# The Impact of Analytics Adoption on Team Performance in Professional Sports: A Longitudinal Analysis of the Lag in Observable Results

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## Abstract

The literature is full of examples of professional sports teams (managers, scouts, players, and fans) using analytics in a variety of ways to analyze and discuss patterns and trends based on descriptive data and to generate predictive models based on these data. Yet, the literature and discussions fail to consider whether analytics usage impacts performance and provides a return on the investment. Previous studies found no significant relationships between analytics adoption by the four, major U.S. professional sports teams and the teams' on-field performance or off-field performance in the year of analytics adoption. However, it is possible measurable results were delayed as this delay in observable performance results is consistent with previous research on technology implementations and has been known to exist for several decades. The current study extends the prior work in this area through analyses of performance data from 2014-2017 and whether these performance data could have been predicted by the teams' analytics adoption. The study finds statistically significant differences in the performance data when looking at the four leagues in combination and separately, but only in the second year or later. Teams should be aware that immediate impacts with analytics may not occur (as would be predicted based on the existing literature), but impacts may be realized in subsequent years. This is a critical aspect to analytics usage, and this lag effect should be considered when adopting new methods and techniques in any part of the organization.

**Keywords:** Analytics, Professional sports, Analytics adoption, Team performance, Results lag

## 1. INTRODUCTION

Business intelligence, business analytics, and big data continue to receive attention in organizations, the press, and academia (e.g., Christakis, Eisenberg, & Krumholz, 2017; Trieu, 2017; Asay, 2018; Brown, 2018; Jaklič, Grublješič, & Popovič, 2018; Knight, 2018). Business analytics is defined as "the use of data to make better, more relevant, evidence-based business decisions" (Freeman, 2016, p. 137), and it includes the tools, technologies, methodologies, and personnel needed to make such decisions. Gartner (2017) estimated business analytics expenditures to be at 18.3 billion USD in 2017, with likely growth to 22.8 billion USD by 2020. A more recent estimate puts the market growth at 33.6 billion USD by 2023 (MarketWatch, 2018).

The primary driver behind the adoption of business analytics within organizations (or industries) is to improve organizational performance factors such as higher revenue, lower costs, better product placement, more efficient supply chain management, higher customer satisfaction, fewer customer complaints/returns, better strategic decision-making, etc. (Elbashir, Collier, & Sutton, 2011; Seddon, Constantinidis, & Dod, 2012; Shanks & Bekmamedova, 2012; Gunasekaran, Papadopoulos, Dubey, Wamba, Childe, Hazen, &

Akter, 2017; Kulkarni, Robles-Flores, & Popovič, 2017; Trieu, 2017). As with nearly every business investment in technology, there needs to be a return on investment in observable value in terms of efficiency, effectiveness, or performance. Unfortunately, this return on investment for business analytics is difficult to measure (James, 2014; McCann, 2014). And if the return on investment cannot be measured, it is difficult to justify the expense and resources.

Even without such justifications, organizations continue to adopt business analytics across nearly all industries, including professional sports. After all, performance (winning) is at the heart of professional sports and arguably the primary goal of any team. While game management and real-time decision making are critical factors in the on-field success of a team, the overall success of the team entails other aspects such as player development, personnel decisions, practice/training methods, marketing, and ticket pricing (Maxcy & Drayer, 2014). Business analytics has the potential to improve performance in any (and all) of these areas.

With so much of professional sports focusing on data, measurement, and results, it would seem that measuring the return on investment from sports analytics adoption should be more straightforward than in other industries. Freeman (2016) found no significant differences with analytics adoption impacting winning percentage or attendance across the four, major U.S. sports leagues—Major League Baseball (MLB), National Basketball Association (NBA), National Football League (NFL), and National Hockey League (NHL). However, the teams in these leagues continue to adopt and implement analytics in many aspects of their operations (Baumer & Zimbalist, 2015; Lindbergh & Arthur, 2016; Breer, 2017; Elliott, 2017; Eustis, 2018; Reuters, 2018). Freeman (p. 154) called for future research to "look at performance measures in future seasons (2015, 2016, and beyond), and assess the impact of the 2014 categorizations on future performance." More specifically, Freeman (p. 154) asked whether "significant differences in on-field and off-field performance arise in future seasons based on current analytics adoption levels [and whether] a measurable lag between adoption and performance results" exists, leading to the following research questions:

- Can performance improvements be observed after analytics adoption for professional sports teams?
- How long before such improvements are observed
- Are there differences across the various leagues?

## 2. SPORTS ANALYTICS

Sports analytics refers to the use of business analytics by professional sports teams. This includes both the use of analytics within organizational processes to improve performance as well as the development of new measures and metrics that are used within these processes. Tools and techniques, whether in recruiting, training, or game-play, that provide owners, managers, trainers, scouts, and players with an understanding of past performance and/or a predictive look at future performance are likely to receive attention (Schumaker, Solieman, & Chen, 2010; Alamar, 2013). Given the abundance of available data, it is not surprising that the professional sports leagues have turned to analytics in the hope of making better decisions.

Professional sports are rooted in statistics and data. While the adoption and use of analytics by professional sports teams in general, and the Oakland A's in particular, gained mainstream attention following the release of *Moneyball: The Art of Winning and Unfair Game* (Lewis, 2004), sports analytics is much older than simply the last 20 years (Schumaker et al., 2010; Maxcy & Drayer, 2014). Bill James is often credited with starting the analytics revolution in baseball in the late 1970s which has, over time, expanded to other professional sports. Slowly at first, but with greater intensity of late, analytics staff have increased (Lindbergh & Arthur, 2016). Leagues, teams, and other organizations are spending more time and money developing new metrics and gathering, analyzing, and interpreting the vast amounts of data (Bhandari, Colet, Parker, Pines, Pratap, & Ramanujam, 1997; Baumer & Zimbalist, 2015; Breer, 2017; Elliott, 2017; Eustis, 2018; Reuters, 2018).

Much about the nature of analytics adoption and use remains secretive and proprietary. Teams often feel it is in their best interest not to publicize their analytics usage in the hope that other teams do not copy proven approaches. Still, there have been attempts at quantifying the analytics usage by the four major professional sports leagues and the teams within them. Maxcy and Drayer (2014) assessed the overall analytics adoption percentages of each of the four leagues. Based on team data, expert opinions, and evaluative data, ESPN (2015)

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released a comprehensive evaluation of all 122 teams and categorized each team into one of five categories: 1-All-In, 2-Believers, 3-One Foot In, 4-Skeptics, and 5-Nonbelievers. These categorizations were based on "the strength of each franchise's analytics staff, its buy-in from execs and coaches, its investment in biometric data and how much its approach is predicated on analytics" (ESPN, 2015). Appendix A shows the teams in the four leagues along with their categorizations, and Appendix B summarizes the findings of ESPN and Maxcy and Drayer.

Appendix B shows a majority of the Category 1 teams are from baseball, and MLB teams are skewed to the higher categorizations. In the NBA, the distribution across the five categories is more even, but with a slight nod to the higher categories. There are no Category 1 NFL teams, and the 32 teams are split between Categories 2/3 and Categories 4/5. The league percentages from Maxcy and Drayer (2014) seem to agree with the ESPN (2015) categorizations for the MLB, NBA, and NFL. However, NHL teams are heavily skewed in Categories 2 and 3, and there are the fewest number of NHL teams in Categories 4 and 5 compared to the other three leagues, a marked difference from the league percentage from Maxcy and Drayer.

Ferrari-King (2016) provided a list of the top analytics teams and the honorable mention teams. The top teams (eight in total) included five Category 1 teams and three Category 2 teams. The honorable mention teams (nine in total) included six Category 1 teams and three Category 2 teams. The 5th ranked team overall and two additional Category 1 teams from ESPN are not in either list from Ferrari-King (2016). While the overlap is not perfect, there is strong agreement regarding the top set of teams utilizing analytics.

Regarding baseball, Lampe (2015) conducted a similar analysis to Freeman (2016) on the 2015 MLB season and found that nearly 37 percent of the variance in team's winning percentage was explained by the team's analytics category from ESPN (2015). Lampe argued that most people assume that analytics usage leads to positive impacts in on-field performance, and these results provided the first glimpse of evidence that this may be true. Lampe provided anecdotal evidence of teams with higher categorizations making the playoffs but also stated that one year of data is not sufficient to make broader conclusions. Finally, Lampe used results from the 2015 season relative to the ESPN rankings (based on analytics usage in 2014). Therefore, 2015 is the second year of analytics usage, not the first as Lampe implied.

Also with regard to baseball, Baumer and Zimbalist (2015) and Lindbergh and Arthur (2016) provided measures of the analytics staff size of professional baseball teams. Baumer and Zimbalist provided staff sizes for 2014 and argued that "an initial reasonable proxy for the sabermetric orientation of a team is whether or not positions are labeled analytic or sabermetric" (Baumer & Zimbalist, 2015, p. 25). Lindbergh and Arthur included staff sizes for 2009, 2012, and 2016. The correlations between these measures of staff size and the ESPN (2015) categorizations range from 0.646 to 0.762, indicating a relatively high agreement between these two measures.

## 3. LAG RESEARCH

Freeman (2016) suggested that one year may not be enough time for the impact of analytics utilization to impact performance, calling for additional longitudinal research. Specifically, he suggested that a lag or delay may exist between analytics adoption and improvements in on-field and off-field performance, assuming improvements can be seen at all.

Major information technology (IT) investments by any organization require some period of time before returns or improvements are realized (Mahmood, Mann, Dubrow, & Skidmore, 1998; Cline & Guynes, 2001; Turedi & Zhu, 2012). Nearly 30 years ago, David (1990) attributed the delay to a necessary period of adjustment for the organization. Brynjolfsson (1993) furthered this line of thought by stating that lags are one of the possible explanations of the IT productivity paradox. Bakos (1998) referred to this lag as a diffusion delay which was further developed by Stratopoulos and Dehning (2000), who called such investments without supporting performance improvements to be irrational, and refined by Goh and Kauffman (2005).

Since the mid-1990s, a great deal of research has attempted to measure this lag or diffusion delay in various industries and with various IT investments and adoptions. Mahmood et al. (1998) argued for a two-year lag between investment in IT and improvement in financial performance, supported by Cline and Guynes (2001) concluding that IT investment is related to firm-level performance when viewed after a two-year lag, by Nicolaou (2004) regarding enterprise resource planning (ERP) implementations seeing higher performance

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after two years of continued use, and by Feng, Chen, and Liou (2005) regarding knowledge management systems implementations seeing productivity results in the second year after implementation. Other studies have shown the lag or delay to be as high as four (Turedi & Zhu, 2012) or even six years (Yaylacicegi & Menon, 2004). Most importantly, studies of IT value, IT diffusion, and business intelligence adoption continue to incorporate a lag or diffusion delay into their research models and continue to find support for the existence of this lag or delay (Chan, 2000; Thatcher & Oliver, 2001; Groznik & Kovačič, 2002; Bradford & Florin, 2003; Rei, 2004; Lee & Kim, 2006; Elbashir, Collier, & Davern, 2008; Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010; Wu & Chen, 2014; Hajli, Sims, & Ibragimov, 2015; Acheampong & Moyaid, 2016; Trieu, 2017).

