.23 | 0 | 1 |
| | 6 | Foggy day | 0.01 | 0.09 | 0 | 1 |
| Precip[f] | 1 | Precipitation | 0.23 | 0.42 | 0 | 1 |
| Season[f] | 1 | 2013 | 0.33 | 0.47 | 0 | 1 |
| | 2 | 2014 | 0.33 | 0.47 | 0 | 1 |
| | 3 | 2015 | 0.33 | 0.47 | 0 | 1 |

Notes: The data sample covers 6852 games from the 2013, 2014, and 2015 MLB regular seasons for all 29 US teams. First home team (HT)-specific season games and rescheduled games are not included (see Section 2.1 for a detailed description of the data cleaning process). Each HT's implied winning probability is calculated from betting odds. Data sources: aRetrosheet.org, bSeahmheads.com, cMBL.com, dLemke et al. (2010), Beckman et al. (2012), ecovers.com, and fdarksky.net (API).

### 2.3 Variable importance ranking and predictor correlations

To compare and assess the observed significance of the differences in the variable importance rankings that are produced by CF, RF, and CCF for the static pre- and within-season forecasts, I follow Lessmann et al. (2010) and compute the corresponding ranking correlation coefficients by means of Kendall's $\tau$. Table A.4 shows all correlation coefficients and the associated $p$-values for the inter- and intra-season comparisons of the RF, CF, and CCF rankings.

**Table A.4 Correlation between variable importance rankings by Kendall's tau.**

| (a) Intra-season model correlation | | | | (b) Inter-season model correlation | | | |
|---|---|---|---|---|---|---|---|
| | | | Within-season | | | | |
| Ranking | RF | CF | CCF | Ranking | Within RF | Within CF | Within CCF |
| RF | 1 | 0.582*** | 0.083 | Pre RF | 0.797*** | 0.465*** | 0.015 |
| | | (0.000) | (0.567) | | (0.000) | (0.001) | (0.930) |
| CF | 0.471*** | 1 | 0.145 | Pre CF | 0.526*** | 0.871*** | 0.102 |
| | (0.001) | | (0.311) | | (0.000) | (0.000) | (0.481) |
| CCF | 0.551*** | 0.440*** | 1 | Pre CCF | 0.422*** | 0.397*** | -0.114 |
| | (0.000) | (0.002) | | | (0.003) | (0.005) | (0.428) |
| | Pre-season | | | | | | |

Notes: Kendall's rank correlation coefficient (Kendall's $\tau$) for variable importance ranking is derived from OOB estimates of random forest and conditional random forest regressions for US home-team-specific MLB game attendance for 4571 games of the regular 2013 and 2014 seasons as a training set. Maximal complex forests are trained using $B = 500$ trees for $M_{ps} = 7$ [$M_{ws} = 12$] randomly chosen predictors at each node of the $P_{ps} = 26$ [$P_{ws} = 37$] included predictors for the pre-season [within-season] model (Hothorn et al., 2015; Liaw & Wiener, 2002). The dynamic month-ahead approach includes an additional categorical variable that accounts for seasonal differences in game attendance. The results show the rankings of predictors' relevance in the forest building process for the permutation importance measures of the biased RF (scaled mean decrease in MSE), the CF (Strobl et al., 2007), and the conditional CF (CCF) approaches (Strobl et al., 2008). *** $p < 0.01$.

The WS CCF ranking is reported to be statistically significantly different from all other PS and WS rankings at a minimum $p$-value of 0.311. All other combinations of differences in importance rankings across models for both PS and WS are not significantly different from each other. Moreover, I note that for the inter-season rank comparison, only the rankings of the PS variables are compared to the relative ranks of the 27 variables in the WS rankings.

The main text only shows the ten most important pre- and within-season predictors for the static forecasting approach. The complete variable importance rankings for the static and dynamic RF and CF permutation importance measures are reported in Table A.5.

