Using Data Analysis to Predict Attendance for NHL Regular Season Games

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  - What do we want Thanksgiving week?

First, let’s plot some raw data.
Attendance* by game, from 2007-08 to 2016-17, for all 30 teams.

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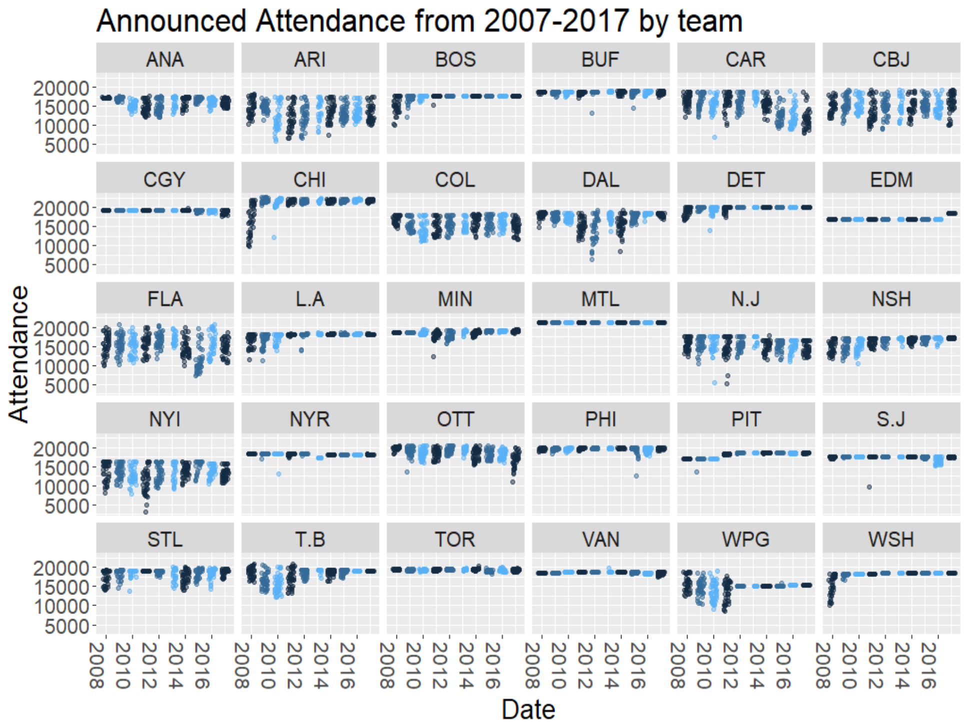
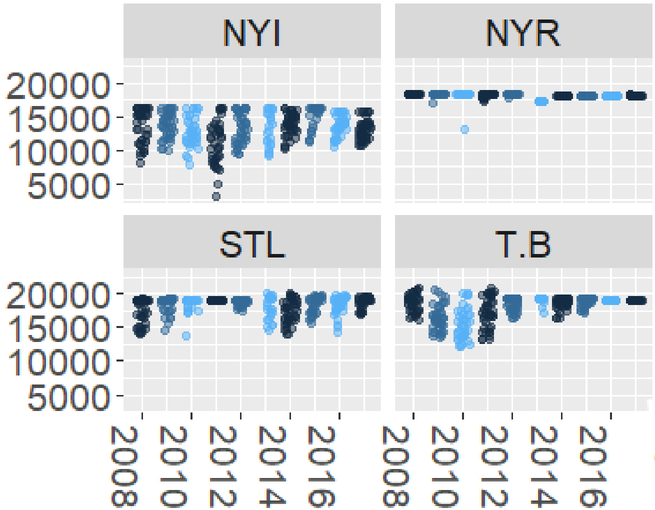
*Announced attendance, as published on nhl.com


Announced Attendance from 2007-2017 by team
ANA
ARI
BOS
BUF
CAR
CBJ
CGY
CHI
COL
DAL
DET
EDM
FLA
L.A
MIN
MTL
N.J
NSH
NYI
NYR
OTT
PHI
PIT
S.J
STL
T.B
TOR
VAN
WPG
WSH
20000
15000
10000
5000
Attendance
2008
2010
2012
2014
2016
Date