This idea of a delay is not completely new to baseball, though prior analyses have not used the existing IT literature as a starting point. Lindbergh and Arthur (2016) attempted an analysis of analytics staff size on winning and found earlier adopters had greater success, as teams with an analyst in 2009 increased their winning percentage by 44 points by the 2012-14 time period (seven extra wins per season), representing a three- to five-year lag. Similarly, Baumer and Zimbalist (2015) noted that the Oakland A's, unlike the implication from the movie Moneyball, did not have immediate success following their adoption of analytics.

The relationship and connection between sports analytics adoption and success/performance is missing from the literature. There have been some efforts at understanding this relationship, but they showed insignificant or limited results. Perhaps this is due to the lag or delay discussed throughout the IT literature. And, if due to the lag or delay, how much time is necessary (how large is the lag)?

## 4. HYPOTHESES

While Freeman (2016) found no significant results in the relationship between analytics adoption and team performance in the subsequent season, the IT lag research discussed earlier suggests that a period of two or more years may be necessary before performance changes are measurable and significant. With this in mind, and considering that the original ESPN (2015) categorizations are now four years old, it is hypothesized that within the four years following the original categorizations (in line with Turedi & Zhu (2012)), teams with higher analytics adoption categorizations will have better performance than teams with lower analytics adoption categorizations.

Winning percentage is arguably the most important on-field performance variable and the most recognizable measure of success. It is also hypothesized that the same effect will be seen when looking at the cumulative winning percentages across multiple seasons (as opposed to single-season winning percentages). Attendance percentage is an indirect but easily obtained measure of off-field performance, as attendance impacts revenues from ticket sales, concession sales, and merchandise/souvenir sales (Freeman, 2016), and attendance impacts on-field performance, at least in baseball (Smith & Groetzinger, 2010). These are formally expressed as H1 through H3.

H1: Teams with higher analytics categorizations will observe higher winning percentages within four seasons.
H2: Teams with higher analytics categorizations will observe higher cumulative winning percentages within four seasons.
H3: Teams with higher analytics categorizations will observe higher attendance percentages within four seasons.

In addition to finding no significant differences overall, Freeman (2016) also found no significant differences when looking separately at the four individual leagues. However, when taking into consideration the league-level data in Appendix B (as previously discussed), MLB teams are clearly further along in their adoption of analytics than teams in the other three leagues. While no leagues saw significant results in the subsequent season (Freeman, 2016), it is hypothesized that MLB teams will be the fastest to observe significant differences in performance within the four subsequent seasons following the categorizations from ESPN. This is formally expressed as H4.

H4: MLB teams will realize performance results more quickly relative to teams from the other three leagues (NBA, NFL, and NHL).

## 5. DATA COLLECTION

This study uses the analytics adoption categorizations from ESPN (2015) and then uses four years of performance data from 2014-2017 for each of the four leagues. As the regular seasons in the NBA and in the NHL span multiple calendar years (and from time to time, this is true in the NFL as well), for the purpose of this study, the 2014 season is the 2014 season in the MLB, the 2013-2014 seasons in the NBA and in the NHL, and the 2014-2015 season in the NFL.

For each team in each league, data from ESPN.com provided the number of wins. These data allow for the calculation of team winning percentages. Winning percentage is more appropriate within and across the four leagues than raw wins for several reasons: each league plays a different number of regular season games (MLB—162, NBA and NHL—82, and NFL—16); tie games are possible in the NFL where a tie counts towards the winning percentage as half a win (but does not appear as such in the counting of wins); overtime/shootout losses are treated as half a win in the NHL and are also tracked separately from regular wins; and, usually for weather-related reasons, a team will occasionally not play a full season (especially in the MLB). Combining winning percentages across multiple years, and still taking into account the previously mentioned caveats, produced the cumulative winning percentages for 2014-15, 2014-16, and 2014-17.

Additionally, data from ESPN.com provided the full season home attendance percentage for each team in each league. As with winning percentage, attendance percentage is more appropriate than a raw attendance number as stadiums within and across the leagues have differing capacities. Using attendance percentage, an 18,000-seat hockey arena is treated equally to a 75,000-seat football stadium. This percentage is the total attendance at all home games divided by the stadium's capacity for the full season (individual game capacity x home games in a season). As some leagues allow their teams to oversell their official stadium capacity in the form of standing room only (SRO) tickets, these attendance percentages can be larger than 100 percent.

## 6. ANALYSES AND RESULTS

To maintain consistency with Freeman's (2016) data analyses, this study employed the same approaches and analyses on the previously described data regarding winning percentages, cumulative winning percentages across multiple seasons, and attendance percentages. Analysis of Variance (ANOVA) tests provided the necessary comparisons of the ESPN categorizations and subsequent performance results (winning percentage and attendance percentage) when looking at all 122 teams combined and when looking at each of the leagues individually. The resulting p-values from the ANOVA tests, as well as the corresponding r-squared values (coefficients of determination), are shown in Appendix C.

**Combined Results: Winning Percentage**
When analyzed as one group, the 122 teams from the four, major U.S. professional sports leagues show no significant difference in winning percentage in 2014 (matching Freeman's (2016) results) or 2015 ($p = 0.1300$ and $0.1154$, respectively). However, in 2016, there is a significant difference ($p = 0.0111$) in winning percentage across the five categorizations. This holds true again in 2017 ($p = 0.0021$). Appendix D shows the graphs of the four individual years, with the pattern of higher categorizations associated with higher winning percentages more definitive in 2016 and 2017.

In addition, while there were no significant results for 2014 or 2015 as individual years, the cumulative winning percentage across these two years is not quite significant ($p = 0.0728$). However, cumulative winning percentages across three years (2014-16) and four years (2014-17) are significant relative to the ESPN categorizations ($p = 0.0184$ and $0.0037$, respectively). Appendix E shows the graphs of the three cumulative winning percentage data, with each graph clearly showing the expected pattern of higher categorizations associated with higher cumulative winning percentages.

**Combined Results: Attendance Percentage**
While the overall winning percentage results showed significant differences in 2016 and 2017, the attendance percentage results found no significant differences in any of the four years.

**League Results: Winning Percentage**
Appendix C clearly shows that the league-specific results for analytics adoption on winning percentage are mostly in the MLB and NBA. There are no significant results in 2014 (in line with Freeman (2016)), but for 2015, 2016, and 2017, teams in both leagues see significant differences in winning percentage based on their analytics adoption categorization. The NFL shows no significant results, while the NHL shows significant results only in 2017. Appendix F shows the graphs of the four leagues for each of the four years, with the defining pattern evident in the MLB and NBA in 2015-2017. Note the winning percentages in the MLB (mostly

between 0.400-0.600) are more closely clustered around 0.500 than the winning percentages in the other three leagues due to the number of games in a season (162) and the law of large numbers relative to the number of games in the NBA and NHL (82) and the NFL (16).

The final analyses regarding winning percentage at the league level look at the cumulative winning percentages across multiple years. The MLB (all three combinations) and NBA (2014-16 and 2014-17) show significant results, while the NFL and NHL show no significant results across any of the combinations. Appendix G shows the graphs of the four leagues for the three cumulative winning percentage data, with the graphs clearly showing the expected pattern of higher categorizations associated with higher cumulative winning percentages for the MLB and NBA, respectively. As with seasonal winning percentages, the cumulative winning percentages in the MLB are much more compact than those in the other three leagues.

**League Results: Attendance Percentage**
Regarding attendance percentage, when the leagues are separated, the MLB shows significant results in 2016, the NFL shows significant results in 2016 and 2017, and the NHL shows significant results in 2017. The NBA shows no significant results. Appendix H shows the graphs of the four leagues for each of the four years, with the defining pattern evident in the previously mentioned years. Note that the attendance percentages in the MLB range as low as 40 percent while the attendance percentages in the other three leagues rarely drop below 80 percent, likely due to the inability to have full stadiums for 81 MLB home games with many weekday games.

**Support for the Hypotheses**
Hypotheses 1-3 stated that teams with higher analytics categorizations will observe higher winning percentages, cumulative winning percentages, and attendance percentages, respectively, within four seasons. Based on the data in Appendix C and the analyses and results described in the last section, Hypothesis 1 is supported, Hypothesis 2 is not supported, and Hypothesis 3 is supported.

Finally, Hypothesis 4 stated that MLB teams will realize performance results more quickly relative to teams from the other three leagues. Based on the data in Appendix C and the analyses and results described in the last section, Hypothesis 4 is partially supported. MLB teams realize significant performance results in terms of their winning percentage faster than NFL and NHL teams, but on par with NBA teams; and MLB teams realize significant performance results in terms of their attendance percentage faster than NBA and NHL teams, but on par with NFL teams.

## 7. DISCUSSION

This study extends Freeman (2016) by investigating performance results following analytics adoption in light of the supporting literature on the lag effect in information technology adoption.

**Interpretations and Implications: Winning Percentage**
The most important finding from this research is that the winning percentages for teams with higher analytics categorizations are significantly higher in two out of the four years (2016 and 2017, see Appendix D). This is true in 2016 even with teams in Categories 1 and 2 having the four lowest winning percentages, and in 2017 with a Category 2 team having zero wins. However, the r-squared values show less than 8 percent of the winning percentages can be explained by analytics adoption in 2014. Therefore, while there is a significant difference across categorizations, the impact across the four leagues combined is relatively small. Still, there is a measurable two-year lag (results in the third season) before performance results are seen overall.

Regarding the individual leagues (Appendix F), both the MLB and the NBA see significant differences in the second season (2015). This finding quantifies the time lag of analytics adoption success in professional baseball and basketball at one year, faster than previous research in other industries, but not immediate. It is interesting to note, however, that the significance levels in the MLB in 2016 and 2017 are decreasing (but still significant). This implies the strongest impact is in the second season. While there is still an impact in seasons three and four, other teams are catching up with their own adoptions and subsequent successes. The significance levels in the NBA are relatively consistent in these three seasons. This is more clearly shown with the r-squared values from these seasons. In the MLB, the r-squared in 2015 is 0.3696, while in 2016 and 2017 it falls to 0.1958 and 0.1836, respectively, meaning 37 percent of the winning percentages in 2015 can be explained by analytics adoption in 2014 (in agreement with Lampe (2015)) with about half of that explanatory power existing in the following two seasons. This high explanatory power in the second season indicates a strong, positive influence of analytics adoption, but not with immediate results. However, in the NBA, the explanatory power remains consistently between 17-20 percent in each of these three seasons (and consistent with the MLB in 2016 and 2017). An interesting point is that the NHL realizes a significant difference in winning percentage in the fourth season (a three-year lag) with 22 percent of the winning percentages explained by analytics adoption.

**Interpretations and Implications: Cumulative Winning Percentage**

Similar to winning percentages in individual seasons with all leagues combined, it is not until the 2016 season is included that significant results are seen (see Appendix E). While the cumulative winning percentages are significantly different in 2014-16 and in 2014-17, the relatively low r-squared values of 0.0455 and 0.0680, respectively, indicate the explanatory power of analytics adoption is not strong across all four leagues combined.

However, the explanatory power at the league level is much stronger (see Appendix G). In the MLB, all three time periods (2014-15, 2014-16, and 2014-17) saw significant results with high r-squared values between 0.3243 and 0.4250, indicating early adopters were able to maintain their advantage and edge over a period of time longer than a single season and that analytics adoption played a large part in explaining the winning percentages. The corollary is that late adopters were not able to "catch up" over time with a single season of winning. In the NBA, there were significant results in 2014-16 and 2014-17, but with lower r-squared values of 0.1537 and 0.1802. These aren't as high as those in the MLB, but are much higher than for all leagues combined. The NFL and the NHL saw no significant results for cumulative winning percentage in any of the time periods which is not surprising given the results for the individual season results for winning percentage.

