ECONOMIC AND HISTORICAL PERSPECTIVES ON STATIONARITY, STRUCTURAL CHANGE AND THE UNCERTAINTY OF OUTCOME HYPOTHESIS IN LONG-TERM NORTH AMERICAN PROFESSIONAL SPORTS ATTENDANCE

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Kinesiology)
in The University of Michigan
2012

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I would like to dedicate this work to my beautiful wife, Caitlin, for her support throughout the research and writing process. Reaching this milestone would have been in serious doubt without her presence every step of the way.

ACKNOWLEDGEMENTS

I would like to begin by thanking my adviser, Dr. Rodney Fort, for mentoring me during my time at the University of Michigan. In addition, I thank the rest of my dissertation committee—Dr. Mark Rosentraub, Dr. Scott Masten and Dr. Kathryn Heinze—for their time and invaluable input at the many stages of this project. I would also like to thank Dr. Young Hoon Lee—who graciously provided statistical programming expertise throughout this entire dissertation—and Dr. Jason Winfree, who put up with incessant ramblings about econometric issues within this work and beyond. Input from Dr. Richard Wolfe was pivotal in starting my career as a graduate student at the University of Michigan, and I appreciate his willingness to go the extra mile to personally assist me in the process. Finally, I would like to thank my fellow graduate students for our constant discussions about sports, economics, management and just life in general during the graduate school process. My experiences in Ann Arbor will be taken with me wherever I go.

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List of Abbreviations and Acronyms

AAFC	All-America Football Conference
ABA	American Basketball Association
ADF	Augmented Dickey-Fuller Unit Root Test
AFL	American Football League
AFC	American Football Conference
AL	American League
APG	Attendance Per Game
AR	Autoregressive Model
ARCH	Autoregressive Conditional Heteroskedasticity Model
ARIMA	Autoregressive Integrated Moving Average Model
BP Method	Bai and Perron Breakpoint Regression Method
CBR	Competitive Balance Ratio
Corr	3-year Correlation (Measure for Consecutive Season Uncertainty)
CSU	Consecutive Season Uncertainty
DFGLS	Dickey-Fuller Generalized Least Squares Unit Root Test
EQ	El-Hodiri and Quirk (1971)
FQ	Fort and Quirk (1995)
GARCH	Generalized Autoregressive Conditional Heteroskedasticity Model
GU	Game Uncertainty
LAPG	League Attendance Per Game
LLR	Local Linear Regression
LM	Lagrange Multiplier
LM-1	One-Break Lagrange Multiplier Unit Root Test with Breaks
LM-2	Two-Break Lagrange Multiplier Unit Root Test with Breaks
MiLB	Minor League Baseball
MLB	Major League Baseball
NBA	National Basketball Association
NFC	National Football Conference
NFL	National Football League
NHL	National Hockey League
NL	National League
OLS	Ordinary Least Squares
PP	Phillips-Perron Unit Root Test
PU	Playoff Uncertainty
TAPG	Team Attendance Per Game
TL	Tail Likelihood (Measure for Game Uncertainty)
UOH	Uncertainty of Outcome Hypothesis
VAR	Vector Autoregressive Model
W%	Win Percent

WFL	World Football League
WHA	World Hockey Association
WinDiff	Win Difference (Measure for Playoff Uncertainty)
WWII	World War II
ZA	Zivot-Andrews Unit Root Test with Structural Change

Major League Baseball (MLB)

ATL	Atlanta Braves
BAL	Baltimore Orioles
BOS	Boston Red Sox (Americans)
CHC	Chicago Cubs (Orphans)
CHW	Chicago White Sox
CIN	Cincinnati Reds (Redlegs)
CLE	Cleveland Indians (Naps; Bronchos; Blues)
DET	Detroit Tigers
HOU	Houston Astros (Colt .45's)
KCR	Kansas City Royals
LAD	Los Angeles Dodgers
LAA	Los Angeles Angels of Anaheim (Anaheim; California; Los Angeles)
MIL	Milwaukee Brewers
MIN	Minnesota Twins
MON	Montreal Expos
NYM	New York Mets
NYY	New York Yankees (Highlanders)
OAK	Oakland Athletics
PHI	Philadelphia Phillies
PIT	Pittsburgh Pirates
SDP	San Diego Padres
SEA	Seattle Mariners
SFG	San Francisco Giants
STL	St. Louis Cardinals
TEX	Texas Rangers
TOR	Toronto Blue Jays

National Basketball Association (NBA)

ATL	Atlanta Hawks
BOS	Boston Celtics
CHI	Chicago Bulls
CLE	Cleveland Cavaliers
DEN	Denver Nuggets
DET	Detroit Pistons
HOU	Houston Rockets
LAL	Los Angeles Lakers
MIL	Milwaukee Bucks
NJN	New Jersey Nets
NYK	New York Knickerbockers

PHI	Philadelphia 76ers
PHO	Phoenix Suns
POR	Portland Trailblazers
SAN	San Antonio Spurs
SEA	Seattle Supersonics
WAS	Washington Wizards (Bullets)

National Football League (NFL)

ATL	Atlanta Falcons
BUF	Buffalo Bills
CHI	Chicago Bears
CIN	Cincinnati Bengals
DAL	Dallas Cowboys
DEN	Denver Broncos
DET	Detroit Lions
GB	Green Bay Packers
KCC	Kansas City Chiefs
MIA	Miami Dolphins
MIN	Minnesota Vikings
NEP	New England Patriots
NYG	New York Giants
NYJ	New York Jets
PHI	Philadelphia Eagles (Eagles/Steelers)
PIT	Pittsburgh Steelers (Pirates; Cardinals/Steelers; Eagles/Steelers)
SDC	San Diego Chargers
SF	San Francisco 49ers
WAS	Washington Redskins

National Hockey League (NHL)

BOS	Boston Bruins
BUF	Buffalo Sabres
CAL	Calgary Flames
CHI	Chicago Blackhawks
DAL	Dallas Stars
DET	Detroit Red Wings
LAK	Los Angeles Kings
MON	Montreal Canadiens
NYR	New York Rangers
PHI	Philadelphia Flyers
PIT	Pittsburgh Penguins
STL	St. Louis Blues
TOR	Toronto Maple Leafs
WAS	Washington Capitals

ABSTRACT

Chair: Rodney D. Fort

The following work extends the breakpoint literature regarding annual attendance and the impact of outcome uncertainty at the aggregate level to the National Basketball Association, National Football League, and National Hockey League as well as at the team level in these three leagues and Major League Baseball. Attendance series for each league under consideration are not stationary overall but are stationary with breakpoints. However, evidence for the presence of a unit root—with or without breaks—is mixed across teams within and between North American leagues. Break points correspond in believable ways to historical occurrences in these leagues and the cities in which many of the franchises reside. Ultimately, the impact of competitive balance varies across both leagues and teams with respect to the time path of stadium attendance, with mixed evidence for Rottenberg's uncertainty of outcome hypothesis. I present implications of breaks and balance effects and suggest future research on attendance estimation in North American professional sports, including further econometric treatment for a fully specified model of long-term stadium attendance that may be censored due to sellouts.

CHAPTER 1

Introduction

1.1 Background, Objectives and Overview of Relevant Literature

In understanding determinants of attendance in North American professional sports, the bulk of work in Sports Economics and Sport Management has largely evaluated balance effects on attendance at the *league-level* (Schmidt and Berri, 2001, 2002, 2004; Coates and Harrison, 2005; Fort and Lee, 2006; Lee and Fort, 2008). Further work in this area has been limited to *short-term* competitive balance and attendance demand issues for Major League Baseball (MLB) franchises (Meehan, Nelson and Richardson, 2007; Tainsky and Winfree, 2010a). Thus, very little is understood about the long-term behavior of game attendance of individual teams and its relationship to competitive balance. Though short term snapshots in time are informative, a full treatment of complete individual team attendance series may help to inform league-level policy in which owners have varying objectives in diverse markets that change dramatically over time. In addition, previous empirical work investigating Simon Rottenberg's Uncertainty of Outcome Hypothesis (UOH, 1956) in North America has overwhelmingly involved analysis of *baseball* attendance. [1] Although there have been

[1] Siegfried and Eisenberg, 1980 (MiLB); Baade and Tiehen, 1990; Domazlicky and Kerr, 1990; Knowles and Sherony, 1992; Bruggink and Eaton, 1996; Coffin, 1996; Kahane and Shmanske, 1997; Schmidt and Berri 2001, 2002, 2004; Butler, 2002; Winfree, McCluskey, Mittlehammer and Fort, 2004; Coates and

some attendance demand studies involving other North American sports leagues (Jones and Ferguson, 1988; Paul, 2003; Schmidt and Berri, 2004; Leadley and Zygmont, 2006; Coates and Humphreys, 2007; Winfree and Fort, 2008), much of the attendance research in the National Basketball Association (NBA), National Football League (NFL) and National Hockey League (NHL) has focused on fan substitution, stadium honeymoon effects, discrimination, and impacts of labor disputes. However, few studies have attempted to directly estimate the impacts of each of the multiple dimensions of uncertainty on league and team attendance, as well as track these attendance levels and their relationship to league policies and other events.

Overall, empirical research has disagreed on the influence of the UOH in practice. Szymanski (2003) reviews the findings of a number of studies, many of which find conflicting results with respect to fan interest and the UOH. As Lee and Fort (2008) note, there is a possibility that leagues have managed balance well enough that there is not a discernible effect on demand as represented by gate attendance numbers. This leaves room for further empirical research, and more recent investigations have found some evidence for interest in certain types of competitive balance (Lee and Fort, 2008; Meehan, Nelson & Richardson, 2007; Rascher & Solmes (2007); Soebbing (2008)).

Gauging determinants of demand for attendance at the league level is a valuable endeavor in and of itself for evaluating league policy and choice variables for team managers, but the variability in preferences for uncertainty of outcome at the team level is another important aspect of league survival (Lee & Fort, 2008). Understanding how fans respond to this balance on an individual team basis can shed light on where the net increase or decrease in league attendance—with respect to competitive balance and uncertainty of outcome—may be derived. The primary purpose of this work, however, is to fill the gaps in the baseball, football, basketball, and hockey literature with a full time series treatment of league attendance in order to evaluate large shocks in attendance through long-term tracking, and secondarily to assess the validity of the predictions by UOH and its multifaceted nature.

Uncertainty itself is often discussed in terms of a direct causal factor in fan interest, when much of its effect (if indeed there is any effect) could in fact be a mediating factor in aggregate fan hope for each home team. Knowledge of the effects of UOH at the team level can help to inform practitioners both how uncertainty mediates this “fan hope” and how it may directly influence interest and excitement for a league with teams in heterogeneous markets. Measuring these effects separately is a difficult (if not impossible) task without survey research, but a team-level treatment of the different realizations of competitive balance and uncertainty may inform ticket pricing—holding constant these variables—and provide further knowledge of the preferences of fans toward winning and uncertainty within each market. Of course, attendance is only one aspect of demand for baseball and I do not evaluate the full revenue function for each franchise in this analysis. Certainly, the effects of balance on television contracts and viewership are also an important and continually evolving aspect in the demand for North American professional sports leagues. Nevertheless, the information regarding trends in attendance contained in this work is an important precursor to understanding determinants of a full sports league demand function for team managers and executives within their own respective market. In addition, empirical understanding of the varying market characteristics that drive team owner decisions will help to inform league level decision making, where these owners with different objective functions must agree on league policies while balancing self-interest based on their own market conditions. Finally, the econometric considerations here inform further panel and cross-sectional analyses at the league and team level. These additional considerations are pivotal to understanding demand for attendance in the leagues considered here, as the limited treatment of dependent variable complications—for example, sellouts result in censored data—ultimately call for further analysis accounting for the properties exhibited here.

The following work extends the previously cited literature with a long-term time series analysis of league attendance in the NBA, NFL and NHL, and franchise attendance in MLB, and in these three mentioned leagues. The empirical process allows for an estimation of attendance shocks that may be related to league policy or other historical events and qualitative evaluation of the relationship of these shocks to any sudden changes in competitive balance. Qualitative evaluation of attendance shocks for shared-market sports teams may additionally shed light on the possibility of fan substitution and fixed sports entertainment demand within individual regions. Knowledge of possible sport substitutes is an important yet mostly uncharted area of sports economics and sport management research. Winfree et al. (2004), Winfree and Fort (2008), Winfree (2009a) and Rascher et al. (2009) have performed informative analyses investigating this topic, but only provide *some* empirical estimation of substitution *between* two sports (NBA and NHL). Winfree (2009b) follows this line of literature with a further empirical investigation of competition between same-owner teams within the same market for all four major North American leagues. As this latest research emphasizes, understanding the competition between shared-market franchises from different leagues has implications not only for team managers, but also antitrust. This issue will be discussed in more detail later.

1.2 A Brief Description of the North American Sports League

A background of the theory and literature regarding professional sports leagues in North America and assumptions behind the study of sports leagues as profit-maximizing firms should prove instructive before assessing the influences that uncertainty may have on these objectives and policies over such a long period. The bulk of economic modeling of professional sports—and ultimately its influence on demand and attendance estimation—stems from Simon Rottenberg's seminal piece "The Baseball Players' Labor Market" (1956). Professional sport in North America is likely best described as a profit-maximizing business, but both Rottenberg (1956) and Neale (1964) highlight how the unique nature of sporting competition requires its own development within the economic modeling literature. The work of Rottenberg (1956) describes the landscape of the market for baseball playing talent in a world of the *reserve clause*, which at that time subjected players to monopsony exploitation by binding a player to a single team for the entirety of his career. However, for the purposes of this work, the effects of the reserve rule itself are of less interest than the reason owners claim that it was instituted in the first place: to preserve competitive balance. El-Hodiri and Quirk (1971) follow this path, developing some of the early economic models of pro sports following the original institution of the MLB draft. Much of the resulting work has aimed at describing how sports leagues function as independent franchises with specific needs for collaboration—converging upon collusive agreements—and the theoretically optimal sports product

(Fort and Quirk, 2011; 2010). The uniqueness of sport described by Neale (1964) is of great interest to the majority of those involved in the relatively young fields of Sports Economics and Sport Management.

The defense of the reserve rule, and one reason for the unique antitrust treatment extended to baseball in the earlier part of the 20th Century, is the idea that league survival relies heavily on an equal distribution of talent among teams in the league: a key topic within the following empirical attendance estimation. It seems inevitable that some franchises will be placed in "better" markets than others and, combined with exclusive territory rights to bar entry by other teams, will have more resources to purchase talent and dominate the league for sustained periods. While "better market" can often mean a larger population, Rottenberg is careful to note that a number of factors go into the demand for baseball (or sports in general), including population, income, team rank, ease of travel to the stadium, and closeness of substitutes within that market. Competitive balance can play an important role in league survival, but Rottenberg explains that the reserve clause and special antitrust treatment are likely unnecessary due to the ability for teams to reassign property rights of players within the league. Ultimately, these policies redistribute revenues from player cost to the owners' bank accounts. Fort and Quirk (1995) reiterate Rottenberg's conclusions in a more modern light with respect to the true objectives of owners and specific league policies that claim to be in place to preserve balance. Whether or not the antitrust treatment is necessary, understanding the influences of uncertainty and balance on attendance demand is an important part of managing both the league and its franchises optimally under profit-maximizing objectives.

This supposed need for a reasonably equal distribution of talent across these variable markets stems from the required cooperation among independent franchises in order to produce a sporting event, and the need for each of the teams in the league to survive in order to be able to continue to produce competitive games. If a single team dominates a league, it could be detrimental to the survival of the smaller market teams, ultimately forcing these teams out of business. Neale (1964) offers an additional understanding of the differences between the economics of a standard firm and those that face sports team owners and league organizers. He presents an anecdote about the need for exciting competition in order for all firms to survive, using an entertaining example referring to the historically dominant New York Yankees, "'Oh Lord, make us good, but not that good,' must be their prayer" (pp. 2). Neale describes professional sports leagues as a special case of the multi-firm plant—with all firms providing the same inputs (talent)—with an ultimate joint product: the true World Champion. Given the similar inputs, but joint production resulting in a reduction in costs for both, Neale ultimately views sports leagues as cartels. As a whole, this characterization tends to overstate the cartelization of the major leagues in North America, as not all aspects of league organization and behavior can be characterized in this way. However, it is useful to discuss this in the context of demand for attendance, as variable market demand can influence the policies that leagues implement to ensure survival. These issues can mask the true motivations of team owners, as described in the literature on Rottenberg's Invariance Principle. I more formally revisit this motivation in Section 1.5.

As Neale describes, the centralization of sports leagues can have the expected effect of increasing profits, but may also maximize output. In this case, it is argued that supply and demand intersect at a point where a monopoly league produces the most universal championship: something that could only be produced through a cooperative effort among multiple franchises within the sport. Although cooperation can be useful in producing sport—and is likely more efficient with respect to *the production of games and rules structures*—the idea that sports are natural monopolies that require centralization in *all* aspects of the sports business (restricting the talent market, apparel and television rights, etc.) has been challenged in a number of instances (the most recent prominent court case being American Needle vs. NFL (2010)). Much of the formal economic modeling stemming from these issues has investigated claims with respect to cooperative league behavior for on-field competition, the appropriateness of collusive single-entity business activities, and the unique antitrust treatment extended toward professional sports leagues (namely, Major League Baseball) in North America.

The unique requirement that each team in a league maintain a high enough level of talent to stay in business and attract fans leads us to an important subject of Rottenberg's seminal work—and a core theory in the analyses presented here—known as the *Uncertainty of Outcome Hypothesis*. As the theory goes, fans prefer to see their home team win games, but also have interest in uncertainty (closeness of competition) for both the game and season outcomes. Under the UOH, we expect that *not knowing* the outcome of a sporting contest or season is positively related to fan demand and overall league interest. But the mediating role of uncertainty in team-level fan interest is also in play, as it allows more fans to have hope for a favorite teams' success. Therefore, the UOH is twofold in that it notes the immediate importance of uncertainty itself (suspense) to fan interest, as well as the need for every team to maintain a respectable talent level—

as determined by their home fans—to keep from going under and ultimately causing the disbandment of a league.

Through the distribution of talent, the UOH plays an important role in modeling the North American Sports League and the behavior by individual teams under league surveillance. This distribution of talent is not only important with respect to individual game outcomes, but also the uncertainty of pennant races and championship races within seasons. Neale (1964) coins this latter non-game-level interest in uncertainty the "League Standing Effect" and explains how the pennant race itself can result in excitement for fans in addition to the game. This idea comes into play in the empirical analysis presented here and introduces the multi-faceted nature of uncertainty in professional sports. More recent analysis has extended the UOH to dynasties and the propensity for certain teams to win year after year (Butler, 1995). I consider this realization of balance within this work, but it is important to note that Rottenberg did not address this in his initial development of the UOH.

In the first year of the new millennium, Major League Baseball's Blue Ribbon Panel reported that competitive imbalance would be detrimental to the survival of the league, echoing some of Rottenberg's early thoughts regarding uncertainty of outcome. The Blue Ribbon Panel Report eventually led to the new revenue sharing structures agreed upon in 2002, including what is now deemed "The Yankee Tax" (Levin, Mitchell, Volcker & Will, 2000). Though some of the conclusions in the Blue Ribbon Panel have met skepticism, the idea that "chronic competitive imbalance" could cause a league to fail (Levin et al., 2000, pp. 1) may have merit with respect to Rottenberg's UOH. If fan interest in individual teams wanes over times of severe imbalance, the UOH would lead us to believe that those teams that are unable to compete on the field may also no longer be able to sustain a profitable business. Thanks to the unique nature of professional sports, this can affect the larger market franchises as well, as their own survival is dependent upon the survival of their opponents (competitors).