Snippet


NYI
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2010
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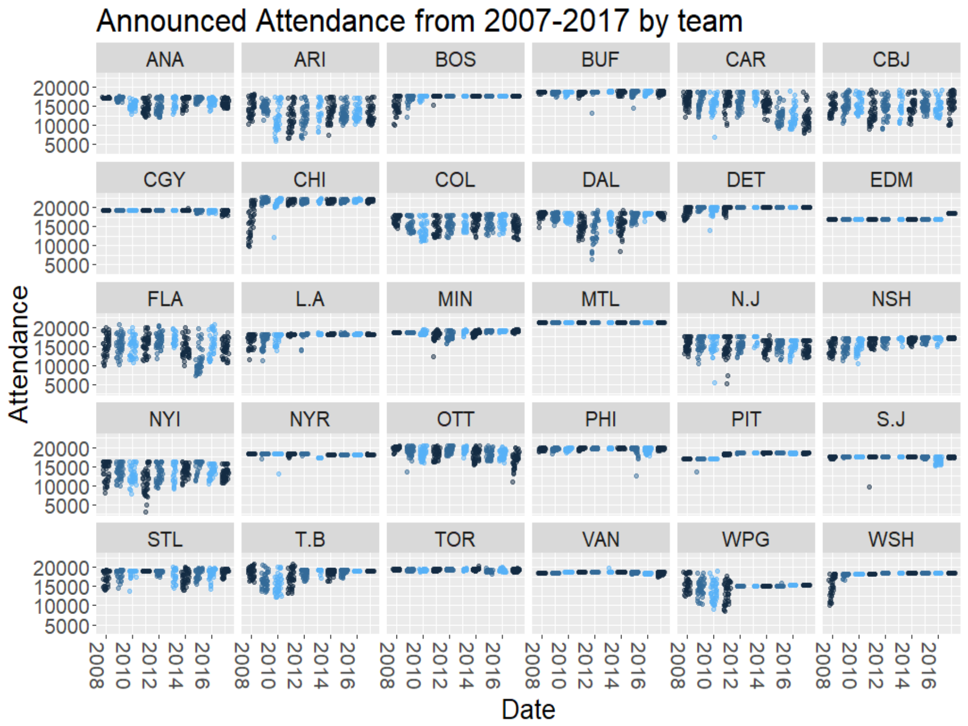
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4. Use several predictor variables (next slide)
5. Announced attendance is outcome we're trying to predict

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- home team and day interaction
- home team and month interaction
  (snowbird months good for us?)

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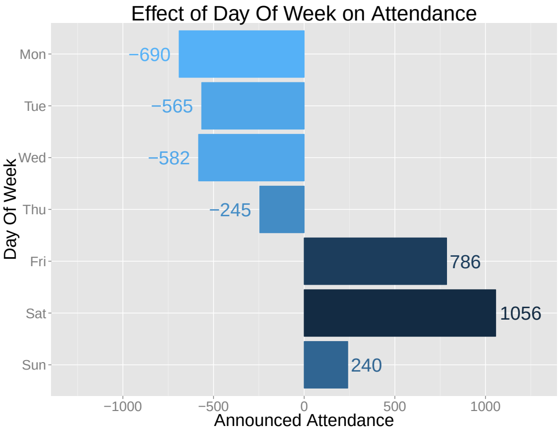
- For example, we find the effect of day, controlling for all of the other variables in our model
- That's an important point. Example: If teams schedule big opponents on the weekend, then the effect of a weekend game could be overstated if we just look at day and ignore opponent.