**Interpretations and Implications: Attendance Percentage**

Overall, with all leagues combined, there were no significant differences in any of the four seasons. At the league level (Appendix H), higher attendance percentages were seen in only one of the four years for the MLB—2016, with an r-squared of 0.1436. As attendance is likely to be higher for winning teams, it is not surprising that the impact of analytics on attendance in the MLB requires an additional year to see significant results. In other words, once the teams with higher analytics categorizations began to have statistically higher winning percentages in 2015, their attendance percentages became statistically higher in 2016 (the following season), though analytics adoption only explained 14 percent of the attendance percentages. However, this same logic does not hold in the NBA where no seasons saw significant attendance percentage differences.

The NFL saw significant differences in 2016 (r-squared = 0.1243) and 2017 (r-squared = 0.1521), but there were no corresponding difference in winning percentages in any of the seasons. The NHL saw significant differences only in 2017 (r-squared = 0.2031), the same three-year lag seen in winning percentage, with similar explanatory power. While owners and general managers might argue that attendance is less important than winning, attendance impacts team revenue (tickets, concessions, and souvenirs) and creates a home-field advantage.

**Research Questions**

Returning to the research questions from the beginning of this study, performance improvements in winning percentage, attendance percentage, and cumulative winning percentage have been found. While Freeman (2016) found no such results when looking at 2014 data, the inclusion of data from 2015-2017 show that lags of one year (winning percentage in the MLB and NBA), two years (attendance percentage in the MLB and NFL), and three years (winning percentage and attendance percentage in the NHL) exist.

**Limitations**

This research used the same analytics categorizations from ESPN (2015) as Freeman (2016), as well as the same measures of performance. The categorizations were subjective, but they come from a trusted source for sports data and analyses. In addition, there is some agreement between the ESPN categorizations and the even more subjective categories of Ferrari-King (2016). Similarly, while other measures such as staff size have been used as a proxy for analytics adoption, the ESPN categorizations go beyond staff size. Regarding the performance measures, winning percentage seems the most obvious, primary measure, but there are many others from which to choose beyond that, such as team revenue and more granular offensive or defensive statistics.

The level or intensity of analytics adoption and use in 2017 will likely be quite different than the level or intensity in 2014. This is a rapidly changing and growing field. Early adopters have likely continued to increase their adoption and usage of analytics, and early non-adopters are able to copy what the early adopters have done. However, the IT literature clearly supports the use of independent variable data from one year to measure dependent variable data in subsequent years in order to identify the lag effect or diffusion delay.

**Future Research**

This study's results elicit additional questions that require future research efforts. One, as mentioned earlier in the Discussion, is why the change in winning percentage is sometimes in the opposite direction from what would be predicted (i.e., teams with lower analytics categorizations saw larger, positive changes in winning percentage than teams with higher analytics categorizations). Another area in need of further research is to analyze analytics adoption at a more granular level—on-field versus back-office utilization—in terms of an impact on performance. It would also be interesting to analyze the results of games played between teams of different analytics categories (i.e., do teams in higher categories win more often?). And a fourth area is to use additional or different performance measures beyond winning percentage and attendance percentage.

## 8. CONCLUSION

Freeman (2016) only looked at the performance in a single year, when it is possible that the impact of analytics adoption takes longer to realize. This study extends the work of Freeman through analyses of winning percentage over time for the 122 teams in the four, major U.S. professional sports leagues since 2014 and whether these performance data could have been predicted by the teams' analytics adoption. The data also include the measurement of attendance as a secondary indicator of performance. Based on the teams' 2014 analytics adoption as reported by ESPN (2015), analyses support the idea that statistically significant differences in teams' winning percentage and attendance exist when looking at performance data from seasons beyond 2014 (namely, 2015-2017). In addition, the differences often remain significant for multiple seasons. This research provides the necessary analyses to investigate the limitation from Freeman (2016) regarding the potential lag between analytics adoption and performance improvements.

Most technology implementations do not produce immediate, measurable results for the adopting organization. Time is needed for the technology to have an impact on the organization's performance. This is no different in the U.S. professional sports leagues. Leagues and teams should be aware that immediate impacts with analytics may not occur, but impacts may be realized in subsequent years depending on the league.

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## APPENDIX A

All 122 teams and their ESPN (2015) categorizations. Teams within leagues are ordered by category (1-5) and then alphabetically by team within each category. Numbers in parentheses represent top 10 and bottom 10 rankings out of all 122 teams. Copied with permission from Freeman (2016).

| MLB | NBA | NFL | NHL* |
|---|---|---|---|
| Boston Red Sox—1 (5) | Dallas Mavericks—1 (8) | Atlanta Falcons—2 | Chic. Blackhawks—1 (10) |
| Chicago Cubs—1 | Houston Rockets—1 (3) | Baltimore Ravens—2 | Boston Bruins—2 |
| Cleveland Indians—1 | Philadelphia 76ers—1 (1) | Cleveland Browns—2 | Buffalo Sabres—2 |
| Houston Astros—1 (2) | San Antonio Spurs—1 (7) | Dallas Cowboys—2 | Columbus Blue Jackets—2 |
| NY Yankees—1 (6) | Atlanta Hawks—2 | Jacksonville Jaguars—2 | Edmonton Oilers—2 |
| Oakland A's—1 (9) | Boston Celtics—2 | Kansas City Chiefs—2 | LA Kings—2 |
| Pittsburgh Pirates—1 | Cleveland Cavaliers—2 | New England Patriots—2 | Minnesota Wild—2 |
| St. Louis Cardinals—1 | Detroit Pistons—2 | Philadelphia Eagles—2 | New York Islanders—2 |
| TB Rays—1 (4) | Golden State Warriors—2 | SF 49ers—2 | Pittsburgh Penguins—2 |
| Baltimore Orioles—2 | Memphis Grizzlies—2 | Buffalo Bills—3 | St. Louis Blues—2 |
| Kansas City Royals—2 | OKC Thunder—2 | Chicago Bears—3 | TB Lightning—2 |
| LA Dodgers—2 | Portland Trail Blazers—2 | Green Bay Packers—3 | Toronto Maple Leafs—2 |
| NY Mets—2 | Charlotte Hornets—3 | Miami Dolphins—3 | Wash. Capitals—2 |
| San Diego Padres—2 | Indiana Pacers—3 | Oakland Raiders—3 | Winnipeg Jets—2 |
| Toronto Blue Jays—2 | Miami Heat—3 | Seattle Seahawks—3 | Arizona Coyotes—3 |
| Wash. Nationals—2 | Milwaukee Bucks—3 | TB Buccaneers—3 | Calgary Flames—3 |
| Chicago White Sox—3 | Orlando Magic—3 | Arizona Cardinals—4 | Carolina Hurricanes—3 |
| LA Angels—3 | Phoenix Suns—3 | Carolina Panthers—4 | Dallas Stars—3 |
| Milwaukee Brewers—3 | Sacramento Kings—3 | Cincinnati Bengals—4 | Detroit Red Wings—3 |
| SF Giants—3 | Toronto Raptors—3 | Denver Broncos—4 | Florida Panthers—3 |
| Seattle Mariners—3 | Utah Jazz—3 | Detroit Lions—4 | Montreal Canadiens—3 |
| Texas Rangers—3 | Chicago Bulls—4 | Houston Texans—4 | Nashville Predators—3 |
| Ariz. Diamondbacks—4 | Denver Nuggets—4 | Indianapolis Colts—4 | New Jersey Devils—3 |
| Atlanta Braves—4 | LA Clippers—4 | Minnesota Vikings—4 | Philadelphia Flyers—3 |
| Cincinnati Reds—4 | Minn. Timberwolves—4 | New Orleans Saints—4 | San Jose Sharks—3 |
| Colorado Rockies—4 | New Orleans Pelicans—4 | NY Giants—4 | Vancouver Canucks—3 |
| Detroit Tigers—4 | Washington Wizards—4 | Pittsburgh Steelers—4 | Anaheim Ducks—4 |
| Minnesota Twins—4 | Brooklyn Nets—5 (118) | St. Louis Rams—4 | New York Rangers—4 |
| Miami Marlins—5 (115) | LA Lakers—5 (113) | NY Jets—5 (114) | Ottawa Senators—4 |
| Phil. Phillies—5 (122) | NY Knicks—5 (121) | SD Chargers—5 (119) | Col. Avalanche—5 (117) |
| | | Tenn. Titans—5 (116) | |
| | | Wash. Redskins—5 (120) | |

***** The Vegas Golden Knights began play in 2017-2018, and are therefore not included here.

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**APPENDIX B**

Team categorizations (ESPN, 2015) and adoption percentages (Maxcy & Drayer, 2014) by league, copied with permission from Freeman (2016).

| League | ESPN Category 1 "All-In" | ESPN Category 2 "Believers" | ESPN Category 3 "One Foot In" | ESPN Category 4 "Skeptics" | ESPN Category 5 "Nonbelievers" | Maxcy and Drayer |
|---|---|---|---|---|---|---|
| MLB | 9 | 7 | 6 | 6 | 2 | 97% |
| NBA | 4 | 8 | 9 | 6 | 3 | 80% |
| NFL | 0 | 9 | 7 | 12 | 4 | 56% |
| NHL | 1 | 13 | 12 | 3 | 1 | 23% |

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**APPENDIX C**

ANOVA p-values across all variables and years by league. Individual cells are shaded according to significance levels of 0.05, 0.01, and 0.001 to aid in interpretation and pattern identification. In addition to the p-values, the corresponding r-squared values (coefficients of determination) are shown.

| | | ALL TEAMS | MLB | NBA | NFL | NHL |
|---|---|---|---|---|---|---|
| **Winning Percentage** | **2014** | 0.1300 (0.0850) | 0.1181 (0.0850) | 0.4231 (0.0230) | 0.3334 (0.0312) | 0.5045 (0.0161) |
| | **2015** | 0.1154 (0.0205) | 0.0004 (0.3696) | 0.0167 (0.1878) | 0.2392 (0.0459) | 0.5985 (0.0100) |
| | **2016** | 0.0111 (0.0526) | 0.0143 (0.1958) | 0.0231 (0.1710) | 0.6721 (0.0060) | 0.6724 (0.0065) |
| | **2017** | 0.0021 (0.0761) | 0.0181 (0.1836) | 0.0143 (0.1959) | 0.6355 (0.0076) | 0.0085 (0.2222) |
| **Cumulative Winning Percentage** | **2014-15** | 0.0728 (0.0266) | 0.0010 (0.3243) | 0.0702 (0.1123) | 0.9217 (0.0003) | 0.4977 (0.0166) |
| | **2014-16** | 0.0184 (0.0455) | 0.0006 (0.3513) | 0.0321 (0.1537) | 0.9031 (0.0005) | 0.7150 (0.0048) |
| | **2014-17** | 0.0037 (0.0680) | 0.0000 (0.4250) | 0.0194 (0.1802) | 0.7821 (0.0026) | 0.5768 (0.0113) |
| **Attendance Percentage** | **2014** | 0.4490 (0.0048) | 0.4322 (0.0222) | 0.5394 (0.0136) | 0.3545 (0.0286) | 0.0998 (0.0938) |
| | **2015** | 0.9779 (0.0000) | 0.1064 (0.0904) | 0.9741 (0.0000) | 0.3152 (0.0336) | 0.1058 (0.0907) |
| | **2016** | 0.5615 (0.0028) | 0.0389 (0.1436) | 0.6142 (0.0092) | 0.0478 (0.1243) | 0.1655 (0.0675) |
| | **2017** | 0.3922 (0.0061) | 0.0865 (0.1013) | 0.5536 (0.0127) | 0.0273 (0.1521) | 0.0124 (0.2031) |