While MLB attendance has thrived over the decade and a half since the 1994-95 work stoppage—and a multitude of teams (22) have been successful at reaching the World Series since 1990—grumblings of Yankee dominance have not ceased in recent years, as fans and small market owners alike have demanded policies to mitigate the perceived decreasing balance in MLB. The concern for Major League Baseball is not a particularly new one, as former Cleveland Indians owner—and soon to be Chicago White Sox owner—Bill Veeck stated in 1958, "The symptoms of near disaster are plain enough: The Yankees make an almost annual farce of the AL pennant race…Interest in big-league baseball is on the downgrade. So is attendance, generally, in spite of glowing Yankee, Brave, and Dodger figures," (Fort, 2006). American League attendance actually *was* in slight decline at this point, but National League attendance was gradually increasing after a massive rebound following the end of World War II in 1945 (Lee & Fort, 2008). There is, therefore, some validity in Veeck's claims at the time; however, the decreasing attendance in the American League shortly recovered and began increasing steeply in 1962. Additionally, despite Veeck's implication regarding the league's balance, Lee and Fort (2005) find that the competitive balance in MLB has continued its gradual *improvement* over the history of both the National and American Leagues. It is also worth noting that during Veeck's short tenure as owner—1946 through 1949—his Indians managed a World Series win, followed by 6 consecutive seasons of 92 wins or more after his sale of the team. And, despite his statements above, Veeck led a group of investors that purchased the American League's Chicago White Sox in 1959. It suffices to say that public claims by team owners should be taken with caution and investigated empirically before making rash conclusions regarding league policy. If revenues and attendance were so terrible, what would motivate Veeck to purchase one of these teams less than a year later?

The NFL experienced similar—and possibly even more—success with respect to revenues and attendance since 1990, but unlike MLB the league has been praised for its ability to create balance and standings turnover. Further work by Fort and Lee (2007) finds improvements in balance for NFL and NHL during the history of the league from trends and structural changes in balance; however, the NBA has gone against the grain and has experienced decreasing balance trends recently. This brings up an interesting dichotomy for sports leagues and the possibility of differing preferences for balance levels across leagues. Understanding how these differences affect attendance in each league will help to inform both league managers—in informing league policy—and team managers, who may use the information regarding UOH to both optimize performance on the field (ice; court) and maximize profits in the front office.

1.3 Fan Preferences in Professional Sport

In addition to his work in uncertainty of outcome, Rottenberg (1956) made some of the first contributions to the literature in the area of demand for professional sport as well (Fort, 2005). Other early works on demand include Demmert (1973) and Noll (1974). As mentioned above, recent analyses have focused more closely on the demand aspect of Sports Management and Economics using a number of methods for short-term analysis.[2] Longer term treatments of attendance demand have been limited.[3] However, a full time series treatment of all leagues at both the league and team level is lacking from the literature.

Fan interest in sport is commonly modeled as demand for attendance dependent on a number of factors including—but not limited to—ticket/concession price, income, population, availability and closeness of substitutes, convenience and travel costs, and tastes and preferences. Interestingly, studies have shown that teams price tickets in the inelastic portion of demand (see Fort (2004) and Krautmann and Berri (2007) for a full review of this literature), but this is likely a result of maximization of profits through joint determination of concessions and tickets prices. Tastes and preferences themselves are made up of a number of factors and are likely extremely heterogeneous across fans. These factors may include home team quality, visiting team quality, interest in the entertainment experience (stadium novelty, alternative game entertainment and promotions, on-field entertainment and athleticism), and outcome uncertainty. It is important to highlight that *the UOH considers preferences of fans*, leaving this portion of work less informed by formal economic theory. Ultimately, the idea that outcome uncertainty is positively related to demand for attendance—as originally posited by Rottenberg—is a *hypothesis* that should be further empirically tested. It is a unique aspect of demand not found in other places, as the creation of uncertainty is a joint

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[2] Baade and Tiehen, 1990; Domazlicky and Kerr, 1990; Knowles, Sherony and Haupert, 1992; Paul, 2003; Coates and Harrison, 2005; Coates and Humphreys, 2007; Meehan, Nelson and Richardson, 2007; Paul and Weinbach, 2007; Rascher and Solmnes, 2007; Soebbing, 2008; Lee, 2009; Davis, 2009; Lemke, Leonard and Tlhokwane, 2010; Tainsky, 2010; Tainsky and Winfree, 2010a, 2010b)

[3] Schmidt and Berri, 2001, 2004; Krautman and Hadley, 2006; Matheson, 2006; Lee and Fort, 2008; Pivovarnik, Lamb, Zuber and Gandar, 2008; Krautmann, Lee and Quinn, 2010

product on the field of play (and likely influenced in certain respects from the front office of the league).

Uncertainty of outcome is ultimately realized through the competitive balance of a league; however, the reader must keep in mind that although the distribution of talent itself (balance) and the UOH are inseparable, there is an important distinction between the two individual concepts in practice (Fort & Maxcy, 2003). Research under the umbrella of the UOH has a foundation in fan response to balance, while those involved in pure competitive balance research are focused on measurement and influences on the actual distribution of talent. These are of course complementary to one another, but the distinction is important in defining the goals of the research at hand. The secondary purpose of this dissertation falls under the former characterization, evaluating *balance impacts on attendance* for sports leagues. The primary purpose here is understand long-term behavior of, and large shocks in, attendance at different levels of aggregation and their relationship to significant historical and league policy events.

At present, there seems to be little agreement on the strength of the UOH in North American Professional Sports. As noted earlier, Szymanski (2003) finds mixed results with respect to the influence of UOH, and ultimately concludes that it has little, if any, effect on interest in sports. However, work up to this point has not investigated all aspects of uncertainty in all leagues, and a majority of study has been performed at the aggregate league level. Understanding the full scope of the UOH calls for investigation at both the league and team level of attendance in order to understand the heterogeneous preferences for uncertainty and how this uncertainty and individual team quality interact with one another to attract fans to sporting events. Before addressing this empirical evaluation, a more formal model of the North American league is presented in order to explicitly describe the mechanisms behind balance and Rottenberg's predictions with respect to uncertainty of outcome and league policy.

1.4 Formal Modeling of the North American Professional Sports League

In this section, I present a simple model of a league of profit-maximizing sport franchises, much of which is adapted from Fort and Quirk (2007; 1995) and El-Hodiri and Quirk (1971). For North American Leagues, the majority of the modeling literature assumes that owners are profit-maximizing with respect to their own individual team, with gate revenues related to team quality and the market size of each team (in contrast to the view that European sports franchise owners are utility/win maximizing subject to some constraints, one important aspect differentiating model assumptions across continental leagues). In other words, gate revenues are increasing in the probability of a home team win and the market size of that team. The team quality is determined by a stock of playing skill units, with some relationship between units of talent and overall team strength. In the absence of revenue sharing or other league restrictions, the simplest single team gate revenue function for a single game with respect to home team quality is defined by,

$$R_i^G = R_i^G\big(w_i(t_i, t_j)\big),$$

with season profits denoted,

$$\pi_i = \sum_{i \neq j}^{n} R_{ij}^G(w_i(t_i, t_j)) - cw_i\,, \qquad \text{or,} \qquad \pi_i = \sum_{i \neq j}^{n} R_{ij}^G(P_{ij}(t_i, t_j)) - cw_i$$

In this notation, gate revenues for team *i* are the total of all single game gate revenue for team *i*'s home games against all other teams. Each single game's gate revenue is a function of the quality (with win percent as a proxy for quality) of the home team (w_i) and the market size of the home team. Team quality is increasing in *t*, talent on the home team, and home gate revenues increase in w_i with decreasing marginal returns for investment in winning.

It is important to note here that the cost of talent, *c*, does not imply a constant marginal cost model. While not formally exhibited in this work, the cost of talent is determined by the standard tatonement process. Prices are "announced" and talent purchase decisions are made at the margin for both teams. The endogenous determination of cost of talent may also be exhibited through Figure 1.1. Here, assume that the two teams end up at points B and C. If so, then there is an incentive for the small market team to sell talent to the larger market team (as long as there is nothing to inhibit the flow from one team to another). This exchange will happen until both teams reach the equilibrium at point A. The process ultimately determines *c* as in any standard economic model, and this result is treated as given throughout the modeling process here.

The subsequent notation, P_{ij}, is taken from El-Hodiri and Quirk (1971), and represents the production function (contest success function, CSF) with respect to talent levels of both teams (i.e. the probability of the home team winning a single matchup, given each team's proportion of talent of the total between team *i* and team *j*) defined as,

$$P_{ij} = \frac{t_i}{(t_i + t_j)}.$$

At this juncture, the imposition of different CSFs can complicate the model, and I proceed with a more simple one-to-one interpretation that is the standard in the literature as follows (Fort & Winfree, 2009). In the characterization of NALs as “closed leagues”, when one team adds talent, it can only come at the expense of another team in the league. This will be important in more specific equilibrium models that look at the distribution of talent and results of league policies like revenue sharing, salary caps, and luxury taxes. In this case, win percent is determined by the proportion of talent on each team relative to the rest of the league, therefore normalizing total talent to 1. By first imposing the “adding up constraint” in professional sports, or the idea that the on-field competitive outcome is inevitably zero-sum, we find:

$$\sum_{i=1}^{n} w_i = \frac{n}{2}, \qquad \text{or,} \qquad \frac{\partial w_i}{\partial t_i} = -\frac{\partial w_j}{\partial t_j}.$$

The zero-sum result for a league simplified to two teams—a method popularized by Quirk and Fort (1992) and Fort and Quirk (1995)—is that $w_i = 1 - w_j$, directly implying our P_{ij} from before, and includes *relative quality only* within the model (Marburger (1997) and Kesenne (2000) consider further absolute quality specifications). The closed league characterization differs from that of many European or other international leagues like soccer, where the talent pool expands beyond a single league.

If a team in League A contracts talent from another League B, the talent available to the other teams in League A is not affected (though, the absolute level of talent is increased and the win percentages can be altered if a single team increases its talent level). In this case, a league may be defined as having an elastic supply of talent. Because of the closed nature of the majority of NALs, the talent supply in leagues analyzed here is defined as perfectly inelastic, and the modeling comes under the assumption that each talent choice is a best response to the other teams' talent choice(s) with the talent elasticity restriction,

$$\frac{dt_i}{dt_j} = \frac{dt_j}{dt_i} = -1,$$

a natural result of the normalization of the sum of league talent to 1. I proceed with the above assumption, following the general model specified in previous literature. With this specification, the logit contest success function is formally assumed away, and owners *buy win percent* in best response to the rest of the league in the static case. To show this, first take the derivative of P_{ij} (or simply the derivative of win percent with respect to talent in the two-team production function for win percent, $w_i = \frac{t_i}{t_i+t_j}$),

$$\frac{\partial w_i}{\partial t_i} = \frac{t_i + t_j - \left(1 + \frac{dt_j}{dt_i}\right)}{\left(t_i + t_j\right)^2}.$$

Substituting from above for $\frac{dt_j}{dt_i}$ and the previous result of a fixed supply, $t_i + t_j = 1$,

$$\frac{\partial w_i}{\partial t_i} = 1 .$$

In other words, there are no scale effects in the relationship between talent and winning. Of course, any sort of more complex relationship between talent investment and win percent is an important issue related to the production function in sports, which has been of interest in more recent literature (Fort and Winfree, 2009). Here, I begin by considering the purchase of win percents by franchise owners as in the classical literature in order to provide a smooth transition from the characterization above. The cost of talent is treated as given and constant for the classical models of NALs, with equilibrium at a point where the marginal revenues of adding talent equal the marginal cost of adding talent for all teams. This can be seen from a simple, two-team case with profits denoted (with Team *i* as the large-market team from here on),

$$\pi_i = R_{ij}^G\big(w_i(t_i, t_j)\big) - cw_i \text{ , and,} \pi_j = R_{ji}^G\big(w_j(t_j, t_i)\big) - cw_j,$$

Where—with our simplifying assumptions about talent and winning—first order conditions follow simply as,

$$\frac{\partial R_i}{\partial w_i} - c = 0 \text{ , } and, \frac{\partial R_j}{\partial w_j} - c = 0 .$$

As expected from theories of profit maximization, teams choose the winning percentage at which the marginal revenue from increasing their talent level is equal to the marginal cost of buying one more unit of talent. Therefore, marginal revenues are equal at c^* for both teams at equilibrium. Because we assume that demand is greater in the larger market, Team *i* buys more talent than Team *j*, and the league is unbalanced. The unbalanced notion implies that $w_i > w_j$, which can be further exacerbated by local television markets and the demand for non-shared luxury box revenues becoming more prominent in new stadium deals.

This model will lay the foundation for the empirical evaluations presented throughout this dissertation, as well as for further exhibitions regarding the effectiveness of policy in controlling balance. It is important to note that the work here discusses only North American leagues. Further applications to European and other sports leagues require further considerations to talent in a league. For more formal exhibition of these league models, the reader is referred to the excellent work by Kesenne (2000a; 2000b; 2001; 2006), Szymanski (2003; 2004; 2006) and Szymanski and Kesenne (2004).

1.5 Owners' Defense of League Policies and the Invariance Principle

Team owners and league managers often proclaim that policies such as the amateur draft and gate revenue sharing are implemented in order to preserve competitive balance and fan interest in the league. However, another important insight in Rottenberg's piece is the *Invariance Principle* (IP). Before the publication of the Coase Theorem (Coase, 1960), Rottenberg recognized the difficulty in defending the reserve rule as a way to ensure equal talent distribution and preserve uncertainty-of-outcome. The rule and its defense, it turns out, was likely to be nothing more than an excuse to redistribute profits to owners from players. He postulated that if the contracted exclusive right to a player's talent can be exchanged, then there is little to keep that talent from flowing to its most highly valued use, irrespective of who owns the rights. In the end, teams will facilitate this flow as long as it is profitable for them to do so. Rottenberg notes that the IP is not restricted to the reserve clause, as the Amateur Player Draft should have similar results: once players are drafted and bargaining takes place between the drafting team and the draftee, these contracts are ultimately sold from a smaller market team to a larger market team with a constraint of decreasing marginal returns to talent investment for the purchasing team (i.e. not *all* of the talent will end up in the larger market).

The ultimate result of the IP, and an important conclusion with respect to the antitrust treatment extended to MLB, is that talent would be similarly distributed with or without the reserve clause (free agency) or draft. Of course, this hypothesis is subject to the restriction that transactions costs are the same—or negligibly different—in either case (Daly and Moore (1981) provide an alternative view of this proposition). Therefore, the talent distribution does not depend on who holds the rights to the player talent (player or team), as long as these rights can be sold. The true motivation behind the reserve clause seems to have been ensuring monopsony exploitation of baseball players, rather than a more equal distribution of talent across the league that team owners insisted on using as a defense of the rule. Most economists would recognize this as the weak version of the Coase Theorem, but Fort (2005) and Sanderson and Siegfried Sanderson (2006) give Rottenberg the due that is oft ignored within the Sports (and more general) Economics literature, despite the publication of "The Baseball Players' Labor Market" a full four years prior to Ronald Coase's famous 1960 addition "The Problem of Social Cost". That is not to discredit Coase and his immeasurable contributions to the field of Economics with the additions regarding efficient allocation through these exchanges without transactions costs (and of course the importance of considering them), but Rottenberg was the first to imply the final outcome. As Fort (2005) describes, the IP itself leads to the need for an interesting test as to the magnitude of transactions costs in NALs. If little changed after free agency began its reign with respect to the distribution and movement of talent, then it may be that the magnitude of the transactions costs within professional sport are not large enough to inhibit the hypothesized consequences of the IP. Depending on fan preferences, player movement may or may not have impacts on attendance differentially across sports markets. Of course, evaluating the magnitude and influence of these costs on player movement and its impact on fan interest would be an interesting addition to the following empirical evaluation; however, I do not specifically visit these issues empirically in this work.

Before continuing on to the formal NAL modeling with regards to the IP, it is important to note that Rottenberg ends his piece by offering his thoughts on pooled revenue sharing and salary caps in a free talent market. His thoughts foreshadow much of the discussion in the following modeling literature such as El-Hodiri and Quirk (1971), Fort and Quirk (1995), Vrooman (1995), Szymanski (2003; 2004), and Fort and Quirk (2007), and Winfree and Fort (2012) in developing formal economic theories about talent and revenue (re)distribution, enforceability of salary caps and alternative methods of compensation, and the importance of both absolute and relative quality to fans. The importance of Rottenberg's work stretches beyond the UOH and IP, much of which is comprehensively reviewed in Fort (2005). The formal modeling that has stemmed from the abundant observations of the father of sports economics, Simon Rottenberg—and the later additions of Walter Neale and others—have built a broad foundation for popular topics throughout the history of the field of Sports Economics. The next sections follow from this traditional economic model of sports leagues presented in Section 1.3 and its application to the Invariance Principle.

1.5.1 League Policies and the Invariance Principle

El-Hodiri and Quirk (EQ, 1971) present one of the early formal models of professional sports in order to investigate the legitimacy of baseball's unique treatment with respect to United States antitrust laws. The authors consider any tendencies for baseball toward more equal playing strengths with both the player draft and the reserve clause under the direction of Rottenberg's seminal piece. This work incorporates Rottenberg's UOH within the revenue specification, claiming that, "As the probability of either team winning approaches one, gate receipts fall substantially," (pp. 1306). Therefore, as exemplified in the previous section, each team has the incentive to become better than their opponents, but not *too much* better.

EQ discusses gate revenues in the context of Rottenberg's UOH, or that visiting team quality is also of interest, and the model for home gate revenues in an n-team league are specified as,

$$R_i^G = \sum_{j \neq i}^{n} R_{ij}^G \left(P_{ij}(t_i, t_j)\right).$$

In this description, each single game's gate revenue is a function of the relative quality of the home and visiting team and the market size of the home team, as presented in Section 1.3. Revenues are increasing in the quality of the home team and profits are maximized at some optimal probability of the home team winning, $P_{ij}^{*} > 0.5$, subject to the CSF mentioned earlier (the logit most commonly used in the literature).

Because the purpose of this section is to review the most pertinent elements of prior modeling, the reader is referred to El-Hodiri and Quirk (1971) for the specifics of their calculations of the time-path of competitive balance under different league policies. Rather, I summarize the pertinent findings with respect to the impositions on the decisions model facing franchise owners according to the authors. The most important conclusion reached from this model is that, under conditions where teams in a league have varying returns to winning *and* the ability to purchase contracts from competing teams, a league will not converge on an equal distribution of talent over time. This is in support of Rottenberg's IP, in which individual teams will have an incentive to buy talent from others if ownership of the player in question would disproportionately increase profits for the buying team. The result under the reserve clause: a continued unequal distribution of talent across the league.

EQ go further to state that, in a situation where the returns to talent investment for all teams are (roughly) equal, the league *would* converge to a place where the teams are of generally equal playing strength. Of course this result would rely on the league allowing more than a single team in markets that could sustain them, which to this day has not been the case (for example, MLB placing only two teams in New York when it could almost surely sustain more). Finally, EQ propose that, given a constant supply of talent and varying market sizes, the league should be of relatively equal playing strength under the reserve rule *only if contract sales are forbidden* (and talent comes from a reverse order draft). This would reduce the ability to move players for profit, for large-market teams to sign players first (due to the draft), and ultimately result in teams being mostly of equal strength across time. The authors conclude that, while professional sports may require antitrust exemption for certain activities, the antitrust exemption of MLB up to that point would have done little to push the league toward equal playing strength among teams. This would lay the foundation for much of the modeling within the proceeding literature as league policies changed substantially with respect to the reserve rule in the coming years.

Fort and Quirk (FQ, 1995) and Vrooman (1995) echo EQ's results with a static approach to the problem that is more easily interpreted. Using the standard two-team model from FQ, we see in Figure 1.1 that there is a divergence from equilibrium (B and C) under the reserve rule when contract sales are not permitted. In this case, the smaller market team would prefer to sell contracts to the larger market team and the talent level competitive balance would converge on A, while the price of talent would fall to c^*. Therefore, in the case where contract sales are permitted, the small market team will continue to sell talent to the large market team up to A. The result is as predicted in EQ: the cost of talent is reduced from c to c^* in Figure 1.1 and players are exploited. Note that in the figure, the cost of talent is horizontal at c and c^*, and equilibrium occurs when $MR=c^*$ as standard profit-maximization conditions would suggest.

Following the presentations of EQ in 1971—and preceding FQ and Vrooman in 1995—Daly and Moore (1981) and Daly (1992) present a dissenting view with respect to the Coasian world without transaction costs inferred by Rottenberg in professional sports. Daly and Moore question the validity of the assumption that individual decision makers (team owners) do not consider the external effects in resource allocation when making decisions. They also suggest that there are additional costs to selling rights of players from team to team that may have effects on the application of the Invariance Principle. The authors propose that these owners will be overseen by a league entity that would cooperate to do what is best for the league. In other words, the league as a whole would encourage a distribution of talent that would be most beneficial for all owners, rather than a single owner. The point is further made that fan confidence—referred to as "contest legitimacy" (Daly, 1992)—relies on balance and rational owners should consider continued fan interest when making profit-maximizing decisions. This seems like a reasonable criticism and is related to the UOH, as league collaboration exists in order to ensure the survival of all teams.