Example: day of week



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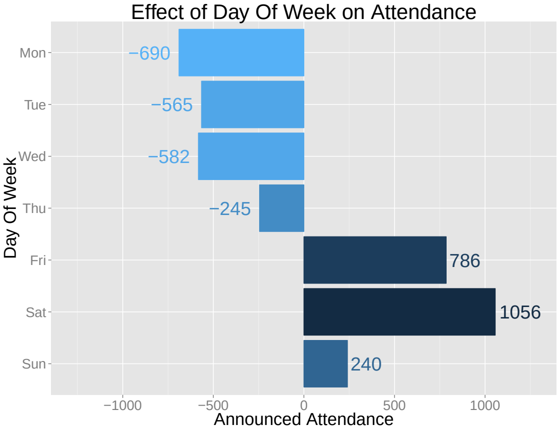

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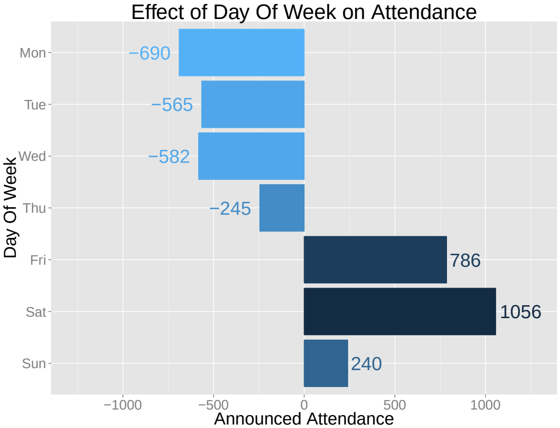

1. Attendance on Saturday is expected to be 1,056 higher than average, “holding all other variables constant."
2. The difference between Saturday and Monday is expected to be 1,746 (1,056 + 690).

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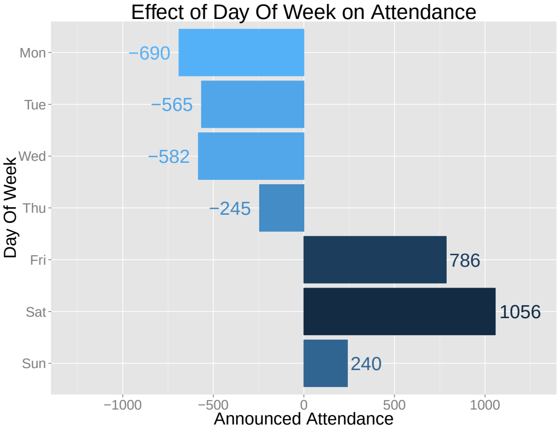
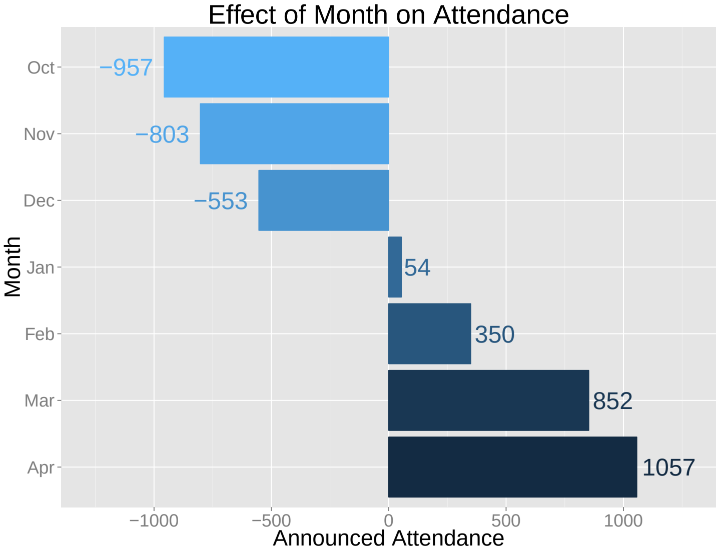
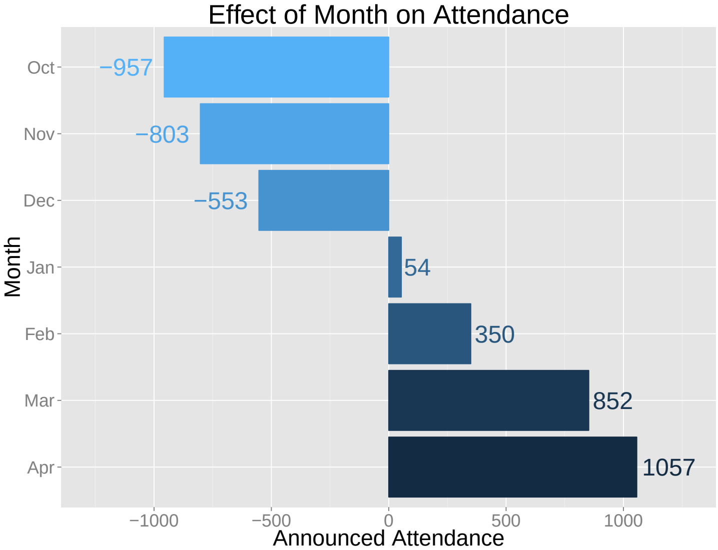