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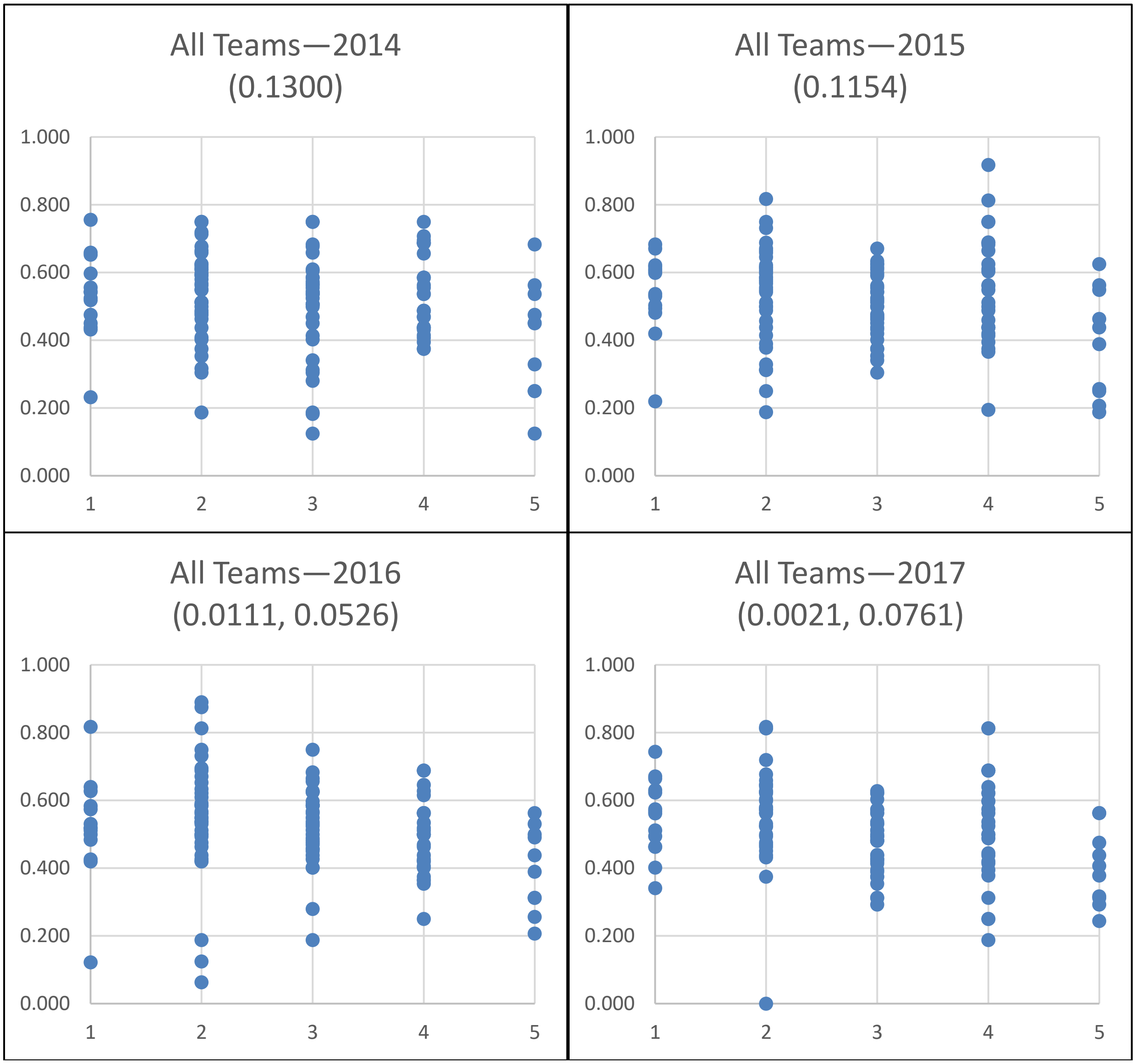
## APPENDIX D

Winning percentages for all teams combined mapped to their ESPN categorization, 2014-2017. Below the graph title are the p-value and r-squared value (if significant) from Appendix C.

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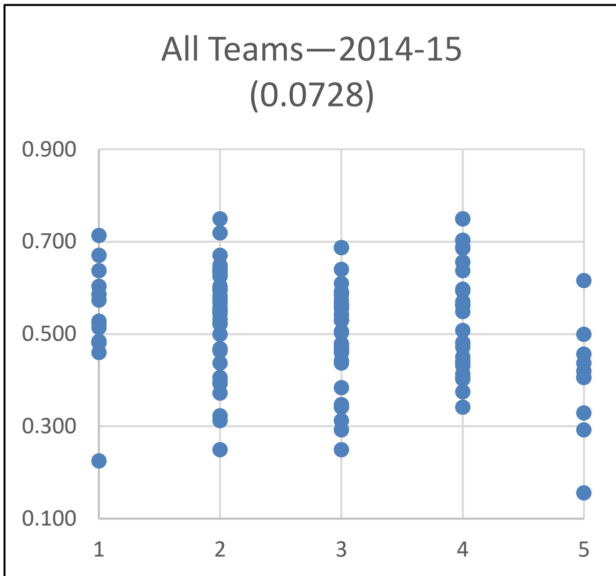
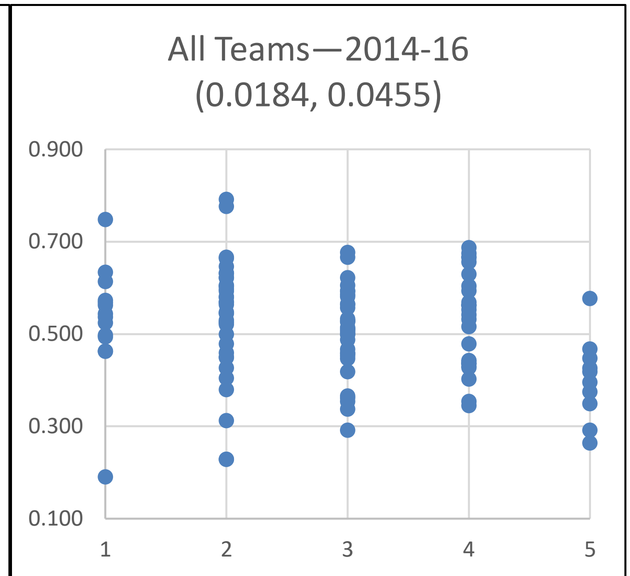
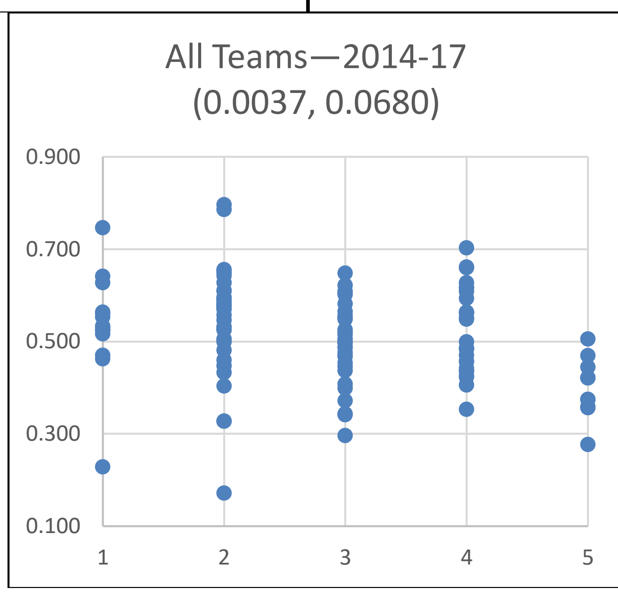
## APPENDIX E

Cumulative winning percentages for all teams combined mapped to their ESPN categorization. Below the graph title are the p-value and r-squared value (if significant) from Appendix C.

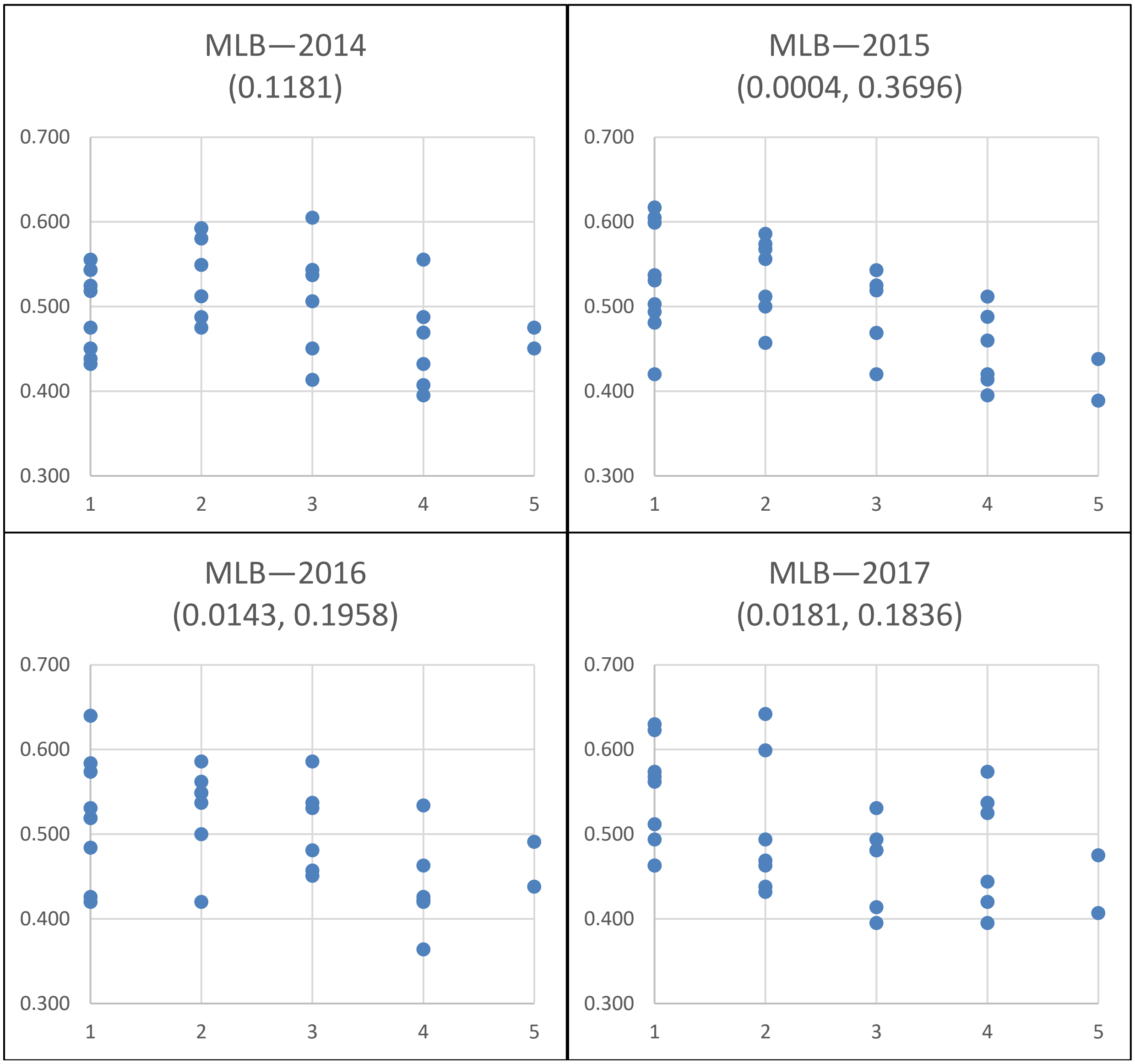


**APPENDIX F**

Winning percentages for all teams by league mapped to their ESPN categorization, 2014-2017. Below the graph title are the p-value and r-squared value (if significant) from Appendix C.