**Table A.5 Random forest and conditional random forest variable importance rankings.**

| | | Pre | | Within | | Month-ahead | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Apr | | May | | Jun | | Jul | | Aug | | Sep | |
| # | Variable | RF | CF | RF | CF | RF | CF | RF | CF | RF | CF | RF | CF | RF | CF | RF | CF |
| 1 | WDay | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 |
| 2 | HT.id | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 3 | HT.NoG | 3 | 9 | 4 | 14 | 4 | 14 | 4 | 13 | 4 | 13 | 4 | 14 | 4 | 13 | 4 | 13 |
| 4 | Distance | 4 | 14 | 10 | 23 | 11 | 23 | 10 | 24 | 11 | 24 | 8 | 24 | 12 | 23 | 8 | 23 |
| 5 | Month | 5 | 7 | 13 | 9 | 12 | 10 | 8 | 9 | 8 | 11 | 11 | 9 | 7 | 10 | 12 | 10 |
| 6 | VTeam | 6 | 13 | 16 | 16 | 15 | 19 | 16 | 19 | 14 | 18 | 14 | 15 | 15 | 18 | 13 | 18 |
| 7 | FWorks | 7 | 12 | 7 | 7 | 5 | 8 | 6 | 7 | 5 | 8 | 6 | 7 | 9 | 7 | 10 | 7 |
| 8 | Capacity | 8 | 2 | 8 | 4 | 8 | 4 | 9 | 4 | 9 | 4 | 12 | 4 | 10 | 4 | 9 | 4 |
| 9 | Night | 9 | 15 | 14 | 13 | 16 | 13 | 12 | 14 | 13 | 14 | 13 | 13 | 13 | 12 | 15 | 11 |
| 10 | VT.DSW | 10 | 18 | 22 | 22 | 25 | 24 | 25 | 23 | 26 | 23 | 25 | 25 | 25 | 25 | 26 | 29 |
| 11 | OPromo | 11 | 10 | 18 | 12 | 19 | 11 | 18 | 12 | 19 | 12 | 19 | 12 | 19 | 14 | 19 | 12 |
| 12 | BHeads | 12 | 16 | 11 | 15 | 13 | 15 | 13 | 15 | 15 | 15 | 15 | 16 | 14 | 15 | 14 | 17 |
| 13 | SBuild | 13 | 6 | 23 | 8 | 23 | 7 | 23 | 8 | 25 | 7 | 23 | 8 | 23 | 8 | 23 | 8 |
| 14 | DivGame | 14 | 19 | 32 | 30 | 30 | 31 | 31 | 31 | 36 | 32 | 30 | 30 | 32 | 30 | 29 | 30 |
| 15 | HT.DSW | 15 | 5 | 19 | 5 | 20 | 5 | 22 | 5 | 21 | 6 | 20 | 6 | 21 | 6 | 21 | 5 |
| 16 | SType | 16 | 4 | 24 | 6 | 24 | 6 | 24 | 6 | 23 | 5 | 24 | 5 | 24 | 5 | 24 | 6 |
| 17 | ILGame | 17 | 20 | 27 | 28 | 32 | 27 | 35 | 29 | 34 | 29 | 31 | 28 | 29 | 29 | 33 | 28 |
| 18 | VT.LCSW | 18 | 24 | 31 | 35 | 28 | 36 | 32 | 35 | 28 | 35 | 29 | 36 | 34 | 35 | 31 | 33 |