1. Attendance on Saturday is expected to be 1,056 higher than average, “holding all other variables constant."
2. The difference between Saturday and Monday is expected to be 1,746 (1,056 + 690).
3. Not surprising. Stuff we knew. But now we’ve quantified.

Month

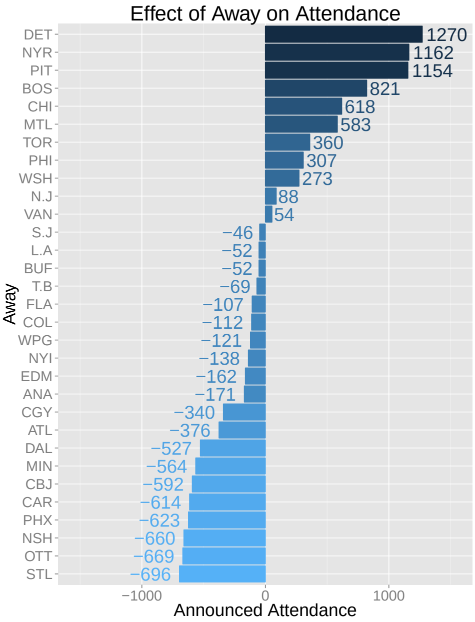

Effect of Month on Attendance
Oct
Nov
Dec
Jan
Feb
Mar
Apr
Month
−957
−803
−553
54
350
852
1057
−1000
−500
0
500
1000
Announced Attendance

Month



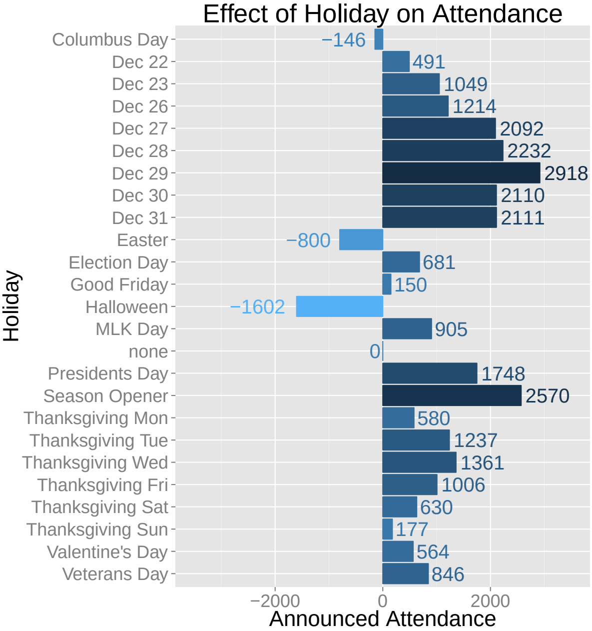
- Attendance increases over the course of the season