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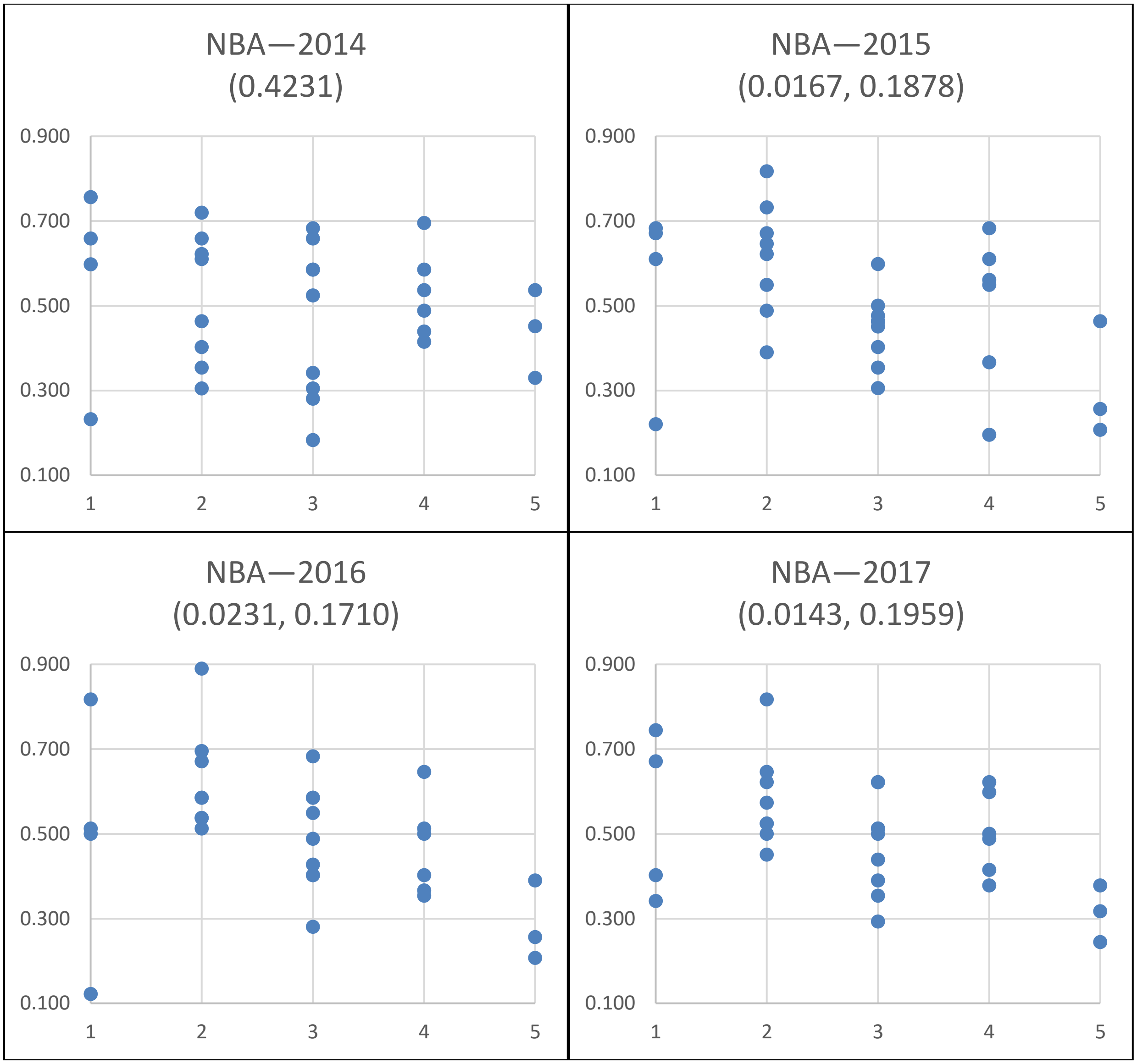
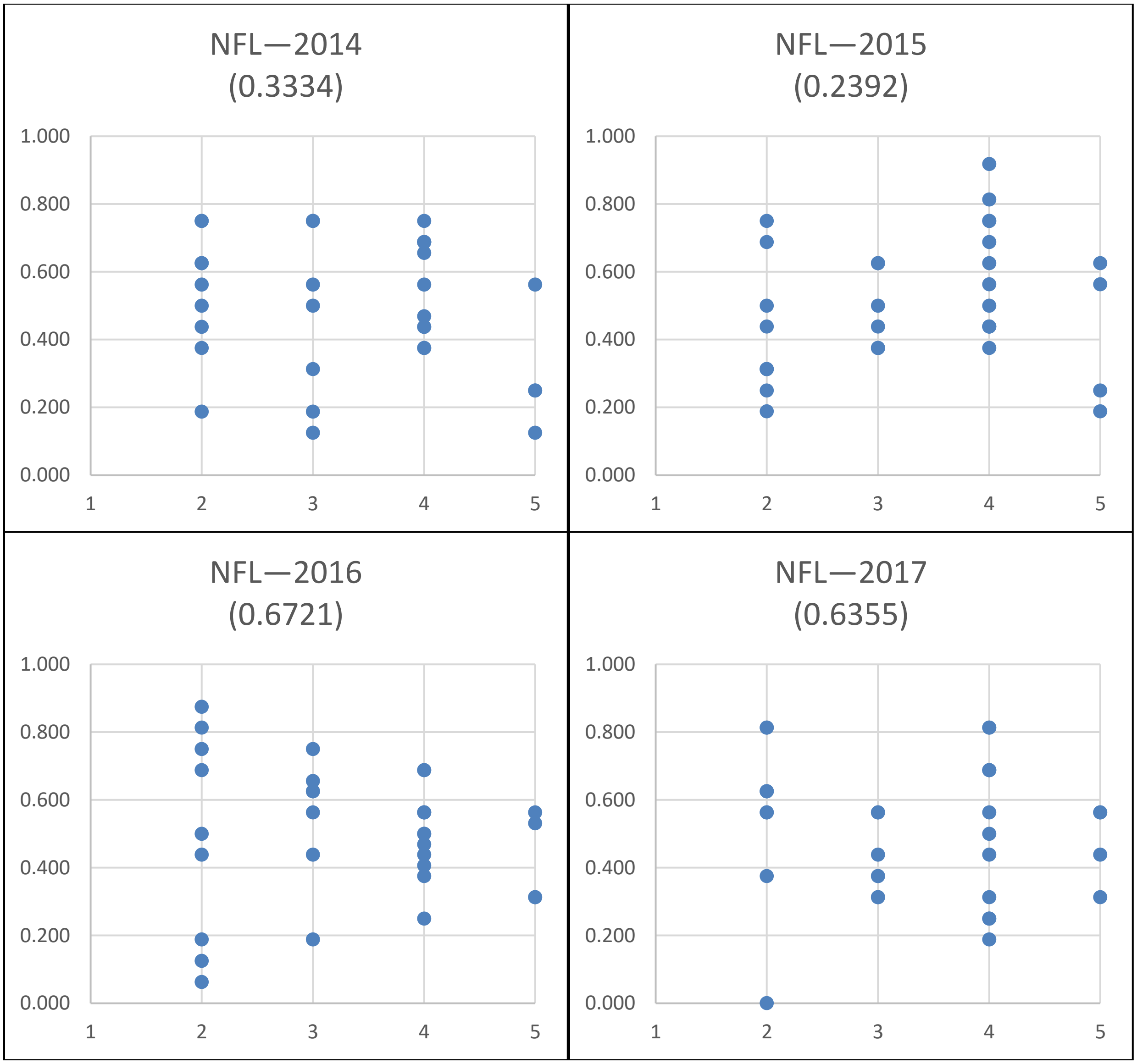
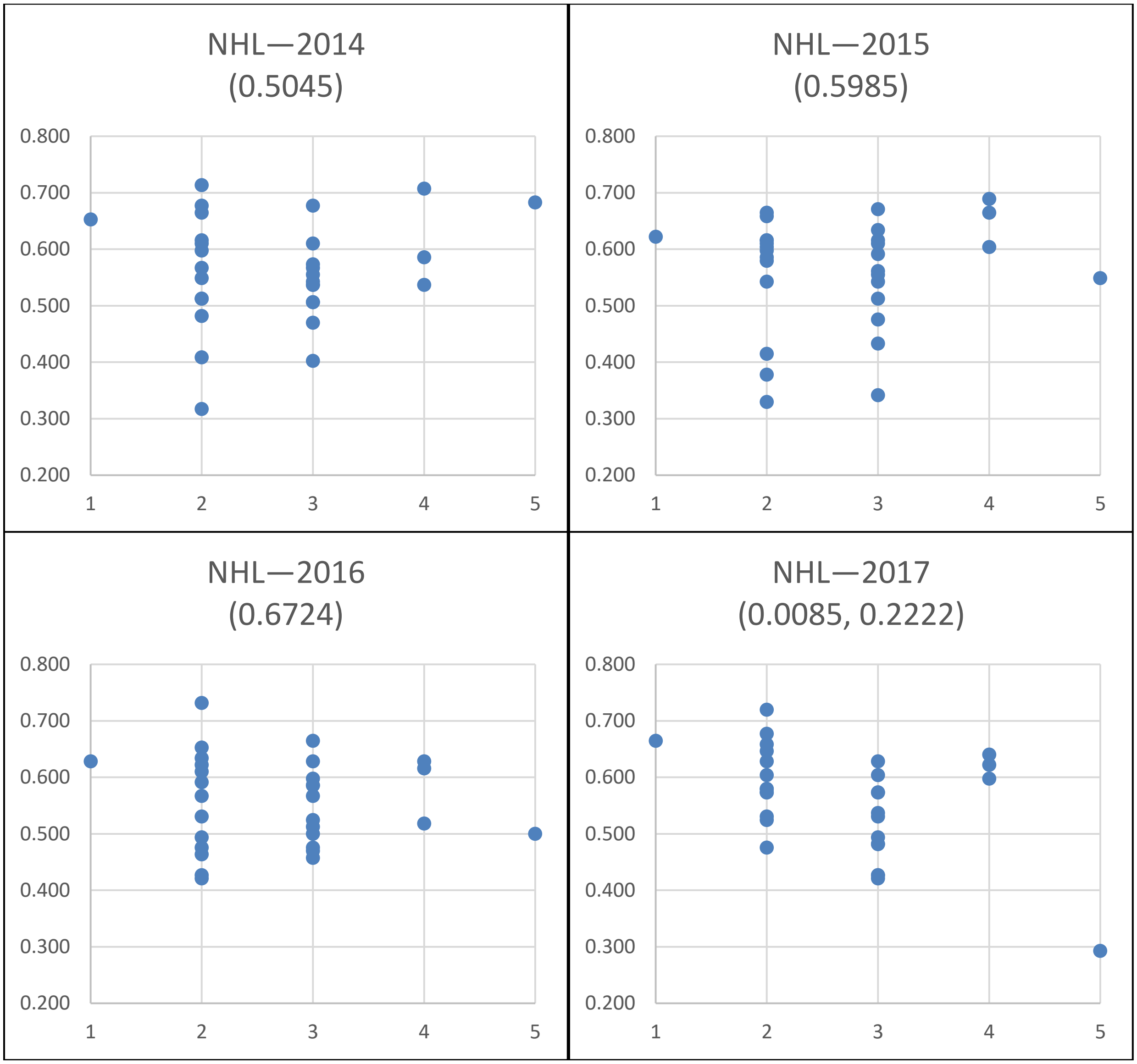
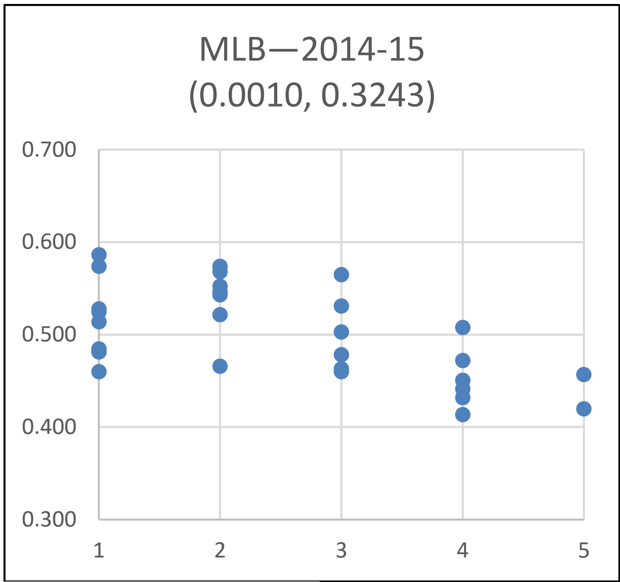