| 19 | CTeams | 19 | 11 | 25 | 21 | 27 | 22 | 28 | 22 | 27 | 20 | 26 | 21 | 27 | 21 | 27 | 21 |
| 20 | DRGame | 20 | 22 | 29 | 32 | 34 | 32 | 34 | 34 | 32 | 37 | 34 | 33 | 36 | 34 | 34 | 35 |
| 21 | ILRGame | 21 | 21 | 26 | 29 | 26 | 30 | 26 | 32 | 24 | 30 | 27 | 32 | 26 | 32 | 25 | 31 |
| 22 | Pholiday | 22 | 23 | 34 | 34 | 37 | 34 | 30 | 33 | 33 | 33 | 35 | 35 | 31 | 37 | 35 | 36 |
| 23 | HT.LCSW | 23 | 8 | 28 | 11 | 29 | 12 | 29 | 11 | 29 | 9 | 28 | 11 | 28 | 11 | 28 | 14 |
| 24 | VT.WSW | 24 | 25 | 33 | 36 | 31 | 37 | 33 | 37 | 31 | 36 | 32 | 34 | 33 | 31 | 32 | 37 |
| 25 | HT.WSW | 25 | 17 | 35 | 25 | 33 | 25 | 36 | 25 | 35 | 26 | 37 | 23 | 37 | 24 | 37 | 24 |
| 26 | DHeader | 26 | 26 | 37 | 37 | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| 27 | lag.GAttend | - | - | 3 | 2 | 3 | 2 | 3 | 2 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 |
| 28 | TempMax | - | - | 5 | 20 | 10 | 20 | 5 | 20 | 7 | 21 | 10 | 20 | 6 | 20 | 5 | 20 |
| 29 | HT.GB | - | - | 6 | 17 | 6 | 16 | 14 | 16 | 12 | 17 | 7 | 18 | 11 | 16 | 11 | 15 |
| 30 | TempMin | - | - | 9 | 18 | 7 | 17 | 7 | 17 | 6 | 19 | 9 | 19 | 8 | 19 | 7 | 19 |
| 31 | HT.Wper | - | - | 12 | 10 | 9 | 9 | 11 | 10 | 10 | 10 | 5 | 10 | 5 | 9 | 6 | 9 |
| 32 | VT.Wper | - | - | 15 | 19 | 14 | 21 | 15 | 21 | 16 | 22 | 18 | 22 | 16 | 22 | 16 | 22 |
| 33 | VT.GB | - | - | 17 | 26 | 18 | 29 | 17 | 27 | 18 | 27 | 17 | 29 | 17 | 28 | 17 | 27 |
| 34 | HT.Wprob | - | - | 20 | 24 | 17 | 28 | 20 | 28 | 22 | 25 | 21 | 26 | 20 | 26 | 22 | 26 |
| 35 | Humidity | - | - | 21 | 27 | 22 | 26 | 21 | 26 | 20 | 28 | 22 | 27 | 22 | 27 | 20 | 25 |
| 36 | Weather | - | - | 30 | 33 | 35 | 35 | 27 | 30 | 30 | 31 | 33 | 31 | 30 | 33 | 30 | 34 |
| 37 | Precip | - | - | 36 | 31 | 36 | 33 | 37 | 36 | 37 | 34 | 36 | 37 | 35 | 36 | 36 | 32 |
| 38 | Season | - | - | - | - | 21 | 18 | 19 | 18 | 17 | 16 | 16 | 17 | 18 | 17 | 18 | 16 |