1.5.2 Gate Revenue Sharing and Competitive Balance

In addition to modeling the ultimate consequences of the reserve clause from the perspective of the Invariance Principle, EQ also specifically consider gate revenue sharing in their work in order to incorporate it into their final conclusions. Below, EQ represent the percentage of gate receipts collected by the home team with the α parameter:

$$R_i^G = \alpha \sum_{j \neq i}^{n} R_{ij}^{G_i} \left(P_{ij}(t_i, t_j)\right) + (1-\alpha) \sum_{j \neq i}^{n} R_{ji}^{G_j} \left(P_{ji}(t_j, t_i)\right),$$

Here, we can see that a proportion each team's revenue function also depends on the receipts from games played at other teams' parks. FQ follow with an updated view of competitive balance in a more modern world of free agency in professional baseball and adapt this revenue function for local (L_i) and national (N) television revenues in the static case. With this, we return to a variant of our original basic revenue function from above,

$$R_i = \alpha \sum_{j \neq i}^{n} R_{ij}^{G_i}\left(Z_{ij}(t), A_i\right) + (1-\alpha) \sum_{j \neq i}^{n} R_{ji}^{G_j}\left(Z_{ji}(t), A_j\right) + \sum_{j \neq i}^{n} R_{ij}^{L_i}(Z_{ij}(t), A_i) + \frac{N}{n},$$

Where, Z_{ij} defines the simplified version of P_{ij} from earlier as the difference between the win percents of the competing teams, A_i indicates the drawing potential of each market, and each owner chooses $Z_{ij}^{*}(w_i^{*}, w_j^{*})$ given $c*$ in equilibrium to maximize profits based on their own market conditions. National revenue is shared equally among teams and its value determined exogenously. Local television revenue is considered unshared with its value determined by the market of each team and the closeness of competition between teams *i* (strong-drawing) and *j* (weak-drawing). FQ simplify the above using a two-team league first *without* local television revenues. I use a simplified version here; first define,

$$R_{ij}^{G_i} = \text{ Game Revenue from Team i's home park and,}$$

$$R_{ji}^{G_j} = \text{ Game Revenue from Team j's home park.}$$

We find that the profit functions for teams *i* and *j* are given by:

$$\pi_i = \alpha R_{ij}^{G_i}(w_i, w_j) + (1-\alpha) R_{ji}^{G_j}(w_j, w_i) + \frac{N}{2} - cw_i,$$

$$\pi_j = \alpha R_{ji}^{G_j}(w_j, w_i) + (1-\alpha) R_{ij}^{G_i}(w_i, w_j) + \frac{N}{2} - cw_j.$$

And employing our previous assumptions, first-order conditions follow:

$$\alpha \frac{\partial R_i}{\partial w_i} - (1-\alpha) \frac{\partial R_j}{\partial w_j} - c = 0,$$

$$\alpha \frac{\partial R_j}{\partial w_j} - (1-\alpha) \frac{\partial R_i}{\partial w_i} - c = 0.$$

It follows that the sharing coefficients drop out of the equation, $MR_i = c^* = MR_j$, ($c^* < c$) in equilibrium, and players receive lower salaries (Figure 1.2). This result hinges on the idea that revenue sharing equally affects the marginal revenue for each of the teams, resulting in a shift downward in Figure 1.2, and reducing the demand for talent (and ultimately the price of it). The fall in talent cost is due to the disincentive to invest in winning because a proportion of the revenue function of each team relies on the success of the other team in drawing fans.

FQ extend this to an n-team league with the full specification of revenues above (non-shared local TV revenue). Ultimately, the idea that the distribution of talent will remain the same does not necessarily hold depending on the way that local television revenues are (are not) shared. Using these revenues in sharing may help to subsidize small market teams substantially, given the systematic responsiveness of local television revenue to the market size and quality of the home team. The net revenue implications for the league—as well as the distribution of profits—depend on the nature of the sharing rules of gate and television (National and Local) revenue sharing and incentives for owners to reinvest in the competitive market for talent. When local TV and gate revenues are subject to the same sharing rules, league-wide profits are larger, as it would lower salary costs while pushing the league toward a distribution of talent that would maximize revenues (pp. 1289).

Szymanski (2003; 2004) argues that past literature has not correctly interpreted $\frac{t_i}{t_j}$, implying that it cannot be consistent with a Nash (equal to zero) and representative of the implication that for every unit of talent that Team *i* invests in, it comes directly from Team *j* (equal to -1) in a non-cooperative environment. He suggests that using an additional specification for *investment* in talent, z_i, is needed in what is deemed to be a non-cooperative talent market game. The claim is that the IP may no longer hold under gate revenue sharing. This defines the exchange between Szymanski (2003; 2004; 2006), Szymanski and Kesenne (2004), Eckard (2006), Fort and Winfree (2009), Quirk and Fort (2007). Winfree and Fort (2012) reconcile the model in order to conform with Nash conjectures by including an additional choice variable—investment in talent—in the modeling of team decision-making. Ultimately this specification exhibits that the IP can still hold under certain conditions for closed leagues. Winfree and Fort (2012) introduce a third dimension into the model—remaining with the two team simplification. With this specification, the authors let $t_1 = t_1(z_1, z_2)$, where z_i denotes the investment made in talent level for each team. Similarly, $t_2 = t_2(z_2, z_1)$. Following Winfree and Fort, I remain at a general level for the modeling under these specifications, with the CSF and team profit functions, respectively, defined as:

$$w_i = w_i\left(t_i(z_i, z_j), t_j(z_j, z_i)\right) \text{ and } \pi_i = R_i(w_i) - z_i,\ i = 1, 2.$$

Here, $\frac{\partial R_1}{\partial z_1} = \frac{\partial R_2}{\partial z_2}$ determines the Nash equilibrium along with the adding up constraint, $w_1 + w_2 = 1$ from before. This model allows the characterization of talent elasticity both Nash equilibrium and Nash conjectures. In this case, $\frac{\partial z_1}{\partial z_2} = \frac{\partial z_2}{\partial z_1} = 0$, and $\frac{dR_1}{dw_1}\frac{\partial t_1}{\partial z_1} = \frac{dR_2}{dw_2}\frac{\partial t_2}{\partial z_2}$. For the complete details of reaching this result, the reader is referred to Winfree and Fort (2012). Ultimately, it can be shown that the IP does not necessarily hold in a closed (or open) league. However, under certain assumptions, ($\frac{dR_2}{dw_2}\frac{\partial t_1}{\partial z_1} = \frac{dR_1}{dw_1}\frac{\partial t_2}{\partial z_2}$, which holds if the marginal product of talent investment across owners equates that of the market, such that $\frac{\partial t_1}{\partial z_1} = \frac{\partial t_2}{\partial z_2}$) the model above collapses to the original FQ model (1995), and the IP holds. Of course, the validity of these assumptions is an empirical matter, eliciting further disagreement from Szymanski (2012). In the end, the purpose of this work is not to confirm or reject the IP, but to lay out the foundation and justification for the empirical work presented here.

1.5.3 Salary (Payroll) Caps, Luxury Taxes and Competitive Balance

Unlike gate revenue sharing, FQ and Vrooman disagree on the impact of payroll caps in professional sports. While FQ state that enforceable caps should tend to improve balance, Vrooman views it simply as a preconceived approach to control player costs with little effect on balance. The assumptions behind the cap discussed in FQ come from the NBA payroll cap which allows a certain percentage of overall revenues to be spent on player salaries and bonuses. There is a simple assumption here in which the total profits are greater under the cap than under free agency—something that seems reasonable for a profit-maximizing group. Assuming that the cap is set in a way that *all teams spend exactly the cap*, we end up with Figure 1.3 as the result. In this case, the weak drawing team gains the triangle *ABDE* in profits, whose area exceeds that of *DFG*. Similarly, the strong drawing team gives up the triangle *AHI*, but this is offset by the rectangle *cc*HG* from the lowered cost of talent. Therefore, all teams can gain in this situation. However, enforcement could be an issue (FQ, 1995)—and this has been the story in the NBA, where certain loopholes have allowed many teams to spend above a "soft" cap. Other ways of circumventing a cap could simply be due to amenities available for players in larger markets, which are not directly accounted for in a cap of payrolls. From Figure 1.3, we can see the reason: larger market teams have more revenue generating potential from the talent on the small-market team and have the incentive to push balance back toward the equilibrium point.

Vrooman, on the other hand, suspects that caps would have little effect on balance even if they were enforceable. Under his scenario, the entire league contributes the same amount of payroll, resulting in zero marginal costs of winning, and ultimately leading to a revenue-maximizing league. Vrooman asserts that with the entire league acting as a single firm, the best players will simply end up in markets where the non-sports salary income is the highest. Because player costs are constant, this could lead to *more* *imbalance* than without the cap since there are not decreasing profits with talent investment for a cap set well below *MR=MC*. If the additional non-salary income is not paid by the franchises, they are not subject to these increasing costs to hire more superstars than would otherwise come to the large market team. The extent to which this would be the case is likely better suited for empirical investigation about the preferences of players to play in markets like New York and Los Angeles. Using NFL as a very simple observational example (which does use a relatively hard cap among other policies for revenue redistribution), we see top players like Peyton Manning making significant non-sports income in smaller markets, raising questions about the latter conclusion that an enforceable cap would actually make balance worse. Even with this observational example, there still seems to be plenty of reason to believe that larger markets would produce more sponsorship and endorsement opportunities on average and at least attract more superstars at the margin.

However, Vrooman's original assertion that balance would not change under the cap may possibly hold in a case where improving balance would not increase revenues for the entire league. Under the assumption that a more balance league *would* increase revenues, even a collusive firm would seem to want to maximize these revenues by ensuring the policy is developed to do so. If the league is already at a revenue-maximizing balance point, then Vrooman's theory as to the ultimate result makes more sense, as the cap is instituted in a way that does not change balance, but simply lowers costs across the league. This is again left up to empirical analysis, and optimal balance in specific leagues is considered theoretically in Fort and Quirk (2010; 2011) from the perspective of owners versus a league planner looking to maximize welfare. Thus far, it seems that the caps in the NBA have done little to promote balance to date (Fort and Lee, 2007), either due to enforceability or by poor design. The overwhelming consensus on the institution of an *enforceable* salary cap in the context of most North American leagues seems to be a path toward more balanced play.

An interesting variant of the payroll cap is the current luxury tax imposed in MLB, referred to as the "competitive balance tax". Figure 1.4 shows the change in balance from A to B, along with a reduced cost of talent similar to that of the payroll cap and revenue sharing policies. While FQ does not explicitly model the payroll tax, Vrooman considers this possibility in a footnote, and Marburger (1997) directly considers the luxury tax. The first theoretical result here is that the slope of the marginal revenue curve for the large market team is reduced, leading to more competitive balance than we would otherwise expect. This is because the larger market team has its marginal revenue function become $(1 - s)MR_i$, and therefore the marginal revenue from investing in talent is lowered for this owner. The additional result is again a lowered cost of talent, since the demand for talent within the league is lowered due to the tax on the large-market team.

The extent to which balance is affected depends largely on the number of teams affected by the tax and the rate of the tax. The tax rate and level at which payroll must exceed to be subject to the tax must be chosen carefully. If the threshold or tax rate are set too high or too low, the new policy may have very little effect on the demand for talent and ultimately not significantly change balance. In addition, the lower wages to players could reward small market teams for having less talent than before depending on how the taxes are redistributed (Marburger, 1997). MLB has a loose league requirement about reinvestment of shared revenues that again runs into an enforceability problem (as teams aren't necessarily incented to reinvest in talent based on their own MR curves). The league has recently chastised the Florida Marlins for not reinvesting revenue sharing into the talent market, but the enforcement of this request is as questionable as proposed by FQ under a standard NBA-type salary cap.

In MLB's most recent collective bargaining agreement, this tax has been applied to the amateur draft and its growing signing bonuses as well. The impact that the tax would have on competitive balance seems rather small, though does seem to reduce the incentive for amateurs to "hold out" for larger signing bonuses. This new league policy is not considered here, though economic models of impacts of the newest collective bargaining agreement would be quite interesting, as much of the agreement addresses pay schemes for amateur players negotiated by a labor union (MLBPA) which does not necessarily represent their interests.

1.6 Summary of Following Work

The rest of this dissertation uses the lessons provided in the theory of sports leagues above, and continues as follows. In the following chapter, I discuss past work in the time series treatment of professional sports attendance and the UOH. Chapter 3 describes the general methodology for the work presented in this dissertation. Chapter 4 presents a full empirical analysis for each of the leagues (NBA, NFL and NHL) while Chapters 5, 6, 7 and 8 present the franchise level investigations (MLB, NBA, NFL and NHL, respectively). Finally, Chapter 9 summarizes implications and limitations of the research, concluding with suggestions for future work beyond the scope of that exhibited here.

FIGURE 1.1: Talent Distribution Under the Reserve Clause (Free Agency)