Away Team



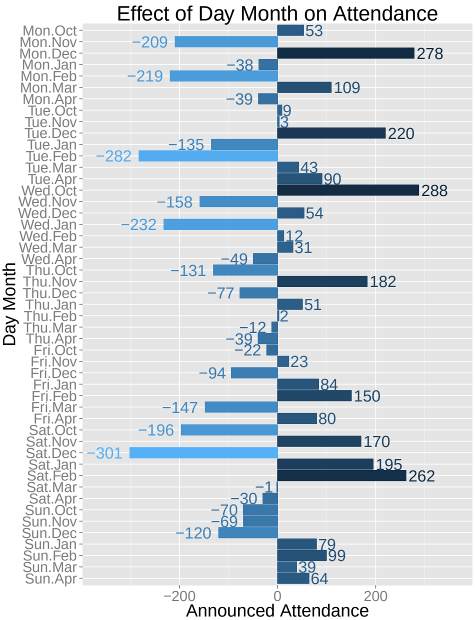
Effect of Away on Attendance
DET 1270
NYR 1162
PIT 1154
BOS 821
CHI 618
MTL 583
TOR 360
PHI 307
WSH 273
N.J 88
VAN 54
S.J −46
L.A −52
BUF −52
T.B −69
FLA −107
COL −112
WPG −121
NYI −138
EDM −162
ANA −171
CGY −340
ATL −376
DAL −527
MIN −564
CBJ −592
CAR −614
PHX −623
NSH −660
OTT −669
STL −696
Away
−1000
0
1000
Announced Attendance

Holidays



Effect of Holiday on Attendance
Holiday
Columbus Day
Dec 22
Dec 23
Dec 26
Dec 27
Dec 28
Dec 29
Dec 30
Dec 31
Easter
Election Day
Good Friday
Halloween
MLK Day
none
Presidents Day
Season Opener
Thanksgiving Mon
Thanksgiving Tue
Thanksgiving Wed
Thanksgiving Fri
Thanksgiving Sat
Thanksgiving Sun
Valentine's Day
Veterans Day
−146
491
1049
1214
2092
2232
2918
2110
2111
−800
681
150
−1602
905
0
1748
2570
580
1237
1361
1006
630
177
564
846
−2000
0
2000
Announced Attendance

Day-month combinations



Opponent-day combinations, Other Notes

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- Last year's record matters too.

Using prediction model to tier games

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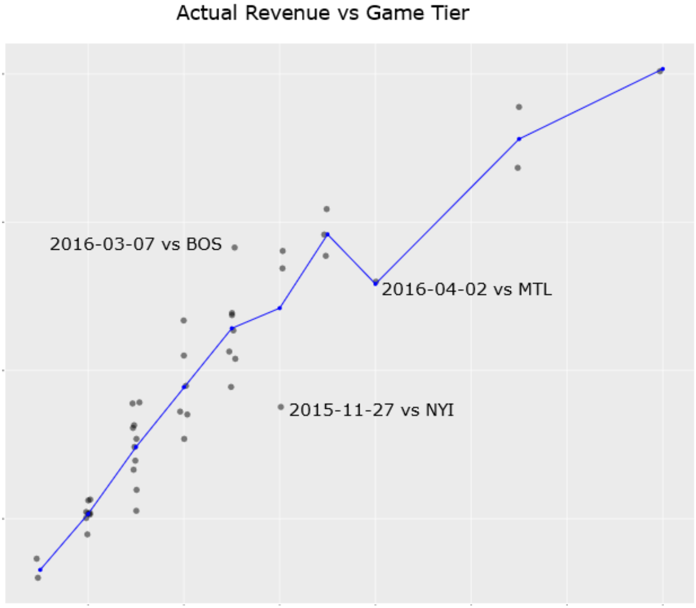
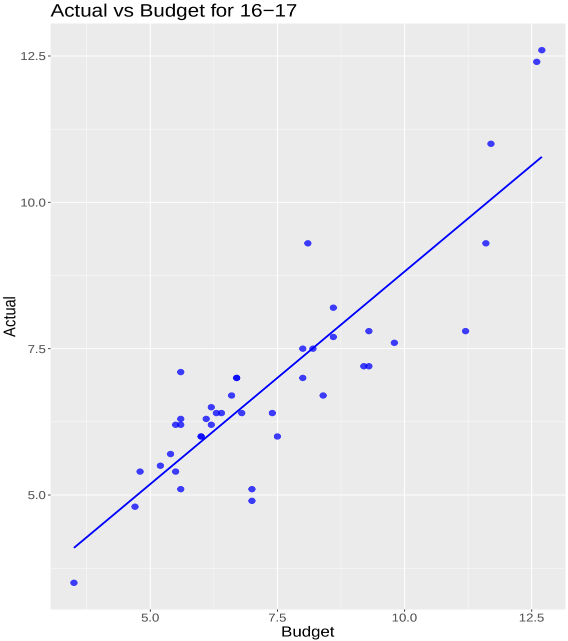