Notes: Variable importance rankings are derived from OOB estimates of RF and CF regressions for US home-team-specific MLB game attendance for 4571 games of the regular 2013 and 2014 seasons as a training set. Maximal complex forests are trained using $B = 500$ trees for $M_{ps} = 7$ $[M_{ws} = 12]$ randomly chosen predictors at each node of the $P_{ps} = 26$ $[P_{ws} = 37]$ included predictors for the pre-season [within-season] model (Hothorn et al., 2015; Liaw & Wiener, 2002). The dynamic month-ahead approach includes an additional categorical variable that accounts for seasonal differences in game attendance. The results show the rankings of predictors' relevance in the forest building process for the permutation importance measures of the RF (scaled mean decrease in MSE) and the CF approaches (Strobl et al., 2007).

Lastly, Table A.6 shows the linear correlations between all numeric predictor variables that are employed in this study.

**Table A.6 Correlations between numeric predictor variables and game attendance.**

| Variables | GAttend | Lag.GAttend | Distance | HT.Wprob | HT.GB | VT.GB | HT.Wper | VT.Wper | HT.NoG | Humidity | TempMax | TempMin | Precip |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GAttend | 1.000 | | | | | | | | | | | | |
| Lag.GAttend | 0.773 | 1.000 | | | | | | | | | | | |
| Distance | -0.050 | -0.042 | 1.000 | | | | | | | | | | |
| HT.Wprob | 0.181 | 0.188 | 0.005 | 1.000 | | | | | | | | | |
| HT.GB | -0.235 | -0.251 | -0.016 | -0.400 | 1.000 | | | | | | | | |
| VT.GB | -0.008 | -0.006 | -0.021 | 0.405 | 0.135 | 1.000 | | | | | | | |
| HT.Wper | 0.264 | 0.268 | -0.011 | 0.390 | -0.580 | 0.069 | 1.000 | | | | | | |
| VT.Wper | 0.032 | 0.007 | -0.013 | -0.372 | 0.084 | -0.566 | -0.285 | 1.000 | | | | | |
| HT.NoG | 0.062 | 0.027 | -0.021 | 0.004 | 0.449 | 0.444 | -0.017 | 0.009 | 1.000 | | | | |
| Humidity | -0.029 | -0.040 | -0.011 | 0.030 | 0.031 | 0.066 | 0.034 | -0.005 | 0.141 | 1.000 | | | |
| TempMax | -0.021 | -0.029 | 0.033 | -0.033 | 0.179 | 0.159 | -0.036 | 0.003 | 0.396 | -0.216 | 1.000 | | |
| TempMin | -0.075 | -0.090 | 0.071 | -0.039 | 0.215 | 0.174 | -0.076 | 0.007 | 0.442 | 0.081 | 0.853 | 1.000 | |
| Precip | -0.088 | -0.103 | -0.078 | -0.013 | -0.013 | -0.036 | -0.003 | 0.020 | -0.071 | 0.405 | -0.093 | 0.039 | 1.000 |

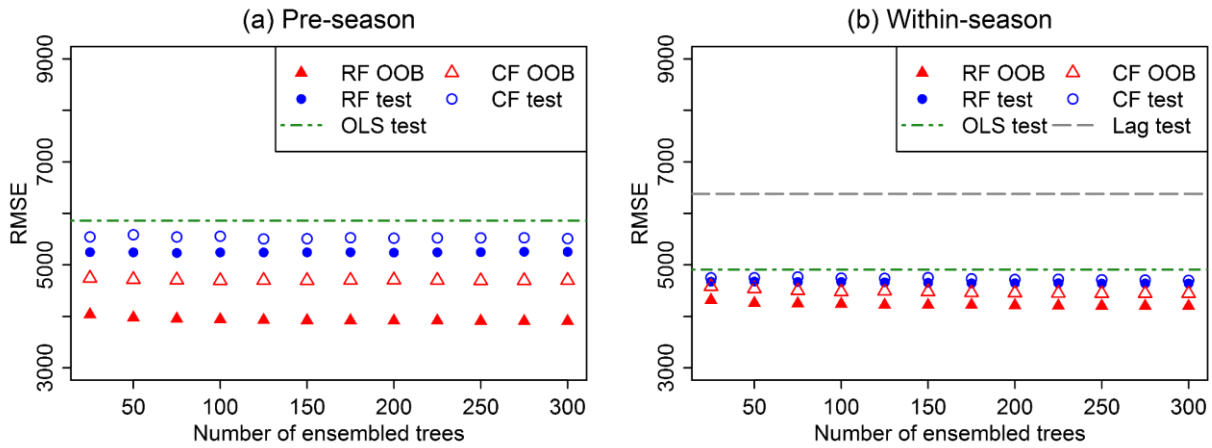
Notes: Correlations between the 13 numeric variables that are employed in this study (see Table A1). Data are based on 6852 individual MLB games from the 2013, 2014, and 2015 regular seasons.

## 3 Model performance evaluation

A popular approach in machine learning model tuning is a systematic grid-search over specific hyper-parameters (Hamza & Larocque, 2005; Lessmann et al., 2010). However, I quickly observed that the predictive performances of both the RF and CF approaches for the pre- and within-season models are not very sensitive to the number of trees per forest. The model performance evaluation in terms of the number of randomly considered predictors at each split is presented in the main paper in Section 3.1.

Figure A.1 shows the predictive accuracy in terms of RMSE on the OOB and test samples for the RF and CF regressions, together with the OLS and naive home-team-specific lagged attendance forecasts (Lag) as a benchmark. The number of randomly chosen predictors in the tree building process, which is denoted as $M$, is set to the suggested default value (one third) and RMSE is reported as the number of trees per forest $B = \{25, 50, \ldots, 300\}$. The corresponding results show that RF yields the most accurate results and RF and CF outperform the OLS model for both the pre-season (a) and the within–season forecasts (b). The OLS model yields RMSEs of 5858 (a) and 4908 (b), while the naive HT-specific lagged attendance forecast (Lag) results in an RMSE of 6377 (b).