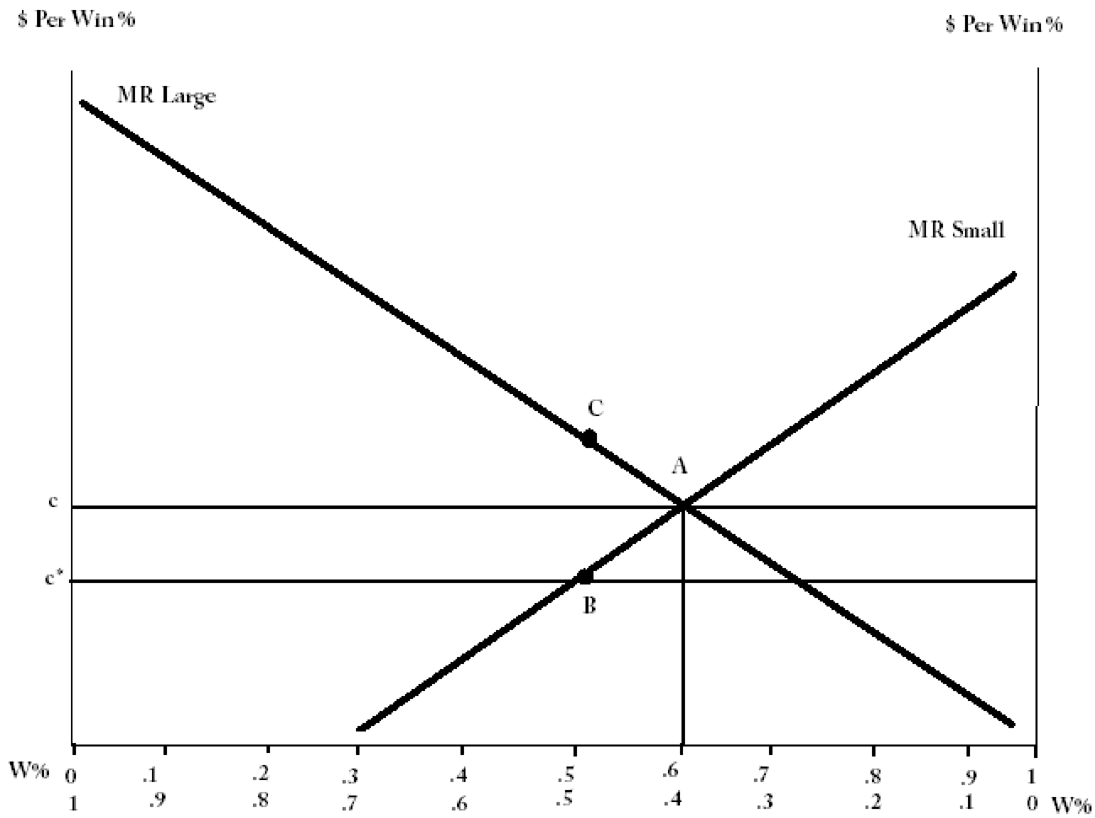


FIGURE 1.2: Talent Distribution Under Home-Away Gate Sharing

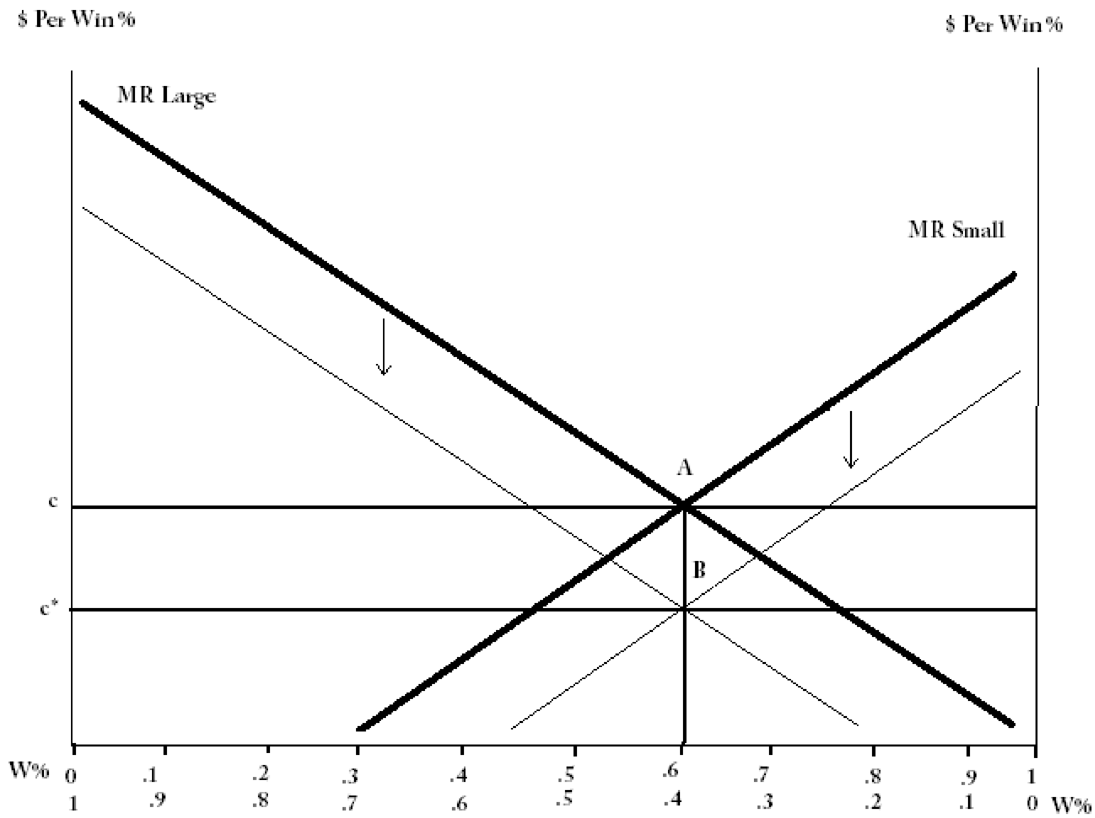


FIGURE 1.3: Talent Distribution Under Payroll Cap

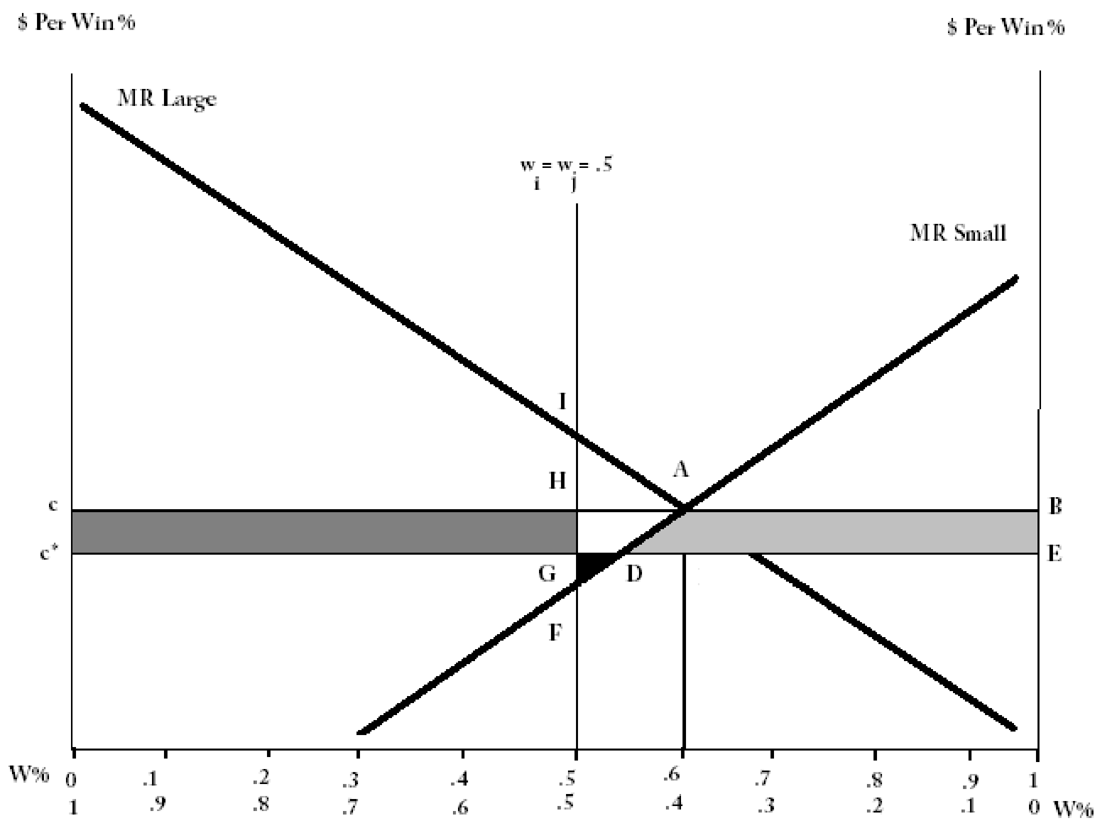
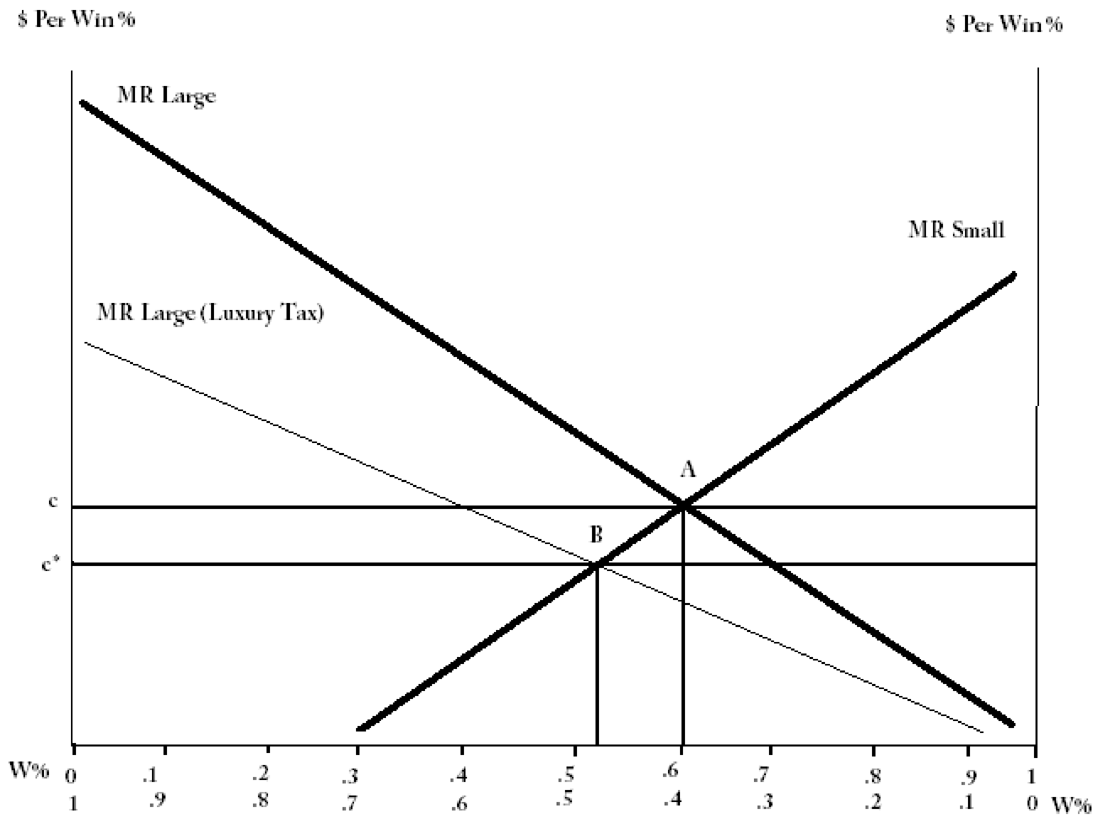


FIGURE 1.4: Talent Distribution Under Luxury Tax for Large Market Team



CHAPTER 2

Time Series Analysis in Professional Sport

2.1 Introduction

Here, it is important to first revisit the distinction between time series tracking of competitive balance, and time series treatment of attendance demand and its relationship to balance and uncertainty, as in Fort and Maxcy (2003). There is a large collection of past work that tracks the time series of *competitive balance* over the long term (Fort and Quirk, 1995; Humphreys, 2002; Schmidt and Berri, 2004b; Lee and Fort, 2005; Fort and Lee, 2007; Fort and Lee, forthcoming). Understanding the time path of balance is important in and of itself with respect to policy considerations; however, its relationship to attendance allows for further analysis of the appropriate level of balance for a league.

Further work with respect to competitive balance and attendance has used approaches such as first differences and autoregressive techniques (AR, ARIMA, ARCH, GARCH, VAR) in order to estimate influences of variables from population and income to taste and preferences on attendance. However, these models may be limited. The work by Bai and Perron described in the following section allows for level data analysis for those series that are stationary with breaks (henceforth, the BP Method) and to clearly understand the influence of these variables on economic outcomes for teams and leagues.

Davis (2009) shows that GARCH or OLS may be a reasonable specification for a model of attendance demand; however, a purely linear model may not correctly account for exogenous shocks in attendance found through the BP Method, especially in longer attendance series. This added ability to estimate breaks in both levels and trends may affect not only coefficient estimates for uncertainty variables, but may also provide more information about impacts of historical events or policy implementations by leagues that is not accounted for in a standard ARCH model. The BP approach has only been used for a single league (MLB) at the league aggregate level of attendance and the UOH, leaving unexplored areas of the time series properties of the NBA, NFL and NHL at the league level. In addition, further application of the BP Method at the franchise level should help to inform each of the four league-level analyses and enhance the understanding of attendance demand, league decision making and the Uncertainty of Outcome Hypothesis.

2.2 Preliminary Treatment and Recent Advances

When working with time series data, there are a number of important issues to account for in order to appropriately estimate regression coefficients over the time path of a dependent variable. Fort and Lee (2006) lay out a schematic for this process for baseball attendance (Figure 2.1). This schematic allows the researcher to follow a logical path in the time series procedure to ensure that the maximum amount of information can be extracted from modeling the data series. Each of the steps in the schematic is explicitly described in the following sections with regards to the data evaluated in this work.

The standard first step in time series analysis is to test for a unit root in the data, usually using one or a combination of the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) or Dickey-Fuller Generalized Least Squares test (DFGLS; Elliot, Rothenberg, and Stock, 1996). If the presence of a unit root is rejected, one may proceed with treating the series as stationary and apply one of many time series modeling approaches. However, if data are found to be non-stationary, then first differences will likely result in analysis on a stationary series once second-order serial correlations are accounted for. Unfortunately, first differences and some traditional autoregressive modeling techniques can limit the analysis and straightforward interpretation of regression coefficients, as I will briefly discuss in the following section.

Standard unit root tests assume that data are distributed around a mean (level) throughout the time series data (allowing a trend), which can limit the power of these tests in the presence of a one-time structural change (Perron, 1989). However, recent advances have allowed for the testing of stationarity with one or two breaks (Zivot and Andrews, 1992; Lee and Strazicich 2001, 2003, 2004) using the Zivot Andrews (ZA) or Lagrange Multiplier (LM-1 and LM-2) tests. These tests detect structural change(s) in the data over time and segment the series into regimes for which stationarity is assessed. The latter (LM-1 and LM-2) are shown to have more appropriate size and power properties and are the best choice for this analysis. Breaks may be found in either levels or trends with the tests, and methodology follows in the footsteps of Perron in establishing a solution to the previously commonly held belief that macroeconomic time series are generally non-stationary.

As a relatively simple example, we can use a white noise series at 300 equally spaced time points in order to visualize the occurrence of mean-shift structural change. For the first 100 time points, the data vary around a mean of zero with normal errors. However, at time point 101, the data abruptly jumps up—an "exogenous shock" as described in Perron (1989)—but continues to *follow the same path* at this higher level (see Figure 2.2). This would suggest that the data generating mechanism is the same, while the shift was created by an exogenous factor. Standard tests, such as the ADF test, may not detect the fact that the data are stationary within each of the regimes around this shock. However, the LM-2 test would likely find this series to be stationary with two exogenous level shifts at time points 100 and 200. The idea behind these tests is to assess stationarity by separating these shocks from the noise function around the mean. Perron (1989) exhibits this issue using the Great Crash of 1929 and the Oil Price Shock of 1973—both considered exogenous—and quarterly GNP data. The ability to model the data as stationary with breaks is advantageous for any series that may be broken into stationary regimes due to structural change or for stationary data with breaks that must be accounted for before estimating standard linear models. Of course, modeling the actual location and size of the break is an important part of properly estimating the coefficients and their respective statistical significance. However, while these tests roughly estimate break dates, the breaks must be more precisely estimated in a subsequent step in the analysis.

Perron (1989) first discusses the modeling of data with breakpoints, and Bai and Perron (1998; 2003) take the structural change analysis one step further, developing a technique to estimate least squares regressions with dates and sizes of structural change in both level and trend simultaneously (BP Method). Lee and Fort (2005; 2006; 2007; 2008) pioneer the BP Method in sports research for both the tracking of competitive balance for the four major North American leagues, as well as testing the Uncertainty of Outcome Hypothesis and its relationship to attendance at the Major League Baseball league-level aggregate. The BP Method applied to stationary data or break-stationary data allows for up to five break dates in level and/or trend along with the ability to separately estimate covariate coefficients across regimes (and ultimately the stationary process occurring between breaks). Allowing only some predictors (in this case, level and trend) to change across regimes is particularly important for shorter series with multiple structural changes to preserve degrees of freedom in the modeling procedure. I follow the Fort and Lee schematic for the analysis of data for those series found to be stationary with breaks (Steps 1, 2.1, 2.1A, and 2.2 in Figure 2.1) in the remaining chapters. Those series found to be nonstationary are left for further analysis beyond the scope of this work.

2.3 Attendance Series as Stationary Processes

I begin the analysis by evaluating the unit-root properties of each series at the league and franchise levels as shown in Figure 2.2. Analyzing stationarity is a useful exercise in itself for a few reasons. First, if attendance is non-stationary, then the use of level data (e.g., demand estimation using panel data) may lead to biased estimates and the direction of the bias is unknown. Using European football, Davies, Downward, and Jackson (1995) were the first to show that ignoring time series behavior in sports data could lead to spurious correlations, posing special problems for demand analysis and policy prescriptions. Jones, Schofield, and Giles (2000) extended these observations. In addition, a technique such as taking first differences of the elements of a time series is a useful but limited approach to a non-stationary series (e.g., no elasticity estimates can be had from first differences). However, as noted in Fort and Lee (2006), if the data are stationary then standard regression applications to level data are appropriate (for example, taking logs gives direct elasticity estimates). For this reason, the authors suggest first testing the attendance series for significant breaks—or shocks—and determining if the data are stationary between these breaks.

If this subsequent unit-root test with endogenously specified break points rejects non-stationary behavior, level-data analysis is restricted by the limits of stationarity—that is, to the data between specific break points in the time series. Lee and Fort (2008) take the analysis of annual league-aggregate MLB attendance in this direction. Finally, if the unit-root test with endogenously specified break points fails to reject non-stationary behavior, data transformation such as taking first differences may be required in order to perform additional regression analysis.

Following this line of reasoning, each league and team-level attendance series will be tested against the null of a unit-root using the Augmented Dickey-Fuller and Phillips-Perron tests with both a constant and a trend variable. The numbers of lags are determined by minimization of the Schwartz-Bayesian criterion for the ADF test, and by the truncation suggested by Newey and West (1994) for the PP test. Unit-roots are further verified using the generalized least squares Dickey-Fuller test as described in Elliot, Rothenberg, and Stock (1996) for all leagues and franchises.

Leybourne, Mills and Newbold (1998) highlight the possibility of spurious rejections with standard unit-root tests when breaks occur near the ends of a non-stationary series. Therefore, I employ the two-break minimum LM unit-root test to support any result from the ADF and PP tests (Lee and Strazicich, 2001; 2003; 2004) using GAUSS code generously provided by Professor Junsoo Lee. The results are further confirmed using the test in Zivot and Andrews (1992), but are not reported here.

As in Lee and Fort (2008), the LM unit-root test statistic with exogenously specified break points is obtained from the regression:

$$\Delta y_t = \delta' \Delta Z_t + \varphi \tilde{S}_{t-1} + \varepsilon_t,$$

where $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t \tilde{\delta} + \varepsilon_t$, t = 2,..., T; $\tilde{\delta}$ are the coefficients in the regression of Δy_t on ΔZ_t, with Z_t representing a vector of exogenous variables; $\tilde{\psi}_x$ is given by $y_1 - Z_1 \tilde{\delta}$; and y_1 and Z_1 denote the first observations of y_t and Z_t. ε_t is the error term, assumed N(0, σ^2). As in Perron (1989), in the most general model (changes in level and trend) with two breaks, Z_t is described by [1, t D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]', where D_{jt} = 1 for $T_{Bj} \geq T_{Bj} + 1$ for j = {1, 2}, and zero otherwise, DT_{jt} = 1 for t $\geq T_{Bj} + 1$ for j = {1, 2}, and zero otherwise, and T_{Bj} stands for the time period of the breaks (Lee and Strazicich, 2003). Following results from this procedure, I employ a one-break minimum LM unit-root test (Lee and Strazicich, 2001) for series that are not rejected at the highest level with the two-break test. This is advisable given that the two-break test can adversely affect the power to reject the null hypothesis in the presence of a *single* break (Lee and Strazicich, 2003).

This last step clearly identifies those team-level attendance time series that remain to be treated under (for example) first differences in subsequent regression analysis.

From this stage of the analysis, one may discern whether strike years have an impact on the underlying assessment of stationarity of team-level attendance time series. Ultimately, unit root tests are performed for both the original data and this adjusted version for all leagues and teams to evaluate the differences between real data and the "counterfactual" data in which the effects of a labor dispute are minimal. I note that, of course, this does not necessarily mirror a league in which labor disputes were non-existent, as impacts from these disputes may have been experienced both before and after the actual work stoppage event. While break dates are roughly estimated in the unit root with breaks procedure, the subsequent BP Method is needed in order to more accurately assess the breaks present in the attendance series (Figure 2.2).

2.4 Structural Change and Demand for Attendance

Due to limitations within the empirical estimation procedures proposed, breakpoint estimation is not employed for current franchises with less than 40 years of existence, as the statistical power of the model is significantly reduced with shorter series (Bai and Perron, 2006). However, I do assess the presence of a unit root for shorter franchise level series. For those league and team series of appropriate length in which a unit-root is rejected, or rejected with breakpoints, I apply the approach of Bai and Perron (1998, 2003; I thank the authors for making their GAUSS code available online) allowing changes in both levels and trends as first described in Perron (1989). This model parallels that of the AL and NL aggregate approach in Lee and Fort (2008). For the BP procedure, Bai and Perron (2003) consider the following regression model with *m* breaks (and *m* + 1 regimes):

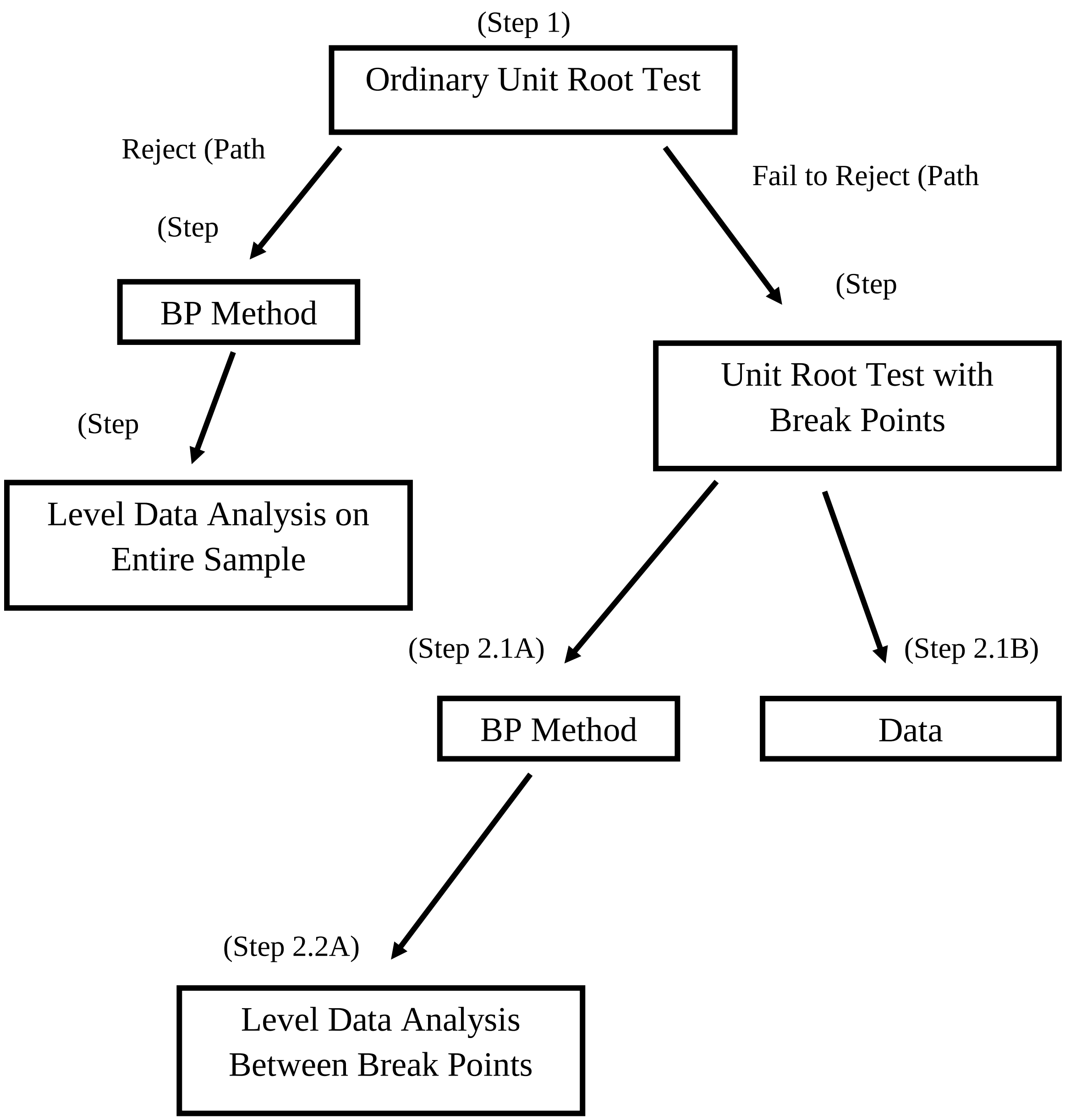
$$y_t = x_t'\alpha + z_t'\beta_j + u_t, \qquad t = T_{t-j} + 1, \ldots, T_j, j = 1, \ldots, m+1.$$

In the above model, the dependent variable at time *t* is y_t with disturbance u_t, while $x_t(p \times 1)$ and $z_t(q \times 1)$ are vectors of covariates and α and β_j are the corresponding vectors of coefficients. The indices ($T_1, \ldots, T_m$) are treated as the unknown breakpoints. The model above indicates a *partial model* when $p > 0$, and a *pure structural change model* when $p = 0$. Under the partial model, only the coefficients for z_t are allowed to vary, while the coefficients for x_t remain constant across regimes (Bai and Perron, 2003).