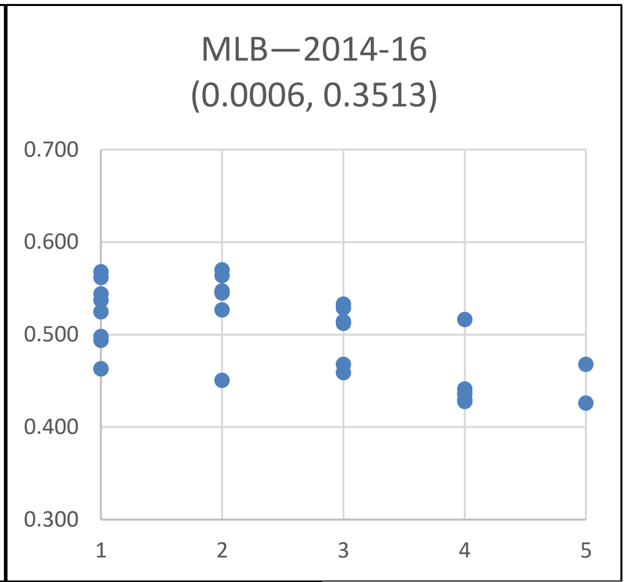

NFL—2014
(0.3334)
1.000
0.800
0.600
0.400
0.200
0.000
1 2 3 4 5
NFL—2015
(0.2392)
1.000
0.800
0.600
0.400
0.200
0.000
1 2 3 4 5
NFL—2016
(0.6721)
1.000
0.800
0.600
0.400
0.200
0.000
1 2 3 4 5
NFL—2017
(0.6355)
1.000
0.800
0.600
0.400
0.200
0.000
1 2 3 4 5

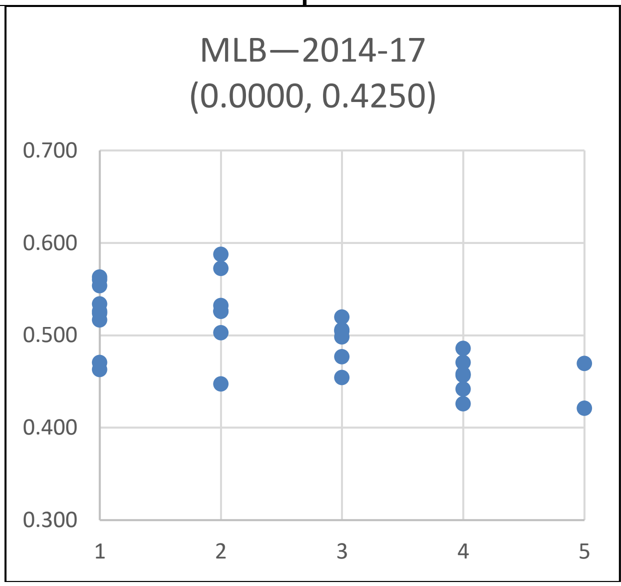

NHL—2014
(0.5045)
NHL—2015
(0.5985)
NHL—2016
(0.6724)
NHL—2017
(0.0085, 0.2222)
0.800
0.700
0.600
0.500
0.400
0.300
0.200
1
2
3
4
5

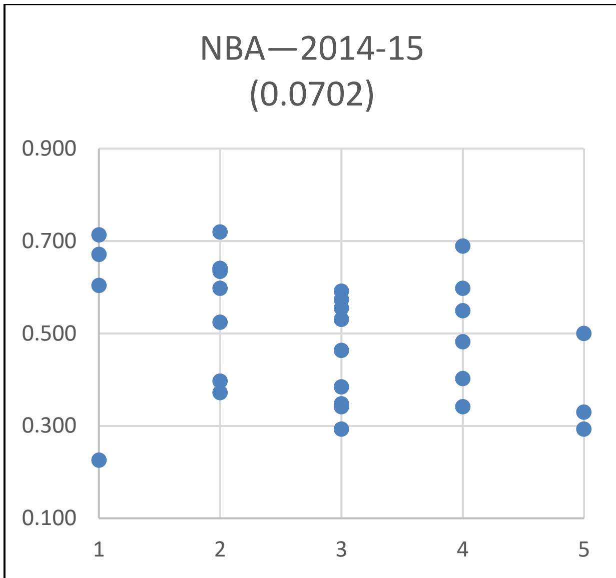
**APPENDIX G**

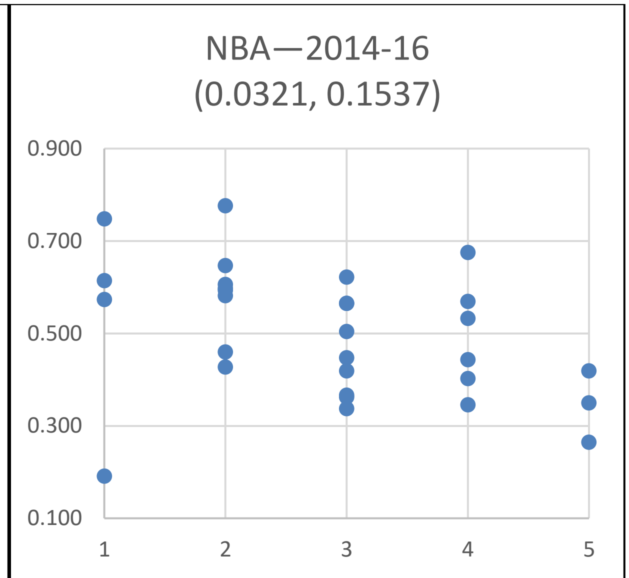
Cumulative winning percentages for all teams by league mapped to their ESPN categorization. Below the graph title are the p-value and r-squared value (if significant) from Appendix C.