Figure A.1 Model performance evaluation: RMSE by number of ensembled trees




Notes: Out-of-sample MLB attendance predictions by the CART (RF), conditional inference random forests (CF), OLS, and lagged attendance (Lag) models for 2281 games of the regular season of 2015 are used as a test set and 6852 games of the regular 2013 and 2014 seasons as a training set. OOB refers to a forest's predictive performance on the out-of-bag (OOB) data. Maximal complex RF and CF are trained using $\mathrm{M}_{\mathrm{ps}} = 7$ $[M_{ws} = 12]$ randomly chosen predictors at each node. The pre-season [within-season] model includes $P_{ps} = 26$ $[P_{ws} = 37]$ predictors and I grow $B = \{25, 50, \ldots, 300\}$ trees per forest.

The RMSEs for both the RF and CF approaches on the OOB and test data stabilize after averaging the prediction results of 50 trees. For (a), the RF (CF) yields minimum RMSEs of 3906 (4693) on the OOB data and 5231 (5503) on the test data. For (b), the RF (CF) yields minimum RMSEs of 4201 (4444) on the OOB data and 4638 (4670) on the test data. While the differences in prediction accuracy across models are stronger for the pre-season forecast, they do not vary substantially when trained with the additional information that is provided by the within-season variables. Moreover, the RF appears to be more affected by issues that are associated with overfitting to the training data, thereby resulting in a low RMSE on the OOB data in (a), which is adjusted based on the additional within-season information in (b). In contrast, the differences in prediction accuracy between the OOB and test data are smaller for the CF approach.

## 4 Pre- and within-season random forest predictions

Section 5 shows the team-specific RF and CF results that are omitted in the main text. Table A.7 shows the resulting prediction accuracy for the dynamic within-season RF approach and Table A.8 shows the static and dynamic CF forecasting results.