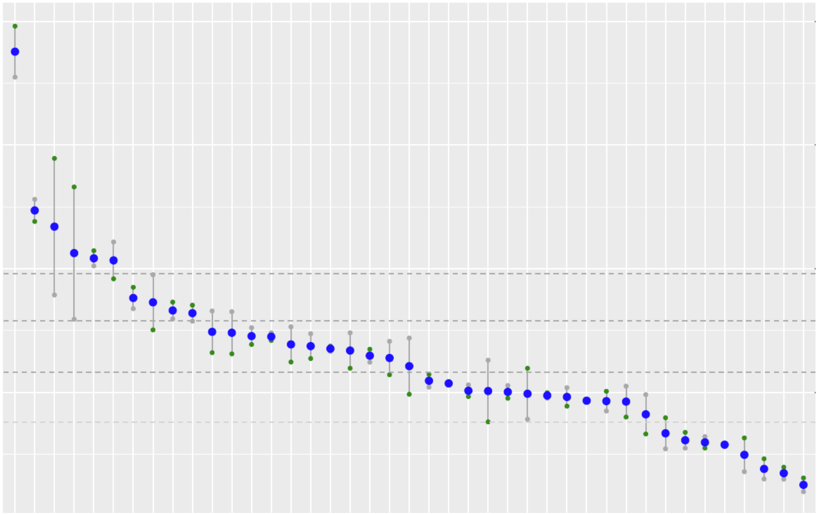
Actual vs Budget for 16-17



Internal data

1. Model using public data (2007-08 to 2016-17)
2. Model using internal data (only 2014-15 to 2016-17, but can use ticket prices and revenue)
3. Average

Predictions for 17-18



Total tickets and tickets 60 days out

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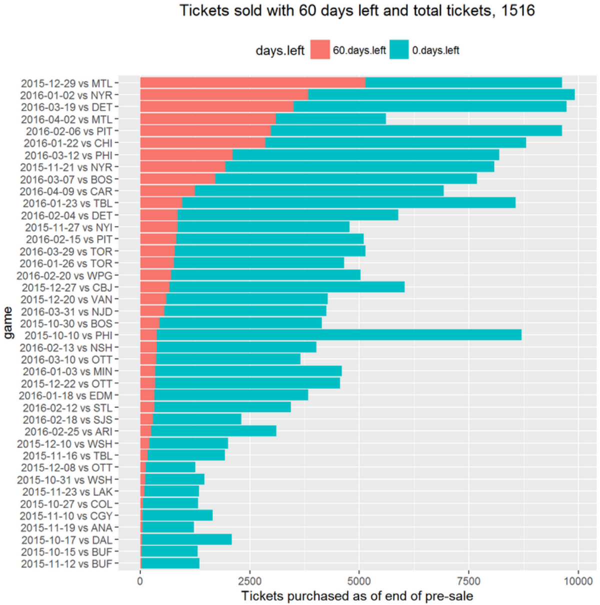

Total tickets vs tickets 60 days out

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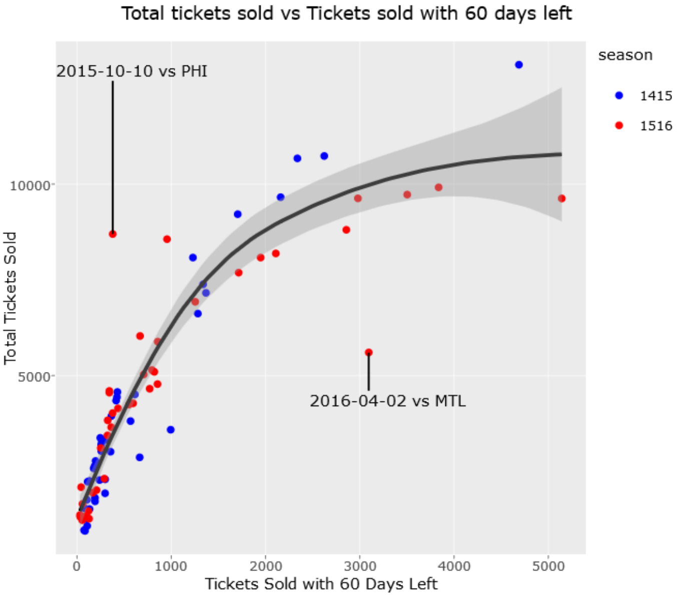