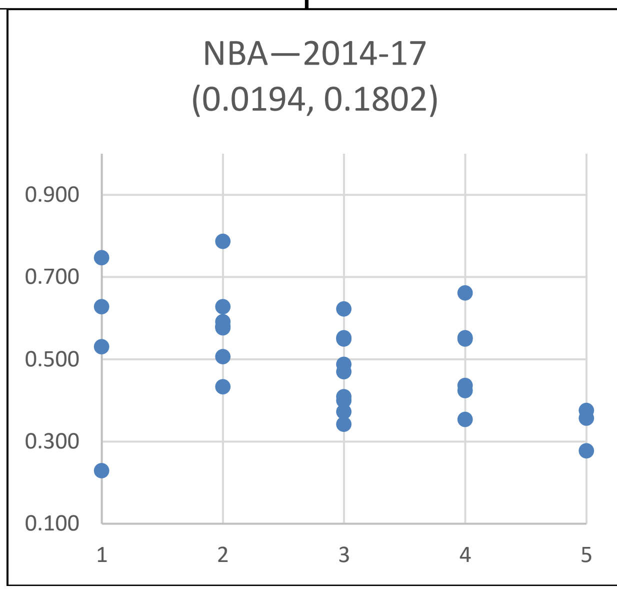


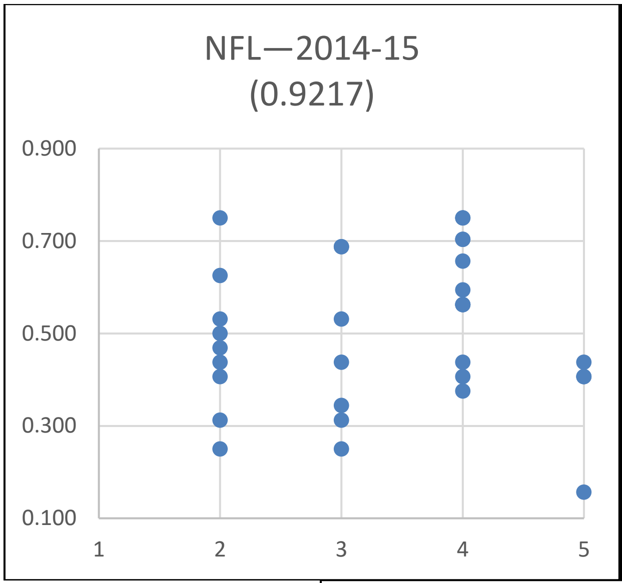



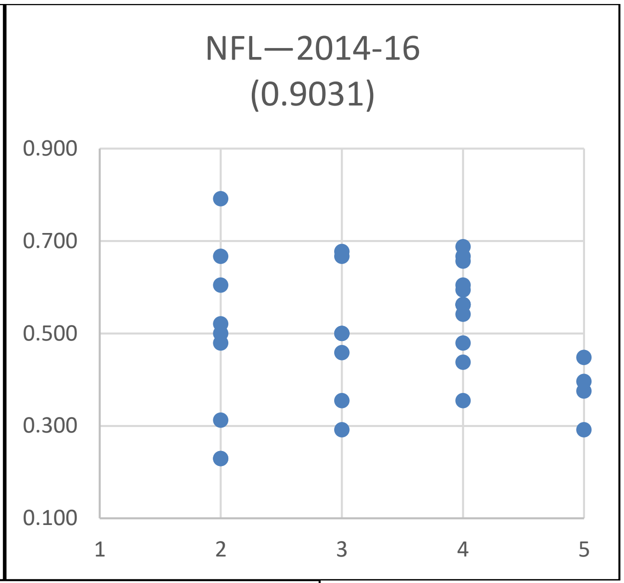



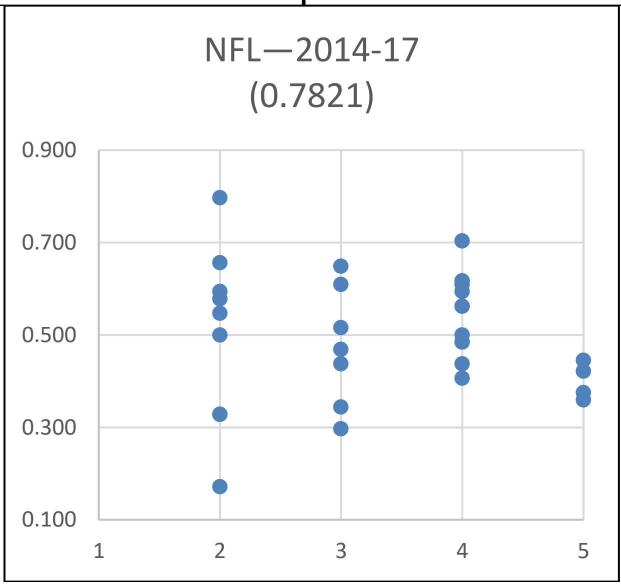

NBA—2014-15
(0.0702)
0.900
0.700
0.500
0.300
0.100
1
2
3
4
5

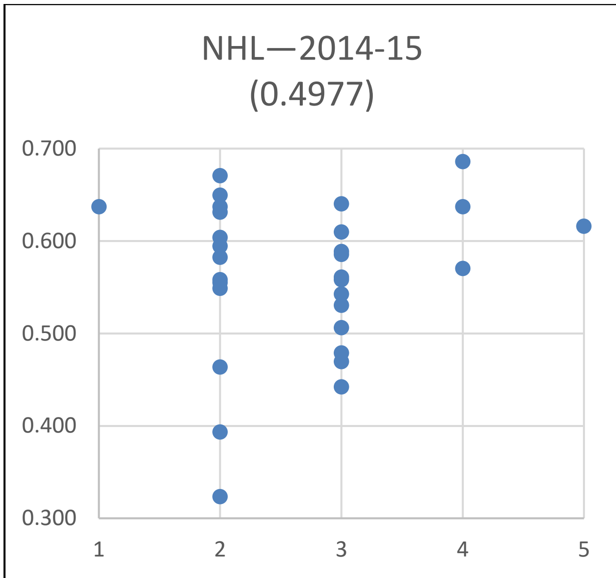

NBA—2014-16
(0.0321, 0.1537)
0.900
0.700
0.500
0.300
0.100
1
2
3
4
5

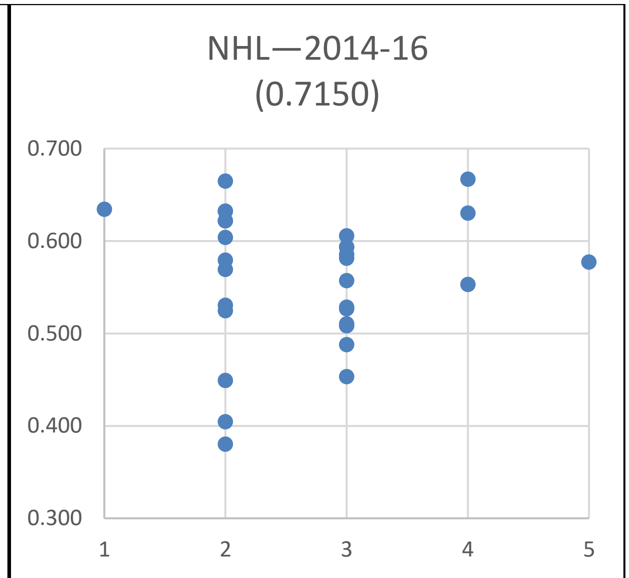

NBA—2014-17
(0.0194, 0.1802)
0.900
0.700
0.500
0.300
0.100
1
2
3
4
5

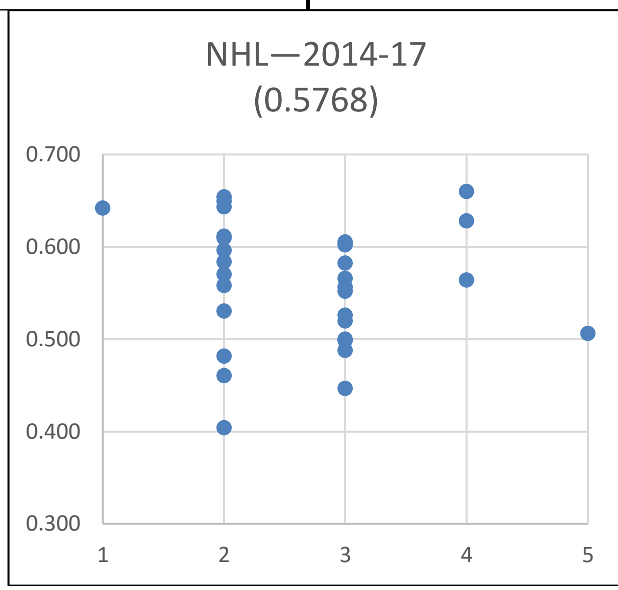

NFL—2014-15
(0.9217)
0.900
0.700
0.500
0.300
0.100
1
2
3
4
5


NFL—2014-16
(0.9031)
0.900
0.700
0.500
0.300
0.100
1
2
3
4
5


NFL—2014-17
(0.7821)
0.900
0.700
0.500
0.300
0.100
1
2
3
4
5

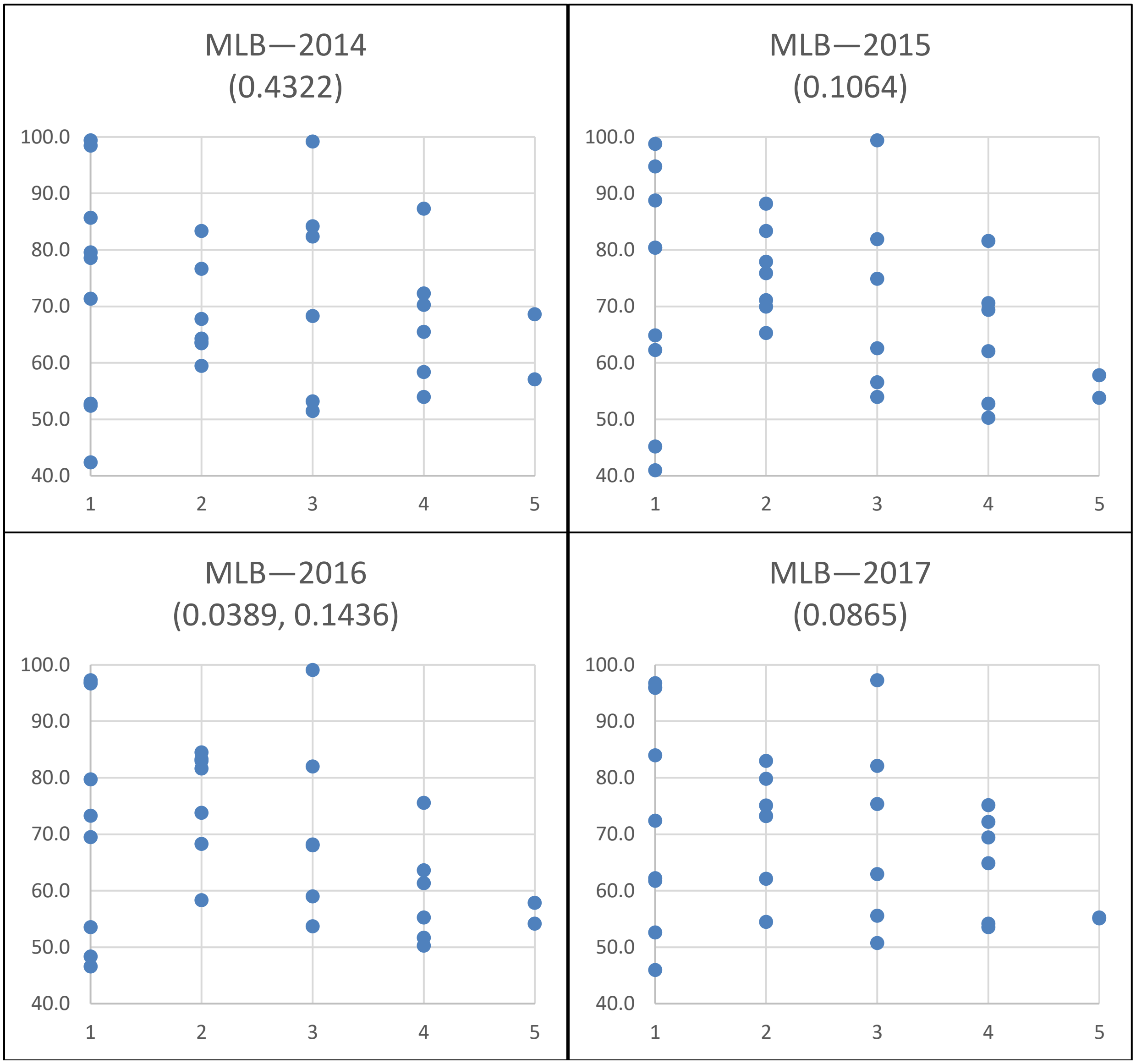

NHL—2014-15
(0.4977)
0.700
0.600
0.500
0.400
0.300
1
2
3
4
5

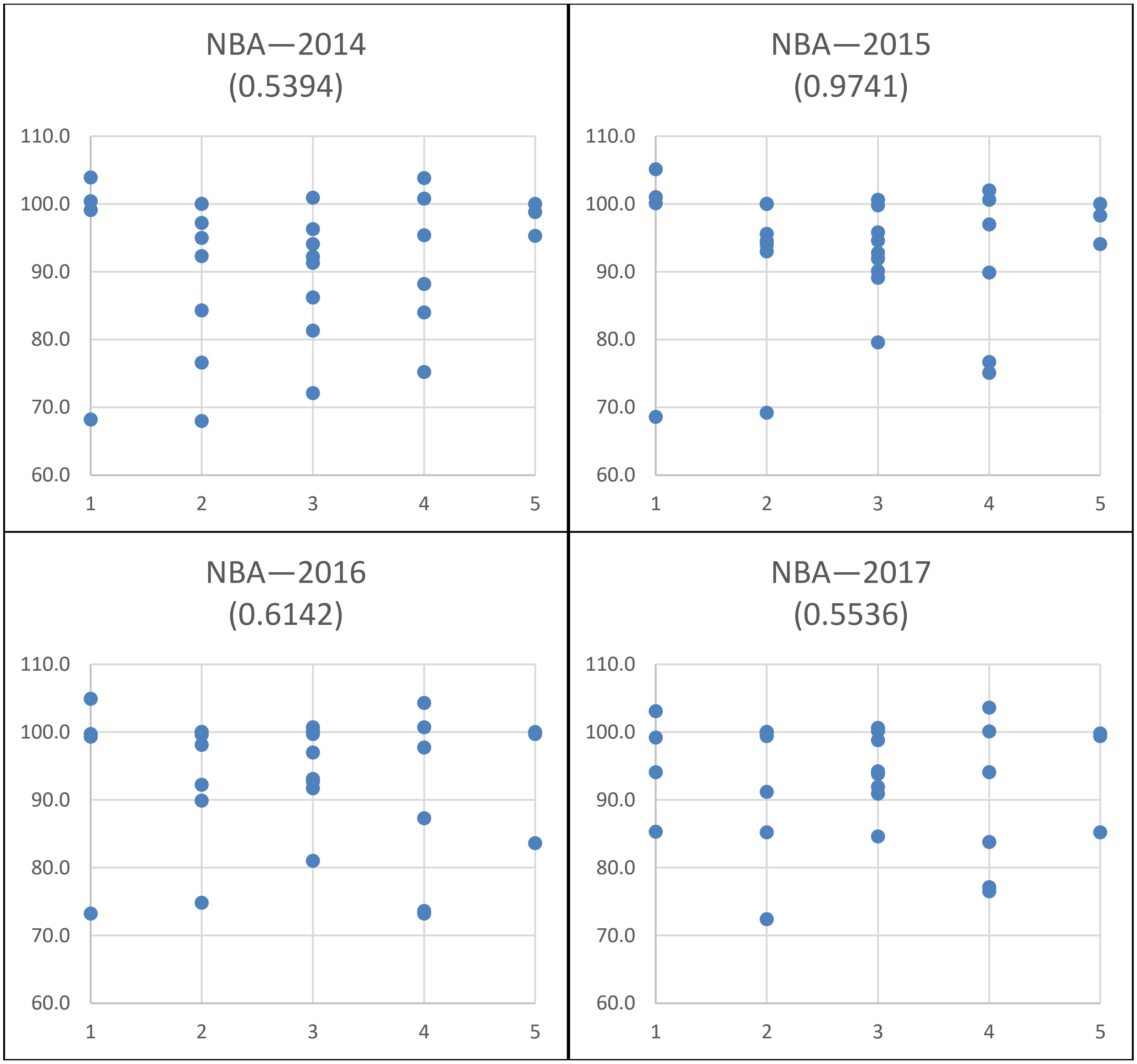

NHL—2014-16