The dependent variable of interest is Team or League Average Per-Game Attendance. I again note that although attendance is often used as a demand proxy, it does not capture the full demand for sport in an age of mass media and large television contracts. Therefore, it is important to keep in mind that these simplistic models estimate attendance and are not necessarily demand estimations for the team or league's entire "sports product". There are other issues that allow limited information from these simplistic models. In particular, the BP Method cannot account for censored data (sellouts). These issues have recently been theoretically considered by Qu and Perron (2007). In addition, important demand covariates like ticket prices are subsumed in a generic time trend throughout. Cross-sectional time series approaches where more data are available will prove enlightening and complementary to the current empirical analysis.

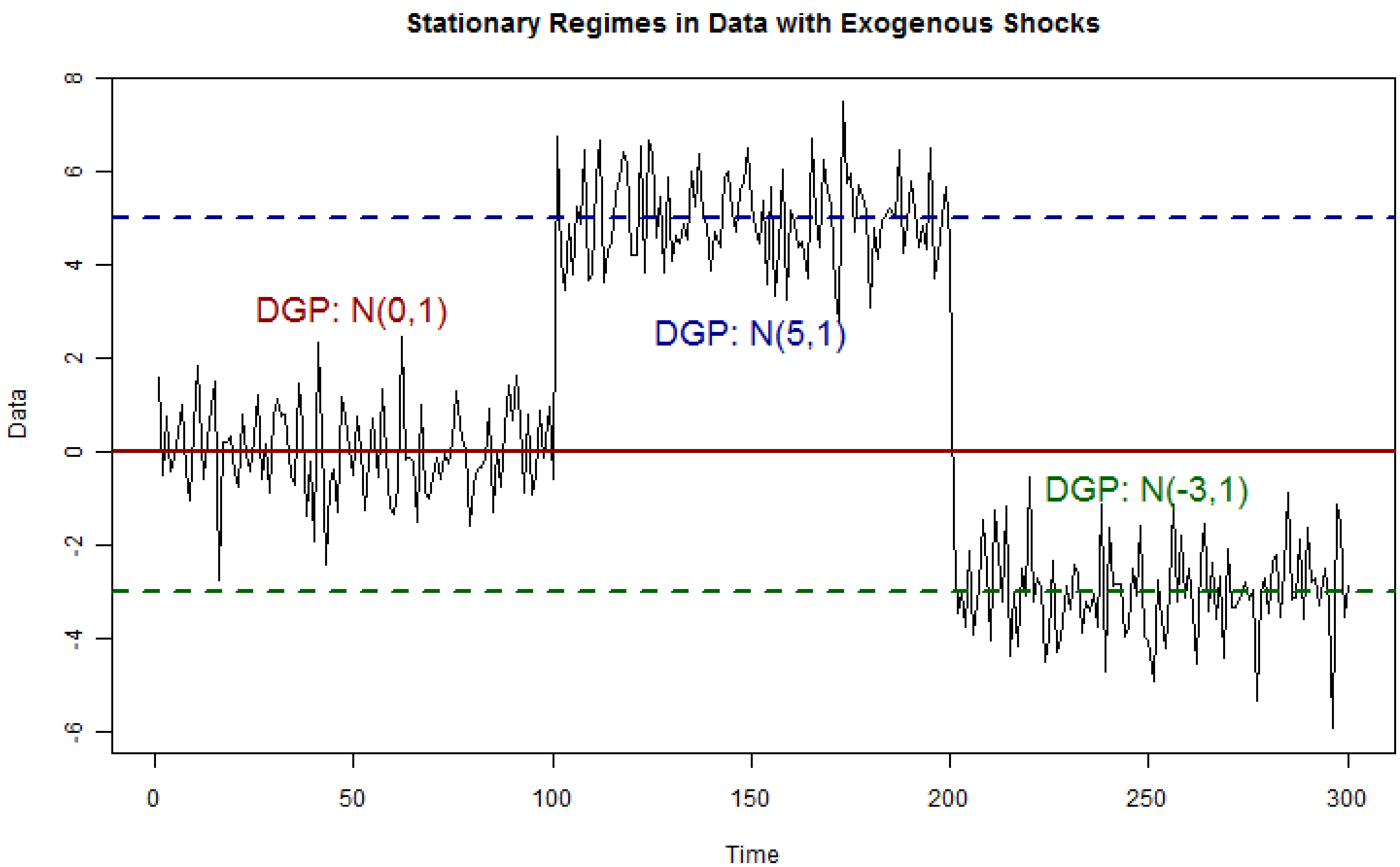
In Chapter 3, I address more specific issues with the data used within this work, including sample size, variance estimation, and covariate considerations. Additionally, I discuss the treatment of labor stoppages and franchise moves throughout the histories of each data set. Finally, I will expand further on some of the econometric issues that I have alluded to above.

FIGURE 2.1: Time Series Modeling Schematic



(Fort and Lee, 2006)

FIGURE 2.2: Random Data Generating Process with Exogenous Shocks



CHAPTER 3

General Methodology

3.1 Predictor Variables and Measurement Issues

Uncertainty of outcome is realized in the form of competitive balance measures when considered in attendance estimation for professional sports. This notion of league balance and uncertainty may be manifested in multiple ways, including *game uncertainty*, *playoff uncertainty*, and *consecutive season uncertainty* (Cairns, 1987; Sloane, 1976). Game uncertainty (GU) refers to the closeness of games, while playoff uncertainty (PU) refers to the closeness of pennant/championship races. Finally, consecutive season uncertainty (CSU) refers to the occurrence of dynasties in a given league (Butler, 1995; Lee & Fort, 2005). Although there have been calls for (Zimbalist, 2002) and attempts at capturing (Humphreys, 2002) these constructs in a single form, each of these measures of balance may prove vital to league success and cater to fan preferences for balance in different ways if the UOH holds in sporting competition (Fort, 2003; Fort & Maxcy, 2003). For this reason, I will consider all three realizations of uncertainty as separate measures within each league and franchise attendance model constructed.

The attendance models employ the GU measure “Tail Likelihood” (*TL*) from Fort and Quirk (1995) and Lee (2004; 2006) using data regarding teams in the upper and lower tails of the distribution of win percentages in the respective league. This measure assumes fans are more responsive to changes in the extremes of the distribution and measures the frequency of teams in these tails. As *TL* increases, this indicates a tighter distribution of win percent, and GU has increased in the given season (see Appendix E for the specifics of its calculation). The UOH would imply that an increase in *TL* would be related to an increase in attendance. This measure has been used extensively in the literature on sports economics across a number of leagues; however, Owen (2011) describes the disagreement over using a binomial-based idealized standard deviation of win percent in leagues with a non-zero possibility of a draw. In this analysis, the NHL falls into a category of leagues in which ties are a common occurrence (I assume that the probability of a tie in the NFL is essentially zero, despite the technically non-zero possibility). Despite some small changes in the measure, I proceed with the standard binomial approach to *TL* using win percent for the NHL, as Owen shows that quantitative differences in using this estimation approach are minimal. In addition, the interest of this demand analysis regards the *changes* in balance across seasons for the same sport league, rather than a comparison of the value of the measure itself across leagues.

Measures for PU (*WinDiff*) and CSU (*Corr*) are also included in the attendance demand regression models. The calculation of *WinDiff* is outlined in Lee and Fort (2008), and is made up of the average difference in winning percentages between division winners and runners-up in each season, as well as the difference between the "last team in" and the "first team out" for each league or division (see Appendices F through I for the specifics of calculation of *WinDiff* for each league). As *WinDiff* decreases, the division races between the winner and first team out of the playoffs is closer, and PU has increased for the given season. UOH would predict attendance to increase with a decrease in the *WinDiff* measure. It is important to note that given the changing rule structures for each league over the course of the attendance series, the calculation of *WinDiff* varies throughout the analysis. Again, although there are minor issues with using win percent for calculating *WinDiff* in the NHL, they likely have little to no effect on the outcome of the model estimations here (Owen, 2011). I also employ an alternative analysis using the number of points back for the NHL, but the results (available upon request) do not differ substantially from the win percent metric. Therefore, I proceed with using one half win for ties in the *WinDiff* measure for the NHL for the remainder of this work.

The CSU measure (*Corr*) consists of the correlation between each team's winning percentage in the current season and its own average winning percentage over the previous three seasons, similar to that of Butler (1995) and Lee and Fort (2008). Higher *Corr*, indicates that same teams are dominant over time, and CSU from year-to-year is declining (the full calculation of *Corr* is exhibited in Appendix E). Based on UOH, we would expect a decrease in the *Corr* measure to be associated with an increase in league attendance. While there is some correlation between these three measures of competitive balance, calculation of the variable inflation factor for the breakpoint models indicates that multicollinearity is of little concern (league balance variable inflation factors were below five, a suggested threshold implying multicollinearity). Therefore, I continue with including all variables within each regression.

The last competitive balance measure considered, coined the Competitive Balance Ratio (*CBR*), comes from Humphreys (2002). This measure combines within and across season balance in a single measure, and includes aspects of both Game Uncertainty and

Consecutive Season Uncertainty. This measure is included only in the breakpoint estimation for MLB franchises. After further consideration, the conflation of across and within season balance in this measure makes it more suitable for balance comparisons across leagues than attendance estimation for a single league across seasons. Therefore, I do not proceed with CBR for any models involving the NBA, NFL or NHL. For more information on the calculation of this measure, the reader is referred to Appendix E and Humphreys (2002).

Finally, I include each team's seasonal winning percentage (*W%*) as an additional input variable for the franchise level regressions. While fans may be directly responsive to competitive balance and uncertainty at the league level, fans likely care about their own team quality first with overall balance as a secondary component to individual team interest. Under this assumption, El-Hodiri and Quirk (1971) first discuss the idea that the optimal probability of a home team win would be between 0.5 and 1. Of course, the coefficient estimate from the team quality variable must be approached with significant caution, as the direction of its causality can become convoluted in interpretations. Teams likely choose their quality in the long run (Fort & Quirk, 1995), rather than respond to short-term attendance shocks. Davis (2008), however, finds a significant relationship between team quality and team attendance, with the direction of causation going from the former to the latter using a VAR model. I assume *W%* is well-suited to control for the expected fan interest in individual teams, as the balance measures control for the changes along the time path of balance in each league when estimating attendance. Because the primary interest of this investigation is the historical tracking of attendance given the league's balance, *W%* is used simply to control for baseline team interest based on quality in each respective season. Since attendees early in a season have little to benchmark the current year's success, it is likely that the previous season's success will have a stronger effect than the current one at these points. However, the current season success is likely more influential later in the season. Therefore, ancillary regression models are also estimated, which include a one-year lagged win percent variable. A detailed description of the calculation of all of the variables included in this dissertation can be found in Appendices E through I.

Because there is some variation in home games played over seasons, Team and League Average Per-Game Attendance is used as the dependent variable of interest (TAPG and LAPG, respectively) by dividing the total attendance for the season by the number of games hosted by each franchise in each year. At the annual league and team level, strike years are included in the eventual analysis of the determinants of attendance. Each league has had a work stoppage or labor dispute at some point in its respective history. Therefore, I make use of both the raw attendance per game (APG, used as a generalization to both TAPG and LAPG from here on) and an adjusted version of each series in which years containing labor disputes or work stoppages are imputed using a simple local linear regression approach (LLR). In this approach, APG for those years in which a labor dispute occurred consists of a weighted average APG of the seasons just before and just following the year in question, as well as those games played within the year in question, if in fact games were played in that season (this is not the case for the 2004-2005 NHL season). While previous literature has made use of indicator variables to denote strike years (Schmidt and Berri, 2002, 2004; Coates and Harrison, 2005), this can adversely affect detection of long-term structural change elsewhere in the data where the series may be partitioned into short subsamples by the indicator variables (Lee and Fort, 2007). The subsamples generated may be so short that endogenously specified break points cannot be determined. This also ensures that later breakpoint estimation is not falsely influenced by the short-term shocks that may result from a work stoppage, as previous research has found short-term effects of strikes, rather than long-term, and the interest of the current research lies more with the long-term structural changes. However, I use both the adjusted and unadjusted APG in order to assure robustness of results from the BP procedure. Only the results of the adjusted data are presented here, with the ancillary analysis on the raw data available upon request. For the team level regressions, further considerations were needed for data imputation. These further considerations are discussed more thoroughly in the respective section for each league and team in Chapter 6 (NBA), Chapter 7 (NFL) and Chapter 8 (NHL).

Given that the NBA, NHL and some teams from MLB and NFL in this analysis have relatively short attendance series (limited to no less than 40 years), I account for size and power issues using a trimming parameter that restricts regimes between breaks to a minimum length Bai and Perron, 2006). In estimating attendance models using the BP Method, care must be taken with respect to the choice to account for changes in variance across regimes. The failure to reject the presence of a unit root without accounting for breaks may be related to both a change in mean and variance across time. Heteroskedasticity can play a role in error variance estimation and ultimately statistical inference if not properly accounted for. In the series analyzed here, I first employ the BP approach *without* accounting for the possibility of changing error distributions across regimes. Although more breaks may be estimated using this approach (see Bai and

Perron, 2006), the significance of the sequential tests could be affected by changing variance across regimes. Some of the models show evidence of time-dependent variance in the errors, suggesting that a more robust model—allowing for heterogeneous error estimates—may be more appropriate.

Additionally, some models are sensitive to the imputation of years in which work stoppages took place. Large spikes or troughs in covariates that are concurrent with strike years or estimated structural changes tend to adversely affect coefficient estimates in the league-level regressions. Both sign and significance of coefficients on balance measures in the regression tend to be influenced due to small changes in the data at the league level. Ultimately, both homogeneous and heterogeneous error variance estimation models are reported at the league and team levels, but the majority of discussion will involve only the latter.

I follow by estimating each of the models, allowing for heterogeneity of errors across regimes for the sequential tests for structural change. This resolves most of the issues with respect to time-dependent errors in the regression estimates, as there do not seem to be systematic errors within each of the regimes for each of the models. Given the multiple variance estimates, I set the trimming parameter to allow no less than 10 observations per regime for the heterogeneous models. For example, if a break is detected in an attendance series (with a length of 40 years) in 1970, then the procedure will not allow a new break anywhere in the interval from 1960 through 1980. This ensures that the procedure does not estimate the variance of a regime with very few data points. For those teams with attendance series longer than 100 data points (MLB only)—and for the homogeneous variance models—I use a trimming parameter of $\varepsilon = 0.15$.

Series with considerably fewer observations have the parameter set to $\varepsilon = 0.20 \; or \; \varepsilon = 0.25$ in the heterogeneous model estimation. This specification also means that the maximum number of estimated breaks for the shorter series is 2 or 3, while the procedure allows up to a maximum of 5 breaks for the longer series and in the homogeneous error variance models. Bai and Perron (2006) discuss this issue in more detail. An additional consequence of specifying multiple variance estimations is that breaks may not be estimated as closely together as with the homogeneous models. However, this may be advantageous in that the model does not attempt to over-fit such short series by estimating spurious breaks because of the limited information about mean reversion of the data. The BP approach could run into this difficulty if the process is modeled as changing structurally, when in fact it would have reverted to the original mean (level) without a break in the shorter series.

3.2 Further Econometric Issues

Along with issues in variance estimation and sellout (censoring) problems, there are other econometric limitations with the breakpoint regression estimations in their current form. In the league-level regressions for NBA, NFL and NHL, there is some concern of correlated errors with respect to Game Uncertainty as measured by *Tail Likelihood*. Because the BP procedure is a simultaneous estimation of breaks and regression coefficients, using errors robust to heteroskedasticity is a complicated programming issue beyond the scope of the current empirical analysis (as is the difficulty with sellouts and censoring of attendance data for some teams). In fact, Bai and Perron (1998) mention this problem early on in their work developing the BP Method.

It is important to also note that using a trend in the long-term regressions is not a replacement for attempting to understand influences of economic factors like ticket prices and general wealth in a given market. Teams could be adjusting ticket prices based on the included variables (like team quality and outcome uncertainty/balance) and this would not be accounted for in the simplistic approach described here. The fact that tickets could be priced based on these covariates could reduce the amount of information gathered through a simplistic model, as any attendance variation that may have occurred due to changes in competitive balance and uncertainty could be mitigated by team managers attempting to maximize profits under these changing conditions. Therefore, I emphasize that the following analysis is not a demand estimation per se, but a look at attendance over time controlling for the changing characteristics of the league.

Finally, while qualitatively evaluating structural change is a useful endeavor itself, this sort of speculation can only reach so far. Further "quasi-experimental" methods that include more economic variables—such as discontinuity designs using panel data—would be complementary to the work proposed here. However, the structural changes found using the BP Method can inform future work regarding policy implications in professional sports leagues in North America.

As an overview, the methodology explained in this section will first be applied to the remaining leagues at the aggregate level: NBA, NFL and NHL. From there, each of the four major North American Leagues will undergo franchise level breakpoint analysis with the considerations listed here. While aggregate information is important for the league, the latter will help to understand underlying influences of both breaks and interest in uncertainty of outcome.

CHAPTER 4

NBA, NFL and NHL League Aggregates

4.1 Introduction

Following previous work at the league aggregate level for Major League Baseball (Lee and Fort, 2008), I proceed with modeling demand for attendance and test the UOH for the National Basketball Association, National Football League and National Hockey League. These three leagues have largely been ignored in the attendance tracking literature due to the immediate availability of baseball data in many cases, as well as the relative stability of MLB franchises when compared to these other leagues. Additionally, the importance of understanding differences between leagues and preferences of fans of these leagues can lend support for both UOH and fan substitution. Finally, because balance is a league level concern—and owners posit that policies are implemented through league agreement—it is important to understand the aggregate effects of uncertainty of outcome on league revenues. Once these are established, further understanding of these effects at the individual franchise level will be complementary to this initial empirical analysis, shedding light on the collective decisions made by owners to implement these policies.

4.2 Data Collection

The availability of NBA, NFL and NHL data varies, and attendance is not as well-recorded as that of Major League Baseball. The data used here come from Sports Business Data (2010) and the ESPN league-specific coverage websites (2010), along with the respective Sports Reference (2010) websites for each league. In addition, there is some disagreement of available data sources for NHL attendance in certain years. Therefore, for the NHL, I average three sources of game attendance for years in which multiple estimates are available, including Sports Business Data (2010), Hockey Zone Plus (2010), and Andrew's Dallas Stars Page (2010). For the league-level analysis, the attendance series are specified as the league average per-game attendance (LAPG), rather than raw attendance, as the number of games and teams have changed substantially throughout the history of each respective league. LAPG is calculated by dividing the total league attendance by the total number of league games played for each year within the series. The number of games for each season was recorded from Sports Business Data (2010) and cross-referenced with historical league standings at the respective league web pages at Sports Reference (2010) to ensure accuracy. The length of each series is subject to the availability of attendance data. The NBA series spans from 1955-56 through the 2009-10 season; NFL attendance data span from 1934 through the 2009 season; and the NHL series spans from 1960-61 through the 2009-10 season.

The NHL is a special case for the *unadjusted* data. The 2004-05 NHL lockout caused the cancellation of the entire NHL season. Therefore, *both* the unadjusted and adjusted LAPG for the NHL contain an imputed value for the 2004-05 season, as the measure would otherwise be undefined for that season. The *adjusted* NHL data contain an additional imputation for the 1994-95 NHL work stoppage.