**Table A.7 Random forest predictions and attendance summary statistics by month and team**

| | Season 2015 | | | Out-of-sample monthly step-ahead RMSE | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Attendance summary | | | Random forest | | | | | |
| HT | N | Mean | SD | Apr | May | Jun | Jul | Aug | Sep |
| All | 2281 | 30197 | 9515 | 4608 | 4481 | 3994 | 4373 | 4424 | 4405 |
| ARI | 80 | 25389 | 7504 | 3989 | 4668 | 3255 | 5353 | 3454 | 4724 |
| ATL | 79 | 24748 | 8298 | 4498 | 3436 | 4567 | 6544 | 7265 | 6987 |
| BAL | 72 | 30001 | 8746 | 5140 | 6597 | 4041 | 6077 | 5991 | 6726 |
| BOS | 79 | 35572 | 1709 | 1987 | 2047 | 1736 | 1503 | 1114 | 1374 |
| CHC | 76 | 36467 | 4210 | 1523 | 2583 | 4459 | 4428 | 3219 | 2776 |
| CHW | 78 | 21687 | 7391 | 2233 | 4910 | 3423 | 3847 | 5253 | 4182 |
| CIN | 77 | 29568 | 7778 | 5264 | 4513 | 3562 | 4531 | 5893 | 4700 |
| CLE | 77 | 17573 | 5783 | 3570 | 3144 | 2848 | 3583 | 3880 | 5090 |
| COL | 76 | 31341 | 6719 | 4559 | 4461 | 3017 | 6042 | 5076 | 4063 |
| DET | 79 | 33576 | 4648 | 2660 | 3221 | 3202 | 2512 | 2103 | 3592 |
| HOU | 80 | 26373 | 6622 | 1843 | 2253 | 5263 | 6259 | 4724 | 4233 |
| KCR | 79 | 33422 | 5061 | 5614 | 5690 | 4878 | 4694 | 2880 | 2765 |
| LAA | 79 | 37092 | 5085 | 4954 | 4834 | 4302 | 3448 | 2020 | 3175 |
| LAD | 80 | 46391 | 4242 | 4564 | 3834 | 3838 | 3930 | 3106 | 3755 |
| MIA | 80 | 21441 | 4439 | 3269 | 3704 | 4649 | 4807 | 3347 | 3330 |
| MIL | 80 | 31207 | 5795 | 3693 | 4518 | 3932 | 3275 | 4238 | 5207 |
| MIN | 79 | 27173 | 6134 | 5391 | 4280 | 4581 | 3030 | 3602 | 4433 |
| NYM | 79 | 31447 | 7151 | 8807 | 4828 | 2549 | 4608 | 6022 | 4651 |
| NYY | 79 | 39814 | 4983 | 5265 | 3884 | 3640 | 4102 | 4009 | 4419 |
| OAK | 80 | 21651 | 6461 | 3985 | 3586 | 4015 | 4636 | 5869 | 5694 |
| PHI | 77 | 23189 | 4564 | 5911 | 6177 | 5303 | 4107 | 3128 | 6591 |
| PIT | 78 | 30744 | 7163 | 4216 | 4643 | 4031 | 2705 | 3350 | 3566 |
| SDP | 79 | 30287 | 7795 | 7213 | 6464 | 4590 | 5047 | 5465 | 5221 |
| SEA | 80 | 26846 | 8984 | 7167 | 8214 | 6446 | 6564 | 3958 | 3750 |
| SFG | 80 | 41673 | 387 | 602 | 331 | 343 | 627 | 237 | 230 |
| STL | 79 | 43380 | 1957 | 2450 | 1912 | 1979 | 1366 | 1190 | 1855 |
| TBR | 83 | 15133 | 4940 | 3426 | 5335 | 2779 | 3984 | 4043 | 4203 |
| TEX | 80 | 30537 | 6412 | 5281 | 4147 | 4593 | 5088 | 7459 | 5235 |
| WAS | 77 | 32453 | 5351 | 2232 | 4120 | 4375 | 4571 | 3144 | 3884 |
| R2 | - | - | - | 0.790 | 0.778 | 0.798 | 0.755 | 0.761 | 0.804 |
| Monthly season 2015 attendance summary | | | | | | | | | |
| N | 6852 | 6852 | 0 | 287 | 408 | 386 | 362 | 402 | 436 |
| Mean | - | - | - | 28154 | 29639 | 30748 | 33006 | 31158 | 28355 |
| SD | - | - | - | 10055 | 9519 | 8879 | 8842 | 9057 | 9945 |

Notes: The out-of-sample month-ahead prediction accuracies for US home-team-specific MLB game attendance for 2281 games of the regular season 2015 are used as a test set. The 4571 games of the regular 2013 and 2014 seasons are used as a training set that is updated after each month. Maximal complex random and conditional forests are trained using $B = 500$ trees for $M_{ws}$ =12 randomly chosen predictors at each node of the $P_{ws} = 38$ included predictors for the dynamic within-season forecast (Hothorn et al., 2015; Liaw & Wiener, 2002).