Similar relationship for *n* days out

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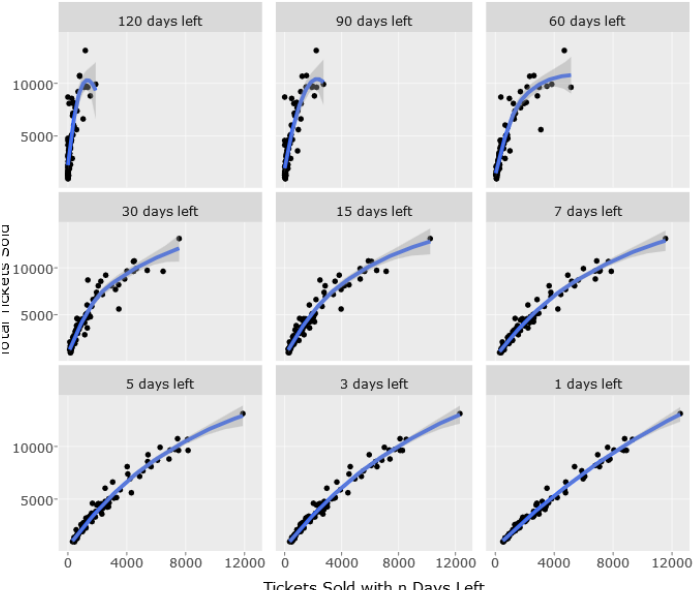

Fin.

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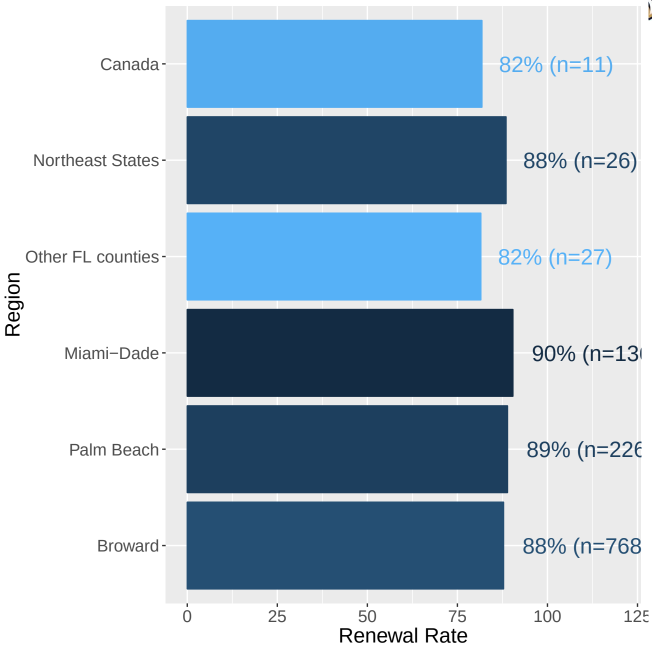
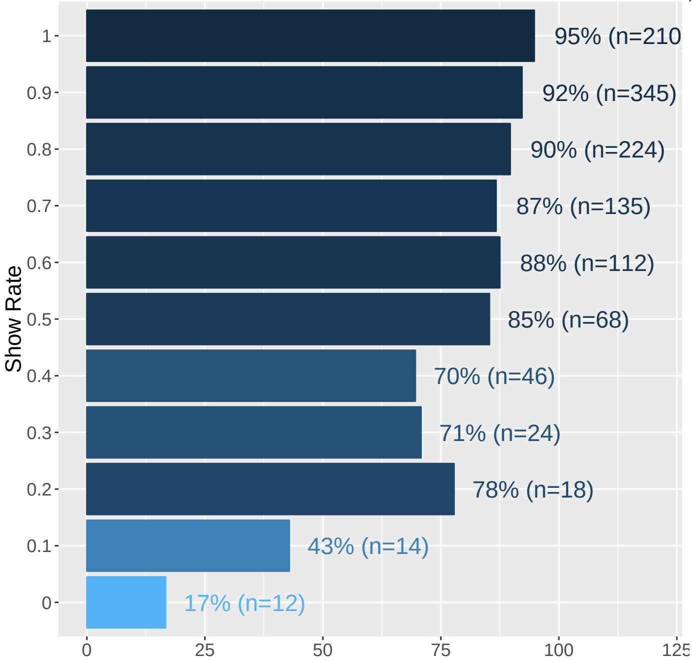
Lead scores