The National Football League attendance series has a few anomalies. First, while the NFL labor dispute in 1987 ultimately resulted in a player strike, owners continued the season with replacement players. Given the likely difference in the absolute quality of play (total league talent) during these games, it seems reasonable that attendance would not be at the same levels as it would have otherwise been with NFL regulars on the field. In addition, the league only played 15 of the scheduled 16 games in the regular season—though this alone should not affect attendance on a per game basis outside (leaving aside effects of known reduced supply on the demand for attendance at the games that were held). For this reason, the NFL adjusted data include an imputed LAPG data point for the 1987 season. For unknown reasons, attendance data for the 1992 NFL season are universally unavailable. Therefore *both* the adjusted and unadjusted data contain an imputed data point for the 1992 season using the same LLR approach as described earlier. Finally, the 1982 work stoppage for the NFL resulted in a shorter season, with teams playing only nine regular season games. I use raw LAPG in the unadjusted data for these nine games, with an imputed LAPG for the adjusted series for 1982. Because the playoff format for 1982 differed—with an 8 game first round format—PU was calculated similarly to that of more recent NFL seasons: including the Wild Card races as the difference in Win Percent between the 8^{th} and 9^{th} place teams in the AFC and NFC. The final adjustment relates to 2008 and 2009 NFL attendance availability. While data for the majority of NFL games were available for the 2008 and 2009 season, a few teams do not report the full season's home attendance. For this reason, I simply assume that each excluded game is equal to that team's average attendance for those games reported, and take the overall per-game attendance for the NFL using these totals. At the team level, current teams that played in any of the AAFC, AFL or NFL in its respective history include the full attendance series available only for those years in which they played in the post-merger NFL.

Lastly, the NBA included some data issues to be addressed. The NBA attendance series spans from the 1955-56 season through 2009-10, but it is important to note that the NBA did not merge with the ABA until 1976. Therefore, any LAPG reported for those years before the merger includes only teams in the NBA at that time. In addition, for the NBA work stoppage in the 1998-99 season—in which 428 games were cancelled—I include an imputed value for the adjusted NBA series similar to the other two leagues. Table 4.1 presents decade averages of each of LAPG for each league along with balance measures calculated as in Appendices F through I (and Appendix J for Major League Baseball). Figure 4.1 shows the behavior of each of the variables over time for these three leagues.

4.3 Unit Root Results

For all league attendance series—both adjusted and unadjusted—ADF and PP tests fail to reject the presence of a unit root with or without a trend (Table 4.2). I follow with using the Lagrange Multiplier tests for stationarity with breakpoints from Lee and Strazicich (2001, 2004). Beginning with the two-break test, there is evidence to reject the presence of a unit root at the 95% critical level for both the adjusted and unadjusted series in all three leagues (Table 4.3). As described in the previous section, if the attendance series are stationary with only a single break, the power of the two-break test may be reduced. Therefore, I apply the one-break test for all leagues to ensure thoroughness, as none of the attendance series were rejected at the *highest* critical level (99%). Using the one-break test, we can reject the presence of a unit root with breaks at the 99% critical level for both the NBA adjusted and unadjusted series (Table 4.4). The only other change in significance from the two-break to one-break test is the NFL *adjusted* series, for which there was not enough evidence to reject the presence of a unit root with only a single break. However, unit root presence was rejected with the two-break test, indicating that proceeding to the BP Method is still reasonable for this series. From here, I proceed under the assumption that all attendance series are stationary with *at least* one break.

4.4 The BP Method and Structural Change in Attendance

Each of the league attendance series are subjected to the BP Method. The league-level attendance regressions and estimated breaks come from the following model:

$$LAPG'_{lt} = \mathbf{z}_{lt}\beta_{li} + \mathbf{x}_{lt}\gamma + \boldsymbol{\varepsilon}_{lt}, \qquad t = T_{i-1} + 1, \ldots, T_i, \qquad i = 1, \ldots, m+1.$$

$LAPG_{lt}$ is league average attendance per game in year t for league l, i indexes the i^{th} regime, and the indices ($T_1, \ldots, T_m$) are treated as the unknown breakpoints. While the notation above could indicate the use of a panel model, in this case the BP procedure is performed *separately* for each league due to programming constraints. The error variance for each league can be found in Figure 4.2, with some evidence that errors are not consistent throughout the entire series. Therefore, both heterogeneous and homogeneous models are evaluated for each league. For the league-level analysis with heterogeneous error variance across regimes, the BP specification is described as:

$$z_t = \{1, t\},\ x_t = \{TL, WinDiff, Corr\}, \text{ and } (q=2;\ p=3)$$

for all leagues, with up to two (NBA and NHL) or three (NFL) breaks allowed in the model. In the models with homogeneous error variance across regimes the specification is the same, but these allow up to five breaks to be estimated within the data for each league.

In Table 4.5, I report the results of the BP tests for breakpoints within the data. The sequential test with allowance for heterogeneous regime errors indicated one significant structural change for the NBA (1987-88), while the NFL (1972 and 1993) and NHL (1974-75 and 1994-95) series were found to have two breaks (break dates and confidence intervals presented in Table 4.6). The procedure first tests the number of breaks (one through five) against the null of no break in the data. These are reported as the $SupF_t(i)$ tests. Next, the sequential test—SupF(i+1, i)—begins by testing two breaks against a single break, three breaks against two breaks, and so on. The number of breaks chosen for the model depends on the results of these tests. However, it is important to note that for the series considered here the number of breaks is limited by the length of regimes between breaks. Therefore, these sequential tests are not always consistent with the ultimate number of breaks chosen for the model. In these cases, the chosen breaks were cross-referenced with a Bayesian Information Criterion procedure (BIC) to ensure accuracy of the model.

The second model, with assumed homogeneous error variance across regimes, finds slightly different results for the break dates. For the NBA, an additional break is found near the 1997-1998 season, while there is an additional estimated break in the NHL changes from in 1966-67, with a one year change to the second break (1975-76). Finally, the second NFL break moves from 1993 to 1997 for the homogeneous model. I note that very little information can be gleaned from the coefficients in Table 4.7 for level shifts in the model. While the first level coefficient is the intercept at the beginning of the series, later shifts must be accompanied by plots for visual inspection of the direction and magnitude of these shifts. For this reason, fitted yearly values of attendance for both of the attendance estimations for NBA, NFL and NHL are plotted in Figures 4.3, 4.4 and 4.5, respectively.

Figure 4.3 shows that the 1987-88 break point for the NBA dramatically increased attendance in both models. After that, while the trend remained positive, it was not as steep as prior to the break point, and the homogeneous error model indicates a flat trend following the second break—a slight downward shift—in 1996-97.

The NFL break point in 1972 shifted attendance slightly downward and the trend declined while the break point for 1993 included no shift but an increase in trend thereafter (Figure 4.4). Neither of the post-1972 trends is anywhere near as steep as prior to that first break point. However, the homogeneous error model indicates a slight upward shift at the second break in 1997, followed by a similar trend from the last break.

Finally, for the NHL in Figure 4.5, the 1974-75 (or, in the homogeneous model, 1975-76) breakpoint was a dramatic shift downward in attendance in both models, followed by the steepest trend in attendance over the sample period. The second break point for the heterogeneous NHL model in 1994-95 involved no detectable shift but witnessed a decline in the trend afterward. However, the lack of a detection of a break in 1966 for the NHL in this initial model likely affected estimation of balance coefficients in the regression. This is a result of the closeness of this apparent shift to the 1974 shift detected in the heterogeneous error model (which requires a certain regime length to estimate different variances between regimes). The homogeneous model estimates an additional break in 1966-67, indicating a downward shift that recovered a bit before the second downward shift in the 1975-76 season. From there, the method estimates a consistent upward attendance trend that becomes attenuated at the 1994-95 break.

4.5 The BP Method and GU, PU, and CSU

Coefficients for the competitive balance measures included in both models are reported in Table 4.8. Turning to outcome uncertainty impacts for the NFL, none of the three measures of uncertainty of outcome are found to have statistically significant effects on attendance levels. Here, the UOH is rejected at every turn for the NFL. This makes the NFL much like the European leagues as assessed by Szymanski (2003). Fort and Quirk (2011) also suggest that this may be due to the smaller inventory of 16 regular season games in the NFL. There are other issues to be addressed with modeling NFL attendance, not the least of which is an issue with the econometric specification of censored data due to sellouts that could result in underestimation of coefficients. This should be addressed in future work on demand analysis for the NFL using cross-sectional tobit models that take into account the attendance breaks found here.

The second striking result is that *GU matters for the NBA and in a way that fails to reject Rottenberg's UOH*. As *TL* rises, so does attendance. If the NBA owners care about balance because fans do, then they are better off facilitating games with close competition. Why this shouldn't also be the case for the rest of the North American leagues remains for future work to determine (Lee and Fort, 2008, find little evidence for Rottenberg's UOH with respect to GU in MLB).

Next, *PU matters for the NBA, but in a way that rejects the UOH*—a decrease in *WinDiff reduces* attendance. So, the NBA is unlike MLB in this regard (Lee and Fort, 2008). If leagues care about balance because fans do, then owners in the NBA and the NHL are better off without close regular season races to the playoffs. Determining just why fans feel this way in the NBA and NHL remains for future work, and may be explained through asymmetrical increases in attendance for large winning markets in these seasons. Lastly, the homogeneous error variance model indicates a significant influence of *Corr* on attendance in a way that *is consistent with Rottenberg*: when the same teams win year after year, the NBA is estimated to experience a decrease in attendance for this model.

For the NHL heterogeneous error variance model, *CSU* and *PU* matter for the NHL in a way that reveals hockey fans *prefer* dynasties and playoff races with *wider* margins. As *Corr* and *WinDiff* increase, CSU and PU worsen, but attendance increases with this worsening of balance. However, it is likely that this result for the NHL is due to the inability of the BP Method to handle two closely adjacent break points. In 1967-68, the

NHL doubled in size from 6 to 12 teams. This expansion had an effect on the competitive balance of the league, especially for CSU measured by *Corr*. The *Corr* measure during the first three years of expansion includes only the six original NHL teams in its calculation, as the expansion teams do not have the required three years' worth of win data to include in the measure. This calculation issue made the CSU variable drop considerably for these three years only, returning to previous levels once all teams have available data to include in the calculation. This may account for the statistically significant effect found for CSU in the NHL. The BP Method is unable to model the entire dip in attendance as an exogenous shock because of its temporal proximity to the following break in 1974-75 (in the model with heterogeneous variance across regimes). The attendance decrease is therefore attributed to the large "improvement" in the CSU measurement during this time and the related preference for dynasties. In a separate model where constant variance is assumed across regimes, the BP Method does indeed choose the NHL attendance dip in 1966-67 as an exogenous shock. However, its magnitude does not account for the entire change, and dynasties are again revealed as a preferred choice by hockey fans.

Still, all-in-all, at least at the annual league level, there appears to be variation in the importance of outcome uncertainty—and the type of outcome uncertainty—that matters for attendance. This suggests that there are truly interesting and insightful differences to be discovered among fans of the major North American sports leagues.

4.6 League Histories and Structural Change

Better historians will be able to add to the offerings on historical episodes for future investigations, but I offer what I can to the historical relevance of structural changes in each league. For the NBA, the related history that occurs to us for the 1987-88 break point concerns expansion and the transition from the Magic-Bird era to the Jordan era. The Charlotte Hornets and Miami Heat joined the league for the 1988-89 season and the Orlando Magic and Minnesota Timberwolves were added the very next season, 1989-90. Ultimately, the NBA added a large Florida market to their league through Orlando and Miami. In addition, three teams moved to new arenas after the 1987 season—Detroit, Milwaukee and Sacramento. While the calculation of LAPG accounts for increase in the number of games, each of these moves nearly doubled seating capacity for these teams. This break also coincides with the end of the Magic-Bird era (Kareem Abdul Jabbar and Magic Johnson would retire shortly; Bird just after them) and the beginning of the Michael Jordan phenomenon (he entered the league in 1984-85 but was a mature NBA player at this time). Detroit would win two championships, but then it was all about Jordan and the Bulls. The shape of expansion suggests a shift of the type in Figure 4.3 (at "T1"). The changing of the guard from Magic-Bird to Jordan could end up helping explain the shift as well. However, since NBA attendance does not seem to respond to dynasties, some other explanation would need to be explored for reduced but still positive trend in NBA attendance after 1987-88. The second break detected in 1993-94 has a flat trend that follows, indicating that NBA attendance demand may have reached its peak or that reported attendance is at or near capacity just following the labor issues in both the NHL and MLB. However, the homogeneous model seems to indicate a slight negative effect of the 1998 labor dispute for the NBA. This presents issues for demand estimation—and further work regarding this issue is recommended—but the upward shift may also open questions of the possibility of fan substitution from these two sports to the NBA. While previous work has found little evidence of hockey-to-basketball substitution (Winfree and Fort, 2008) it would be interesting to revisit the question with respect to professional baseball and basketball.

The earlier break point for the NFL is proximate to the AFL-NFL merger (first season, 1970) at the lower end of the break point confidence interval. In addition, a rival league—the World Football League—was established in 1974, but folded in 1975, and may have had an effect on NFL attendance during this short period. Fort and Lee (2007) also find a break point in NFL competitive balance at this time, but the finding here is that NFL attendance does not respond to any type of competitive balance. Thus, while the calculation of LAPG accounts for an increase in the number of games, there can still be residual impacts on fan tastes for the "new" NFL. There also was a 42-day training camp strike that may have soured the fans for that season. For the later trend change, the break point season 1993 is the first season where both expanded free agency and the salary cap were in place. While it is well documented that not much happened to balance due to this institutional change, it is quite possible that fans found these impositions to their liking. In addition, 1993 marked the first NFC contract to new entrant FOX, expanding the number of games on TV and introducing a host of viewer-friendly on-screen innovations in FOX broadcasts.

For the NFL homogeneous model, the 1966 flattening of attendance coincides with the first Super Bowl (played in January of 1967). While the Super Bowl has become a national event in this day and age, it may not have had the support from NFL fans early on. Because this analysis includes *only* NFL attendance in those years before the NFL-AFL merger, any inferences on Super Bowl popularity by fans of the AFL and its teams must be left for further investigation. The final break detected for the NFL comes in 1981, where the attendance trend begins to increase again. This break coincides with labor disputes in both the NFL and MLB, but one must take note that there was also a significant change in the way the game was played during this time. Joe Montana was drafted in 1979, while Dan Marino became the first quarterback to throw for 5,000 yards in a single season in 1984. These were two of the most prominent quarterbacks in NFL history, at least up to that point in time. During this time, the importance of quarterbacks in the offensive game was being recognized, and passing increased significantly throughout the 1980s—from 159 yards per game in 1978 to 211 in 1989 and 230 in 2011 (Football Reference, 2012). This increase in attendance may indicate that fans have preferences for the high-excitement passing game in comparison to the traditional, hard-nosed rushing attack.

Finally, for the NHL, the only real rival league threat in the NHL's history, the WHA (1972-73 to 1978-79), was proving economically troublesome at precisely the time of this break point. Bobby Hull had switched to the WHA for its first season and was joined, probably not coincidentally given the break point, by Gordie Howe for the 1973-74 season. Youngsters Wayne Gretzky and Mark Messier joined the WHA for the 1978-79 season. When it ceased operations after the 1978-79 season, four WHA teams merged into the NHL (Edmonton Oilers, New England Whalers, Quebec Nordiques and Winnipeg Jets). NHL attendance made a quick recovery near the end of the WHA and it experienced an upward trend from this point through the 1993-94 season. The second structural break coincides with the 1994-95 owner lockout that shortened the season to 48 regular season games. Even adjusting LAPG for the 1994-95 lockout, perhaps there was an aftermath to the first major labor-management conflict in hockey. Interestingly, however, the BP method does not detect any similar response by hockey fans for the 2004-05 lockout in either the heterogeneous or homogeneous model. This may be due to the closeness of this season to the end of the attendance series, as the BP Method does not allow for break estimation within a certain distance from the endpoints. Lastly, the initial break detected in the homogeneous model indicates a large downward shift in 1966 at the time of significant expansion for the league. Whether this is a product of poor attendance in these new markets (especially for the Golden Seals), a lack of interest thanks to further competition for the Original Six, or a combination of both is difficult to say. While the expansion seemed to have resulted in a dip in attendance, the league recovered quickly just before the second break near the formation of the WHA.

4.7 Economic Significance of Outcome Uncertainty

Statistical significance does not guarantee economic significance. Therefore, I take an approach that incrementally improves balance measures in the leagues to estimate the effects this would have on its attendance and stadium revenues, as in Lee and Fort (2008). The revenue data are from Team Marketing Report for 2009 from Sports Data (2010). For GU, statistically significant for the NBA, I improve *TL* by the average change in the measure from year to year. For PU, statistically significant for the NBA and NHL (heterogeneous model), the gap of the playoff race is closed by a single game.

Finally, for CSU—statistically significant for the NHL in the heterogeneous model and the NBA in the homogeneous model—I improve *Corr* to indicate teams are somewhat less dominant over time. Resulting changes in attendance are determined, and I apply the correctly normalized dollar values from the Team Marketing Report data for 2009. The results are in Table 4.9 (NBA) and 4.10 (NHL).

If the NBA were able to take action that improved GU while somehow decreasing PU in these incremental fashions, the league would enjoy a 0.85 percent increase in revenues from the former and a 0.45 percent increase in revenues from the latter. While statistically significant, this result indicates that the economic significance of outcome uncertainty to the NBA is minimal, about $16,594 per game or $680,354 for 41 home games for a team. However, according to the homogeneous model, this change in revenues is doubled if the league can improve CSU as well. This would seem to require extreme micro-level management for an increase in, at most, 1.7 percent in total league revenues.

Exactly the same approach and logic also reveals that the statistical significance of PU and CSU for the NHL ends up relatively trivial, economically. If the NHL were able to take action that improved PU and CSU in the incremental fashion devised here, the result would be about a 1.68 percent increase in league revenues translating into $878,343 per team for 41 home games. However, this is based on the model with heterogeneous variance across regimes. For the alternative model, neither coefficient is statistically significant for the NHL.

4.8 Summary and Conclusions

I use the BP Method to assess the time series behavior of annual league attendance per game for the NBA, NFL, and NHL. The series are all non-stationary, but stationary with break points. This result should be of interest to statistical analysts using level data. If they wish to avoid spurious correlation outcomes, they should exercise caution and use the stationary subsets of the attendance data we identify. In addition, there is believable correspondence between various historical occurrences and the direction of shifts and trend changes in these North American leagues, suggesting cross-section/time series investigation of merger, expansion, the presence of rival leagues, changes in player era dominance in the NBA and NHL, and how the imposition of salary caps and free agency impact fan perceptions.

I also estimate the effects of Game Uncertainty and Playoff Uncertainty addressed directly by Rottenberg, and Consecutive Season Uncertainty—which he did not address—on gate attendance in each of these leagues. Under the current treatment, none of them matter for NFL attendance. The same is true of GU in the NHL and CSU in the NBA. Further, when one of these types of outcome uncertainty is statistically significant for annual league attendance, the evidence on Rottenberg's hypothesis is mixed at best. Playoff Uncertainty matters for both the NBA and NHL, and CSU matters for the NHL, but in a way that rejects Rottenberg's hypothesis. Only GU in the NBA is statistically significant and fails to reject the UOH. Almost certainly these results will prove interesting in all further cross-section/time series assessments of the role of fan preferences in attendance demand. It would also be interesting to extend these findings relate to television demand as a next step in the analysis.

It is important to note that this analysis does not consider sellouts for league-aggregate attendance, and this could be one reason for the null finding with respect to the effects of balance measures on NFL attendance. More work is needed to evaluate the effects of uncertainty on NFL attendance because of this issue. Unfortunately, the breakpoint method only allows for ordinary least squares regression at this point in time, and further evaluation of the statistical properties of the breakpoint method are necessary for pushing forward with the technique for other regression specifications. Further inspection at the franchise level for some teams—especially in the NFL—would certainly be enhanced by an added consideration of sellouts in a limited dependent variables framework. This is recommended in the short term, between breaks found in the data presented here.

Nonetheless, despite the statistical significance of the estimated outcome uncertainty coefficients, the economic significance tends to be minimal. Marginal alterations in outcome uncertainty can improve league revenues by 1.34 percent in the NBA and 1.63 percent in the NHL. It may be that the leagues in this analysis have managed balance well enough that it does not negatively affect fan interest in the league.

Given that balance seldom matters—and when it does it does not matter much—leads to some final research suggestions. There is now ample evidence that outcome uncertainty matters very little for North American pro sports *in the way Rottenberg suggested*. However, Rottenberg's is the typical logic espoused by team owners, acting through their league, as justification for policy impositions like the draft, revenue sharing, and salary caps. If not for the sake of balance, then why are the policies actually supported? Economists are well equipped to examine the distributional consequences of these policies between players and owners, and some owners and others.