**Table A.8 Static and dynamic conditional random forest predictions by month and team.**

| Conditional random forest out-of-sample RMSEs | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Static forecast | | | Dynamic monthly step-ahead forecast | | | | | |
| HT | Pre | Within | Diff | Apr | May | Jun | Jul | Aug | Sep |
| All | 5523 | 4705 | 818 | 4780 | 4655 | 4198 | 4589 | 4523 | 4519 |
| ARI | 4793 | 4523 | 270 | 4183 | 4790 | 3258 | 5622 | 3747 | 4710 |
| ATL | 7516 | 6436 | 1080 | 5968 | 3892 | 4852 | 6932 | 7638 | 7005 |
| BAL | 6589 | 6213 | 376 | 4858 | 6897 | 4393 | 5987 | 6292 | 6938 |
| BOS | 1886 | 1411 | 475 | 1566 | 1545 | 1548 | 1548 | 1055 | 1409 |
| CHC | 5116 | 3619 | 1497 | 2264 | 2409 | 4444 | 4162 | 3347 | 2853 |
| CHW | 5176 | 4603 | 573 | 3180 | 4997 | 3761 | 3834 | 5682 | 4467 |
| CIN | 5400 | 4988 | 412 | 5878 | 4692 | 3564 | 4588 | 5597 | 4869 |
| CLE | 4922 | 4016 | 906 | 4138 | 3422 | 3032 | 3956 | 4518 | 5650 |
| COL | 5874 | 4809 | 1065 | 4581 | 4857 | 2928 | 6195 | 5056 | 4246 |
| DET | 3493 | 3208 | 285 | 3934 | 3645 | 3262 | 2468 | 2119 | 3545 |
| HOU | 7059 | 4770 | 2289 | 1603 | 2176 | 5324 | 6475 | 4774 | 4616 |
| KCR | 4976 | 5480 | -504 | 5746 | 6655 | 5407 | 5544 | 3808 | 3414 |
| LAA | 4438 | 4079 | 359 | 4792 | 5277 | 4564 | 3647 | 2292 | 3389 |
| LAD | 4238 | 3886 | 352 | 4567 | 3946 | 4061 | 4032 | 3076 | 3747 |
| MIA | 4051 | 3887 | 164 | 3037 | 4018 | 4625 | 5177 | 3395 | 3130 |
| MIL | 4343 | 4600 | -257 | 4003 | 4757 | 4058 | 3573 | 4305 | 5577 |
| MIN | 5699 | 4434 | 1265 | 5788 | 4507 | 4569 | 3362 | 3873 | 4367 |
| NYM | 7536 | 6387 | 1149 | 8156 | 4981 | 2709 | 4826 | 5680 | 5185 |
| NYY | 4720 | 4251 | 469 | 5232 | 4161 | 3709 | 4207 | 3979 | 4100 |
| OAK | 5135 | 5096 | 39 | 4862 | 3113 | 4194 | 5179 | 6257 | 6163 |
| PHI | 10259 | 6400 | 3859 | 6185 | 6283 | 5494 | 4683 | 3235 | 6112 |
| PIT | 4684 | 4196 | 488 | 5217 | 4878 | 4498 | 3624 | 3591 | 3914 |
| SDP | 6533 | 5890 | 643 | 6659 | 6660 | 4528 | 5455 | 5600 | 5501 |
| SEA | 7317 | 6580 | 737 | 6595 | 8240 | 7054 | 6535 | 3942 | 3912 |
| SFG | 772 | 380 | 392 | 375 | 307 | 378 | 565 | 292 | 355 |
| STL | 2205 | 1697 | 508 | 2132 | 1641 | 2016 | 1413 | 1259 | 1469 |
| TBR | 4625 | 4095 | 530 | 3227 | 5046 | 3303 | 4070 | 4254 | 3800 |
| TEX | 7356 | 5868 | 1488 | 6357 | 4691 | 5205 | 4908 | 6616 | 5394 |
| WAS | 4260 | 4047 | 213 | 2849 | 4016 | 4790 | 4907 | 3616 | 3843 |
| R2 | 0.663 | 0.755 | -0.092 | 0.773 | 0.76 | 0.776 | 0.73 | 0.75 | 0.793 |
| Monthly season 2015 attendance summary | | | | | | | | | |
| N | - | - | - | 287 | 408 | 386 | 362 | 402 | 436 |
| Mean | - | - | - | 28154 | 29639 | 30748 | 33006 | 31158 | 28355 |
| SD | - | - | - | 10055 | 9519 | 8879 | 8842 | 9057 | 9945 |

Notes: The out-of-sample month-ahead prediction accuracies for US home-team-specific MLB game attendance for 2281 games of the regular season 2015 are used as a test set. The 4571 games of the regular 2013 and 2014 seasons are used as a training set that is updated after each month. Maximal complex forests are trained using $B = 500$ trees for $M_{ps} = 7$ [$M_{ws} = 12$] randomly chosen predictors at each node of the $P_{ps} = 26$ [$P_{ws} = 37$] included predictors for the pre-season [within-season] model (Hothorn et al., 2015). The dynamic month-ahead approach includes an additional categorical variable that accounts for seasonal differences in game attendance.

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