(0.7150)
0.700
0.600
0.500
0.400
0.300
1
2
3
4
5


NHL—2014-17
(0.5768)
0.700
0.600
0.500
0.400
0.300
1
2
3
4
5

**APPENDIX H**

Attendance percentages for all teams by league mapped to their ESPN categorization, 2014-2017. Below the graph title are the p-value and r-squared value (if significant) from Appendix C.




NBA—2014
(0.5394)
NBA—2015
(0.9741)
NBA—2016
(0.6142)
NBA—2017
(0.5536)
110.0
100.0
90.0
80.0
70.0
60.0
1
2
3
4
5

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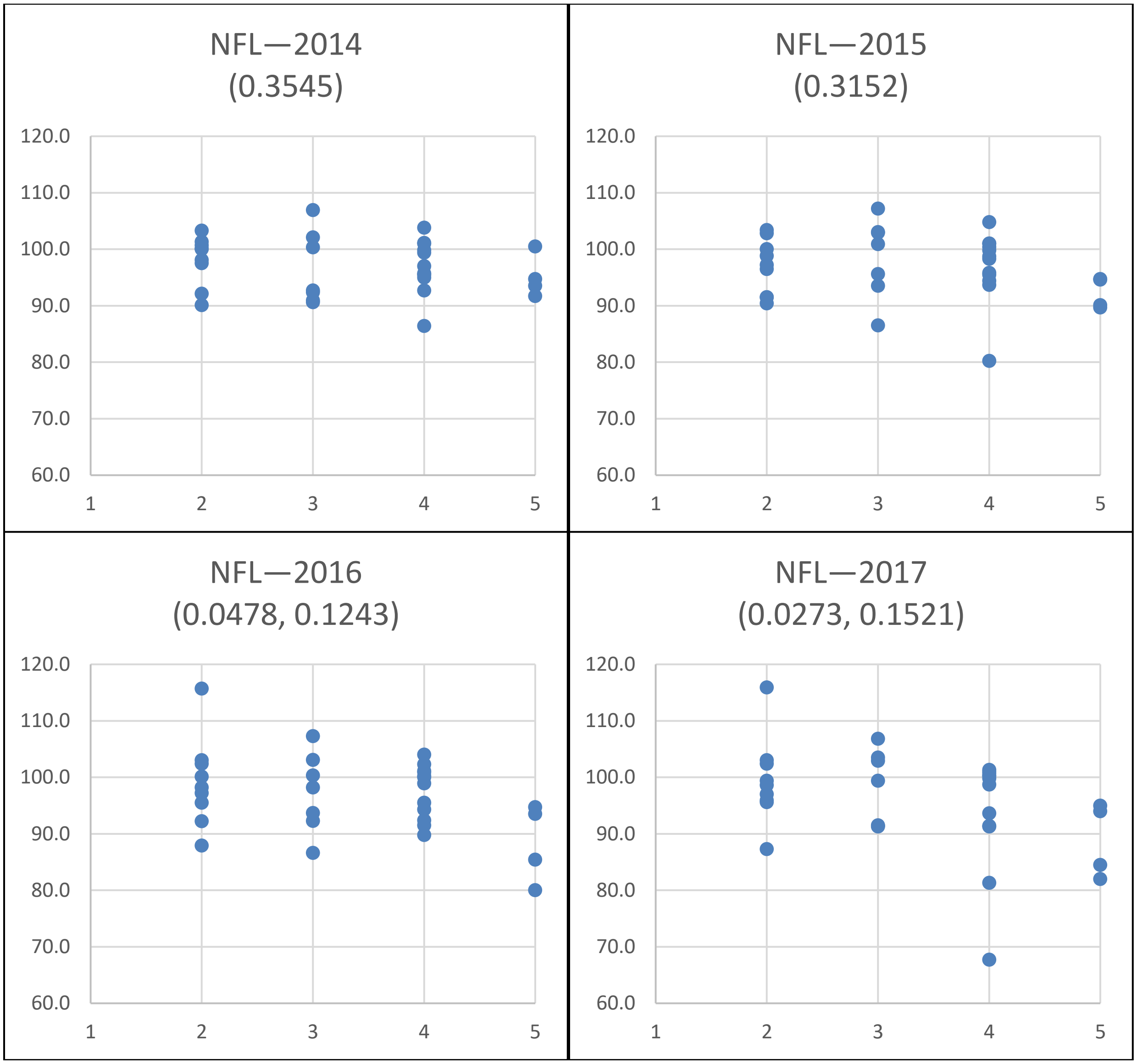

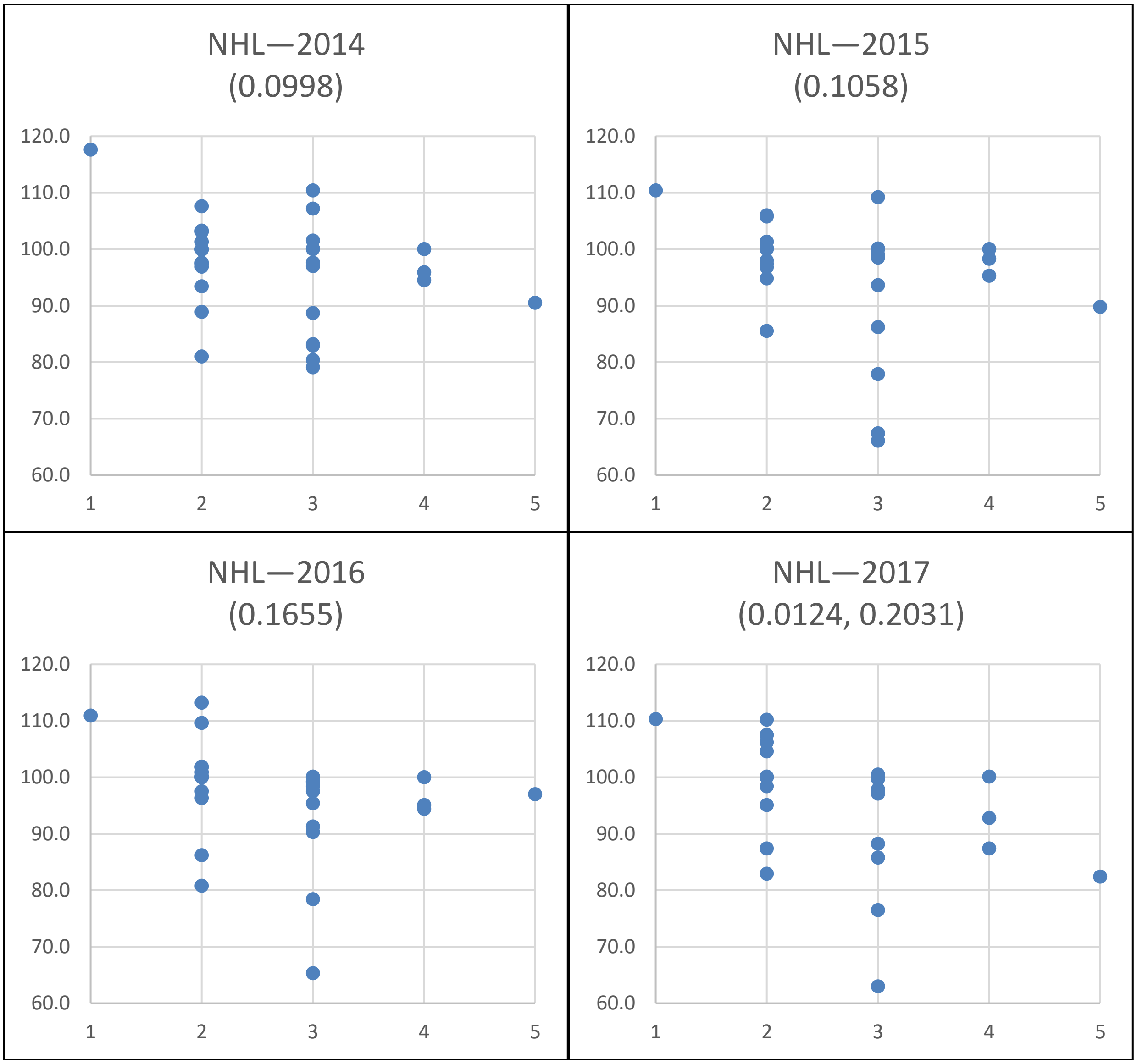
NHL—2014
(0.0998)
120.0
110.0
100.0
90.0
80.0
70.0
60.0
1
2
3
4
5
NHL—2015
(0.1058)
120.0
110.0
100.0
90.0
80.0
70.0
60.0
1
2
3
4
5
NHL—2016
(0.1655)
120.0
110.0
100.0
90.0
80.0
70.0
60.0
1
2
3
4
5
NHL—2017
(0.0124, 0.2031)
120.0
110.0
100.0
90.0
80.0
70.0
60.0
1
2
3
4
5