TABLE 4.1: Decade Averages for LAPG and Balance Measures (NBA, NFL and NHL)

League/Measure	*1930's*	*1940's*	*1950's*	*1960's*	*1970's*	*1980's*	*1990's*	*2000's*	*Overall Avg.*
NBA LAPG			4,778	5,714	9,644	12,110	15,836	17,204	11,436
NBA TL			0.24143	0.02209	0.20135	0.05249	0.04432	0.10475	0.11171
NBA PU			0.08235	0.09243	0.07622	0.07073	0.06100	0.06664	0.07590
NBA CSU			0.40989	0.55819	0.28533	0.65375	0.60459	0.48786	0.50078
NFL LAPG	18,205	26,521	31,211	44,349	54,326	54,048	57,732	64,478	47,432
NFL TL	0.18876	0.16654	0.49508	0.47047	0.86188	1.36331	1.04093	0.99809	0.72494
NFL PU	0.13792	0.12595	0.0959	0.14083	0.12145	0.09318	0.10666	0.11890	0.11652
NFL CSU	0.64674	0.48338	0.38231	0.42758	0.51756	0.35743	0.35435	0.34454	0.42832
NHL LAPG				12,658	12,837	13,842	15,539	16,879	14,351
NHL TL				0.17446	0.08124	0.52115	0.64654	0.66000	0.41668
NHL PU				0.06925	0.08830	0.07628	0.05511	0.04150	0.06609
NHL CSU				0.52700	0.76185	0.63050	0.48290	0.45656	0.57176

TABLE 4.2: League-Level ADF and PP Tests

League		*NBA*	*NBA Adj.*	*NFL*	*NFL Adj.*	*NHL*	*NHL Adj.*
T (seasons)		55	55	76	76	50	50
ADF (*p*)	Constant	-0.880 (2)	-0.883 (1)	-1.919 (1)	-2.017 (1)	-1.206 (1)	-1.210 (1)
ADF (*p*)	Trend	-1.282 (1)	-1.287 (1)	-2.231 (1)	-2.233 (1)	-2.674 (1)	-2.682 (1)
PP (*l*)	Constant	-0.963 (3)	-0.965 (3)	-1.700 (3)	-1.774 (3)	-1.401 (3)	-1.399 (3)
PP (*l*)	Trend	-1.418 (3)**	-1.406 (3)	-2.174 (3)	-1.905 (3)	-3.000 (3)	-2.987 (3)

Data unadjusted for strikes.

p: the number of lags

l: lag truncation.

***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 4.3: League Level LM Test

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	*Test Statistic*	*Critical Value Break Points*
NBA	7	1972/73, 1996/97	3.958***, -1.170	-5.771**	λ = (0.33, 0.76)
NBA Adj.	7	1972/73, 1996/97	3.959***, -1.050	-5.714**	λ = (0.33, 0.76)
NFL	3	1966, 1986	-0.279, 5.711***	-6.071**	λ = (0.43, 0.70)
NFL Adj.	3	1972, 2000	-4.703***, 3.590***	-6.076**	λ = (0.51, 0.88)
NHL	6	1973/74, 1985/86	-4.463***, 6.066***	-6.347**	λ = (0.28, 0.52)
NHL Adj.	6	1973/74, 1985/86	-4.427***, 6.056***	-6.323**	λ = (0.28, 0.52)

Data unadjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See Lee and Strazicich (2003) Table 2 for critical values. ***, ** = significant at 99% and 95% critical levels, respectively.

TABLE 4.4: League Level LM Test

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	*Test Statistic*	*Critical Value Break Points*
NBA	7	1992/93	3.882***	-5.255***	λ = 0.69
NBA Adj.	7	1992/93	3.811***	-5.182***	λ = 0.69
NFL	0	1972	-2.217**	-4.892**	λ = 0.51
NFL Adj.	8	1980	-3.412***	-3.431	λ = 0.62
NHL	3	1976/77	-3.056***	-4.638**	λ = 0.34
NHL Adj.	3	1976/77	-2.990***	-4.580**	λ = 0.34

Data unadjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 4.5: League Level Sequential Break Point Test Results

League	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$	*UDmax*	*WDmax*
NBA (Het.)	200.41***	114.62***				200.41***	200.41***
NBA (Hom.)	173.22***	116.31***	117.52***	146.87***	190.49***	190.49***	348.87***
NFL (Het.)	239.40***	162.98***	117.42***			239.40***	239.40***
NFL (Hom.)	309.56***	194.75***	160.09***	132.37***	117.68***	309.56***	309.56***
NHL(Het.)	68.73***	33.98***				68.73***	68.73***
NHL (Hom.)	71.62***	80.27***	128.25***	164.21***	205.57***	205.57***	376.48***

League	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
NBA (Het.)	2.92				**1**
NBA (Hom.)	35.81***	35.81***	35.81***	11.52	**2**
NFL (Het.)	13.39**	14.84**			**2**
NFL (Hom.)	24.49***	24.29***	7.77	10.84	**2**
NHL(Het.)	50.80***				**2**
NHL (Hom.)	58.00***	14.11**	25.54***	10.11	**2**

***Significant at the 99% critical level
**Significant at the 95% critical level
*Significant at the 90% critical level

TABLE 4.6: League Level Break Test Results (Adjusted)

League	T_1	T_2	T_3
NBA (Het.)	**1987-1988** [86-87, 88-89]		
NBA (Hom.)	**1987-1988** [86-87, 88-89]	**1997-1998** [96-97, 00-01]	
NFL (Het.)	**1972** [71, 73]	**1993** [91, 94]	
NFL (Hom.)	**1972** [71, 73]	**1997** [96, 99]	
NHL (Het.)	**1974-1975** [73-74, 75-76]	**1994-1995** [93-94, 96-97]	
NHL (Hom.)	**1966-1967** [65-66, 66-67]	**1975-1976** [74-75, 76-77]	**1994-1995** [93-94, 95-96]

Notes: 90% confidence intervals are in [].

TABLE 4.7: League Level Breakpoint Regression Results

League	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4
NBA (Het.)	298	2453	71	13326				
	*(30.26)****	*(6.04)****	*(4.06)****	*(16.63)****				
NBA (Hom.)	299	2,554	236	7,168	35	10,195		
	*(33.45)****	*(6.93)****	*(4.80)****	*(3.81)****	*(0.87)*	*(7.61)****		
NFL (Het.)	1118	13182	334	38041	675	17335		
	*(35.90)****	*(12.47)****	*(4.58)****	*(10.03)****	*(6.25)****	*(2.31)***		
NFL (Hom.)	1,116	12,823	316	38,288	406	36,160		
	*(36.99)****	*(12.28)****	*(5.88)****	*(12.51)****	*(2.44)***	*(3.13)****		
NHL (Het.)	144	10611	229	6407	122	10272		
	*(4.51)****	*(24.52)****	*(9.01)****	*(7.90)****	*(3.78)****	*(6.89)****		
NHL (Hom.)	621	9,912	131	11,217	215	7705	102	11,839
	*(7.59)****	*(23.40)****	*(1.96)**	*(16.26)****	*(9.62)****	*(9.59)****	*(4.14)****	*(9.96)****

***Significant at the 99% critical level
**Significant at the 95% critical level
*Significant at the 90% critical level
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively.

TABLE 4.8: League Level Breakpoint Regression Results

League	*γTL (GU)*	*γWindiff (PU)*	*γCorr3 (CSU)*	$\bar{R}^2 (R^2)$
NBA (Het.)	2337 *(3.86)****	6953 *(2.62)***	-636 *(-1.79)**	0.990 *(0.991)*
NBA (Hom.)	2,086 *(3.94)****	6,885 *(2.80)****	-805 *(-2.44)***	0.992 *(0.993)*
NFL (Het.)	1013 *(1.21)*	5004 *(1.00)*	-1107 *(-1.05)*	0.984 *(0.986)*
NFL (Hom.)	1,307 *(1.60)*	5,030 *(1.03)*	-507 *(-0.48)*	0.985 *(0.987)*
NHL (Het.)	412 *(1.33)*	7488 *(2.12)***	1062 *(3.20)****	0.919 *(0.982)*
NHL (Hom.)	186 *(0.80)*	-2,939 *(-0.95)*	887 *(2.86)****	0.955 *(0.965)*

***Significant at the 99% critical level
**Significant at the 95% critical level
*Significant at the 90% critical level

TABLE 4.9: NBA Economic Impact of Outcome Uncertainty Measures

	NBA (Het.)		NBA (Hom.)		
Value	***GU***	***PU***	***GU***	***PU***	***CSU***
2009 LAPG	17,132	17,132	17,132	17,132	17,132
2009 Var.	0.030	0.073	0.030	0.073	0.550
Coef. Est.[a]	2,337	6,953	2,086	6,885	-805
Elasticity	0.004	0.030	0.004	0.029	0.026
ΔVariable[b]	0.064	0.012	0.064	0.012	0.171
Inc. Factor	213.33%	16.44%	213.33%	16.4%	31.1%
ΔLAPG	146.2	*-84.5*[d]	135.2	*-82.5*	137.4
% ΔLAPG	0.85%	*-0.49%*	0.79%	*-0.48%*	0.80%
Rev. Per Att[c]	$71.93	$71.93	$71.93	$71.93	$71.93
Δ Game Rev.	$10,516	-*$6,078*	$9,725	-*$5,934*	$9,883

a. Coefficient taken from Model 1 and follow the approach of Lee and Fort (2008, pp. 291).
b. All measure changes imply an improvement in balance.
c. Revenue per attendee data come from Team Marketing Report Fan Cost Index (2009).
d. *Italic* font indicates disagreement with Rottenberg's Uncertainty of Outcome Hypothesis.

TABLE 4.10: NHL Economic Impact of Outcome Uncertainty Measures

Value	**NHL (Het.)** *PU*	**NHL (Het.)** *CSU*	**NHL (Hom.)** *CSU*
2009 LAPG	17,476	17,476	17,746
2009 Var.	0.061	0.378	0.378
Coef. Est.[a]	7,488	1,062	887
Elasticity	0.026	0.023	0.019
ΔVariable[b]	0.012	0.184	0.184
Inc. Factor	19.67%	48.68%	48.7%
ΔLAPG	*-89.4*	195.7	-163.3
% ΔLAPG	*-0.51%*	*-1.12%*	*-0.93%*
Rev. Per Att[c]	$75.14	$75.14	$75.14
Δ Game Rev.	*-$6,718*	*-$14,705*	*-$12,271*