Lead scores



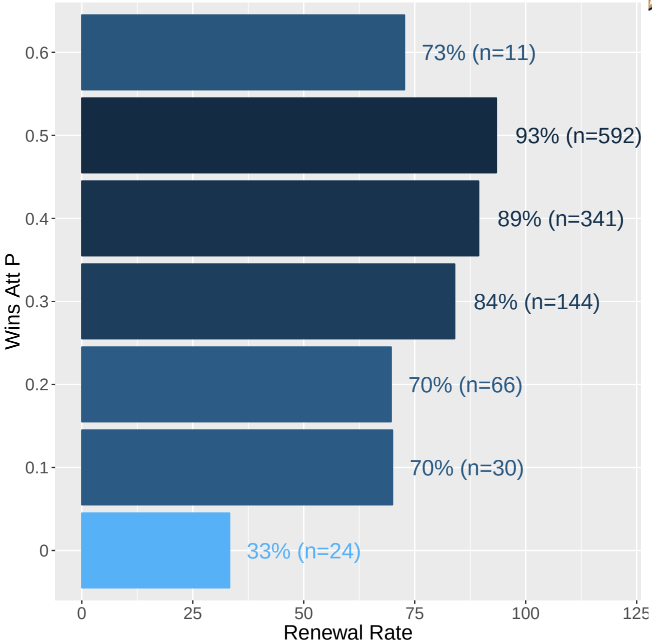
Canada
Northeast States
Other FL counties
Miami−Dade
Palm Beach
Broward
82% (n=11)
88% (n=26)
82% (n=27)
90% (n=13
89% (n=22
88% (n=768
Region
0
25
50
75
100
125
Renewal Rate

Show rate

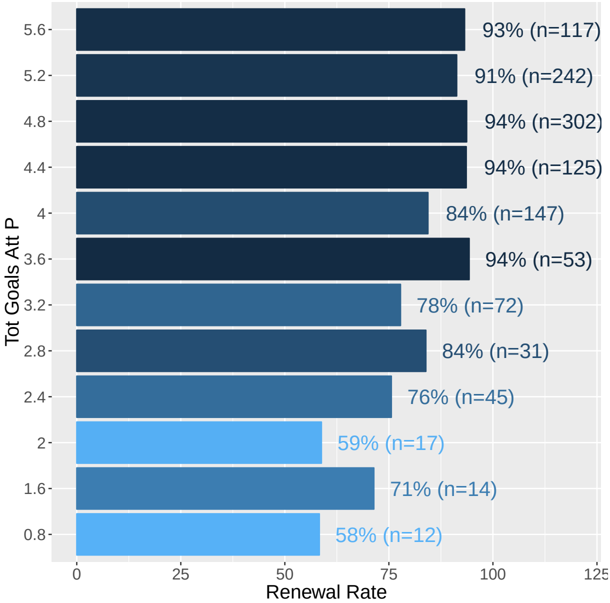


Show Rate
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
95% (n=210
92% (n=345)
90% (n=224)
87% (n=135)
88% (n=112)
85% (n=68)
70% (n=46)
71% (n=24)
78% (n=18)
43% (n=14)
17% (n=12)
0
25
50
75
100
125

Win% in games attended



Average total goals in games attended



Proportion of 1-goal games in games attended