FIGURE 4.1: Time Path of Adjusted LAPG and Competitive Balance Measures

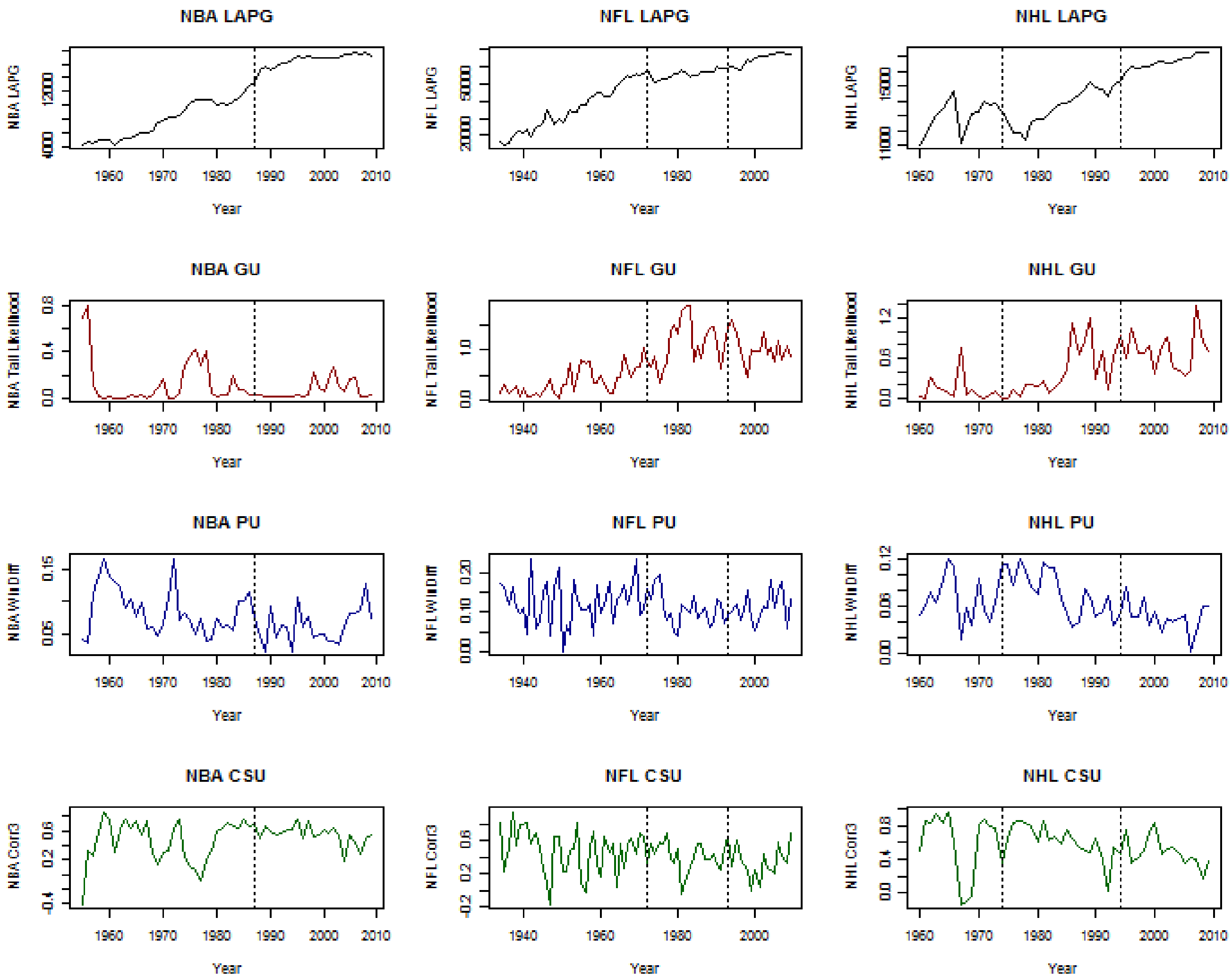


FIGURE 4.2: Residuals for League Level Heterogeneous vs. Homogeneous Models

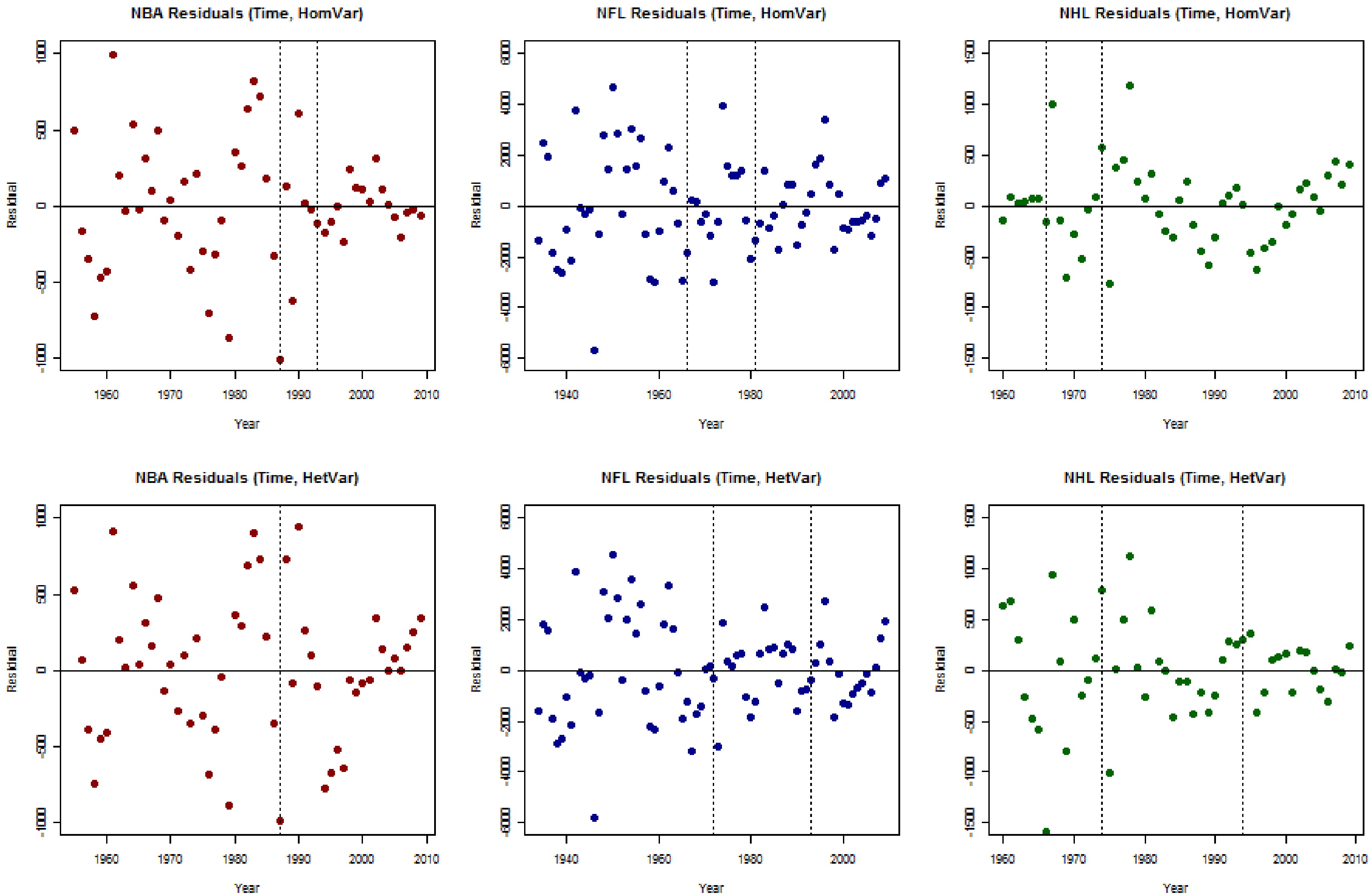


FIGURE 4.3: Fitted NBA TAPG

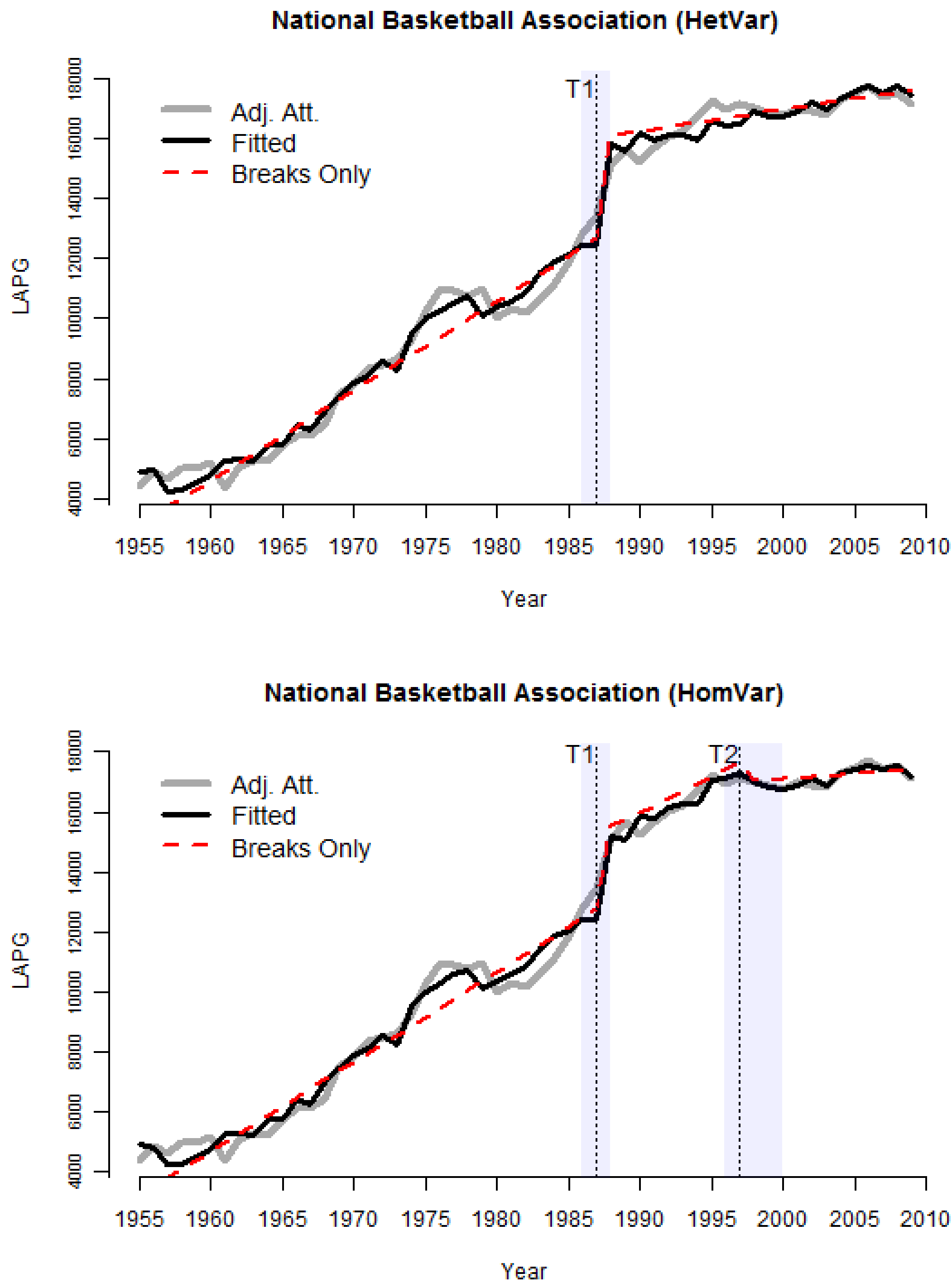


FIGURE 4.4: Fitted NFL TAPG

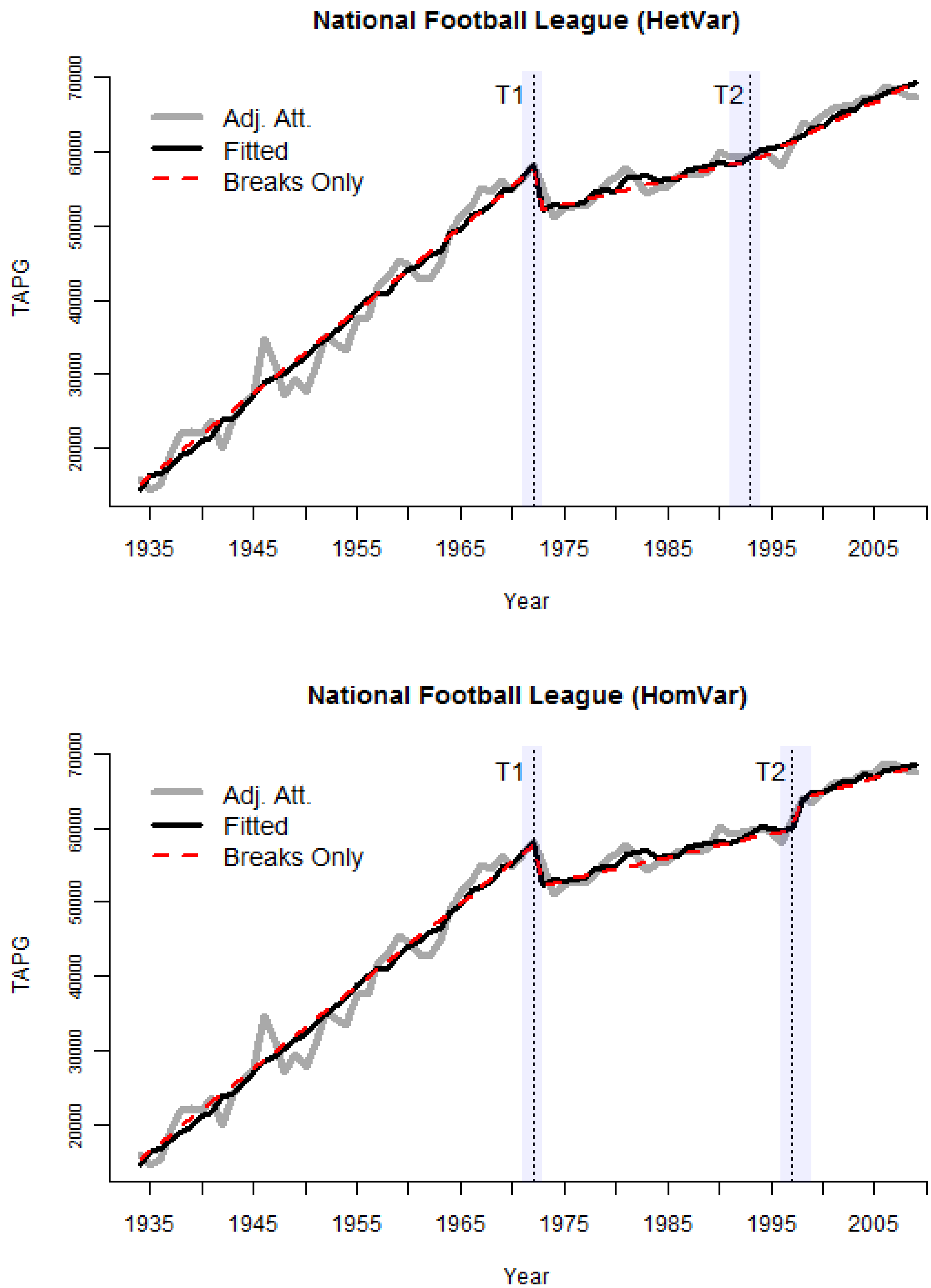
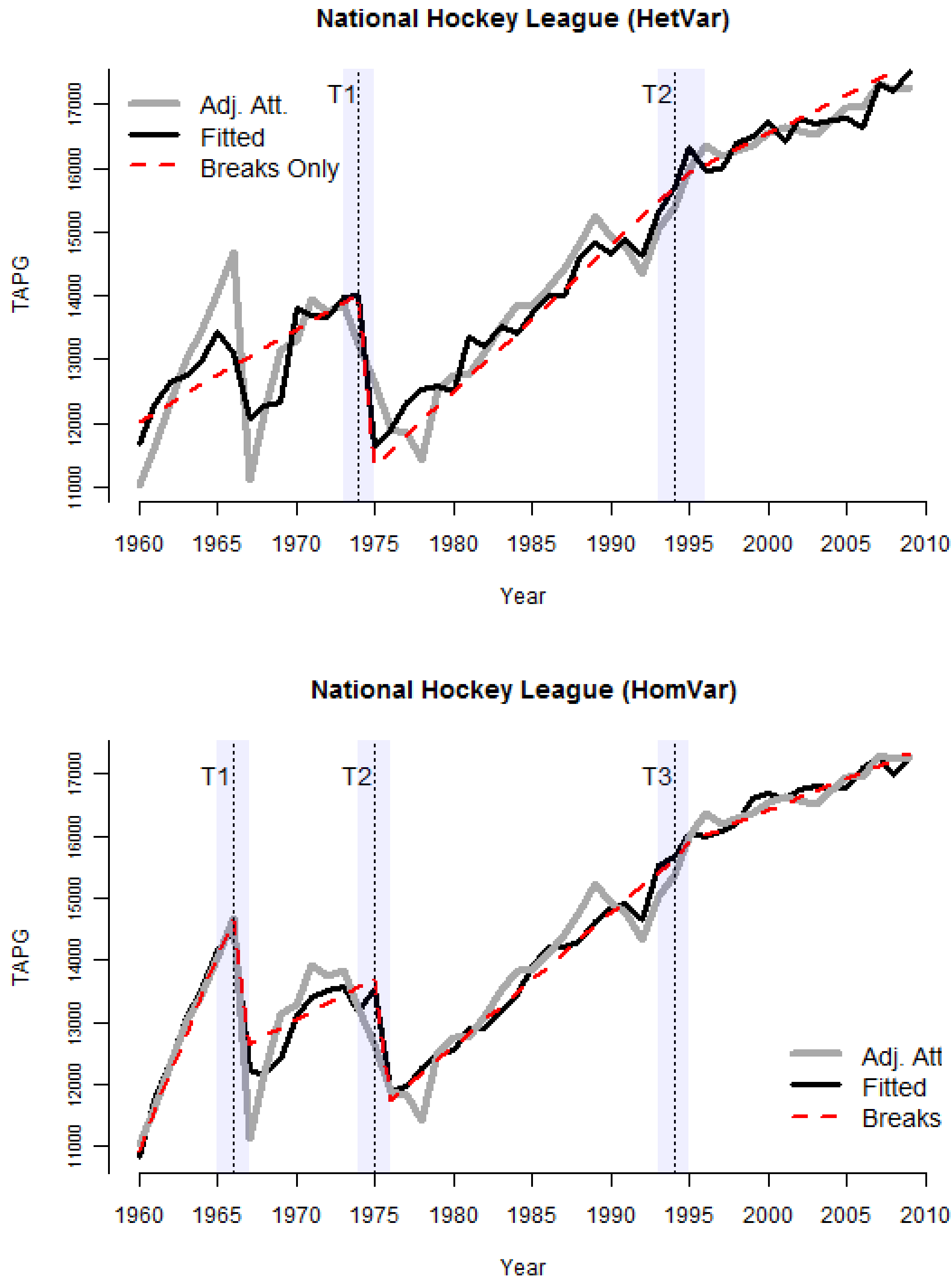


FIGURE 4.5: Fitted NHL TAPG



CHAPTER 5

Major League Baseball Franchises

5.1 Background

While Lee and Fort (2008) employ the BP Method for aggregate Major League Baseball attendance, there is much to be learned from proceeding with its application at the franchise level. I fill this gap in the literature in this chapter, as well as for the other three major leagues in the following three chapters . The addition of the franchise level analysis informs the statistically significant positive effect from Lee and Fort for the Playoff Uncertainty variable on attendance. Applying a similar approach at the team level may further show why only PU was found to be statistically significant and how this relates to the teams that are the most successful on the field. In addition, it could be that at the aggregate, fans are not particularly interested in game level or consecutive season uncertainty; however, this may differ across franchise markets and also relate to the success of each individual team. For example, results here show that—holding constant team quality—fans of the Red Sox find a low level of CSU particularly abhorrent: no surprise given the Yankee dynasties of years past. These relationships will be expanded upon in later sections. The following section describes the data collection process and results from the franchise level BP models for Major League Baseball.

5.2 Data and Methods

As in the previous chapter, the data used for this portion of the analysis come from multiple sources. The attendance and team win percent data for each of the MLB franchises come from Sports Business Data (2009) and are cross-referenced at Baseball-Reference (2009). I recorded the number of home games (used to calculate per-game attendance) from Retrosheet (2009), and verified team standings, expansion, and location changes with the previous two sources. Summaries of Team Average Per Game Attendance (TAPG), American and National League balance measures, team win percents, and the history of games back from the playoffs and number of postseason appearances can be found in Tables 5.1 through 5.5, respectively.

As before, the eventual breakpoint methodology requires lags of particular length, precluding analysis of recent expansion teams in (Arizona, Colorado, Florida, and Tampa Bay) and the most recent franchise move (Montreal to Washington, D.C.). Team attendance series consist of thirteen American League (AL) franchises, twelve National League (NL) franchises and one franchise that has spent time in both leagues (the Milwaukee Brewers). For those franchises that have relocated, I begin the attendance series in the first year of the most recent location. For example, the San Francisco Giants series spans from the year of the franchise's move in 1958 through the 2009 season. The original New York Giants team is considered a separate franchise and is not used for this analysis. Further the derivatives of the two versions of the Washington Senators (1901-1960 and 1961-1971)—the Texas Rangers and the Minnesota Twins—are considered separate franchises from either Senators team. I continue with modeling only current franchises found to be stationary in the precursory tests for the presence of a unit-root or unit-root with breakpoints.

To adjust for work stoppages, MLB franchise attendance totals in 1981, 1994 and 1995 are averaged with the years preceding and following the season in which there was a labor dispute, and this is referred to as the *adjusted* data. This is again a simple LLR approach with equal weighting on each year, similar to that of the league aggregate approach in the previous chapter.

Following the unit-root analysis, those team attendance series found to be stationary were subjected to the BP Method as described in Chapter 3. The team level attendance regression and estimated breaks come from the following model:

$$TAPG'_{ft} = \mathbf{z}_{ft}\beta_{fi} + \mathbf{x}_{ft}\gamma + \boldsymbol{\varepsilon}_{ft}, \quad t = T_{i-1} + 1, \ldots, T_i, \quad i = 1, \ldots, m+1.$$

$TAPG_{ft}$ is team average attendance per game in year t for franchise f, i indexes the i^{th} regime, and the indices $(T_1, \ldots, T_m)$ are treated as the unknown breakpoints. Although the notation above could indicate the use of a panel model, in this case the BP Method is performed separately for each franchise due to limitations in the methodology and to evaluate the heterogeneous impacts at the team level. As in Lee and Fort (2008), I estimate two separate models for MLB franchise attendance to evaluate the multi-faceted nature of competitive balance: Game Uncertainty (GU), Playoff Uncertainty (PU), and Consecutive Season Uncertainty (CSU). The first model (Model 1) is described as follows:

$z_t = \{1, t\}$, $x_t = \{TL, WinDiff, Corr, W\%\}$, and $(q=2; p=4)$

The second model (Model 2) employs Humphrey's "Competitive Balance Ratio" (CBR, 2002) in addition to *WinDiff*. The use of CBR combines elements of both GU and CSU, and it is therefore included in a model only with PU as to avoid redundancy in the model. Win percent is again included for the reasons stated above. In this model:

$z_t = \{1, t\}$, $x_t = \{CBR, WinDiff, W\%\}$, and $(q=2; p=3)$

For both models, coefficients on the time trend and level are allowed to change across regimes, whereas the coefficients pertaining to the competitive balance and team quality variables are not. These are classified as the partial model in Bai and Perron (2003). I proceed with an ancillary model for baseball franchise attendance that includes an additional one year lagged team quality variable (*W%* in the previous season). I perform this for both Model 1 and Model 2, and refer to these as Model 1B and Model 2B. The notation above is identical with the exception that there is an additional independent x_t variable within the model.

Finally, for each of the Model 1 estimations, I also employ the BP Method with homogeneous error variance across regimes, as described in the previous section, as well as with a one year lagged win percent covariate for each franchise. The results of each of these additional regressions are presented in Appendix A. For brevity, from here on I narrow the discussion to *only* Model 1 and Model 2 with heterogeneous variance estimates and current season win percent. While there were some break date changes across models, they were relatively minor and the statistical significance and direction of balance coefficient estimates are virtually identical. Fitted plots of each model for each team are excluded from this dissertation, but are available upon request.

There were some instances where the estimated model did not agree with the results of the sequential test, in which case I cross-referenced the chosen model with both the Bayesian Information Criterion and the Schwarz Criterion provided by the BP Method output. This was usually needed only for those attendance series with very small breaks or for those series with initially estimated breaks in too close of temporal proximity for the subsequent regression model. From here I focus the discussion on the *adjusted* data for sixteen teams, as model differences between the real and adjusted data were negligible. The results of the Bai and Perron sequential testing procedure can be found in Table 5.12 for Model 1 and Table 5.14 for Model 2. The San Diego Padres were found to have no breaks using the BP Method. While unit root tests indicated a stationary series with breaks, the breaks may be too small for the method to detect. The Padres' ADF and PP tests indicate very little evidence for rejecting a unit root for this series *without* breaks, so it may be misleading to continue with ordinary least squares (OLS) treating the attendance series as level data.

5.3 Unit Root Results

There is substantial agreement between the ADF and PP tests with respect to Major League Baseball franchise attendance. Both reject unit root (indicating trend stationarity) at the 95% level or higher for five teams—the Chicago White Sox, Cincinnati, Detroit, Pittsburgh, and St. Louis (Table 5.6). For these five teams and the remaining 21 non-stationary series, I follow with two-break LM tests of stationary behavior with endogenously specified break points. The two-break LM tests reject non-stationary behavior at the 99% level for ten additional teams (Table 5.7). The remaining eleven (Atlanta, Chicago Cubs, Houston, Kansas City, Los Angeles Angels, Minnesota, New York Mets, New York Yankees, Philadelphia, San Diego, and San Francisco) were subjected to the one-break LM test (Table 5.8). The results reject non-stationary behavior at the highest level for the Chicago Cubs, Houston, San Diego, and San Francisco. In addition, the Minnesota and New York Mets series—for which the unit-root null is not rejected with the LM two-break test—is rejected at the 95% level with the LM one-break test. Reasonably, only Atlanta, Kansas City, Los Angeles Angels, New York Yankees, and Philadelphia unadjusted series remain for eventual treatment under something like first differences.

Following the same steps on the data adjusted for potential impacts of strikes produces some different outcomes. For the ADF and PP tests, the only difference is failure to reject non-stationary behavior for St. Louis (Table 5.9). The two-break LM test with endogenously specified break points indicates rejection of non-stationary behavior (95% level or higher) for eleven of the remaining 22 series (Table 5.10). Continuing with the one-break LM test for the remaining eleven series (Atlanta, Chicago Cubs, Cleveland, Houston, Kansas City, Los Angeles Angels, Minnesota, Montreal, New York Mets, New York Yankees, and Texas), the test indicates rejection of the null of non-stationary behavior at the 95% level or higher for five additional franchises (Table 5.11). For the adjusted data, Atlanta, Kansas City, Los Angeles Angels, Minnesota, Montreal, and the

New York Yankees remain for subsequent treatment under something like first differences.

Staying just with the adjusted data results (Tables 5.10 and 5.11), I turn to only brief observations on these break points since the clear indication for all but a few teams is further investigation of the significance and qualitative impact of break points under the BP Method. Only a few teams have been in their current locations long enough to have break points much before the 1970s (St. Louis, Boston, and Chicago Cubs). The 1970s saw breaks for just a few (New York Mets, Philadelphia, San Francisco, and Baltimore). Nearly all of the action in terms of break points is from the 1980s to the end of the sample (eight teams in both the 1980s and 1990s). Again, a full analysis of break location for each team requires the BP Method, provided in the following section.

5.4 Breakpoint Analysis and Uncertainty of Outcome Results

For both models, the procedure finds break dates in common with Lee and Fort's (2008) league level analysis for many teams under consideration (Tables 5.13 and 5.15). First, a number of teams experienced attendance breaks near the end of World War II, consistent with the AL and NL aggregate findings, likely due to the end of World War II and the return of a large number of soldiers to the U.S. (many of them players—like Ted Williams—who also increased the absolute quality of the game on the field). Model 1 indicates that eight of the teams in existence before 1950 experienced a large attendance break in 1945 or 1946 (excluding only the Chicago Cubs), while Model 2 revealed that seven teams had a breakpoint in these years (excluding both the Cubs and the Chicago White Sox). I also find a number of common breakpoints (and confidence intervals for the breaks) in the range from 1927 to 1932, indicating that there may have been an effect of The Great Depression on some fans' ability to attend games at the time. Interestingly, this was not apparent in the aggregate MLB analysis of Lee and Fort (2008). However, Lee and Fort (2005) do estimate structural change in Major League Baseball's *competitive balance* series near the Depression Era for both the NL and AL.

There are some breakpoints detected during extended periods of on-field success near Strike Years, indicating a longer term structural change in attendance following a short-term shock for some teams. Despite imputing strike years with a local linear regression, about half the team attendance series experienced shifts or trend changes in attendance levels following (or just before) one of the significant strike events in MLB history (1981 and 1994-1995). After the labor disputes, I find that many teams experienced a rapid recovery in attendance levels even after estimated breaks (Boston and Philadelphia, for example). Previous work has found that shocks are relatively short term near work stoppages (Schmidt and Berri, 2002, 2004; Coates and Harrison, 2005), and this analysis seems to confirm that while there tends to be a short-term attendance dip following a strike, the trend behavior of attendance can change dramatically even after these short-term level changes to make up for this shift. The coefficients and significance for each of the trend (α_M) and level (β_M) changes can be found in Table 5.16 and Table 5.18 for Models 1 and 2, respectively. It is important reiterate that while the trend coefficients can be read directly off the table, the shift estimates are not as clear. The first level coefficient (represented by β_1) can be interpreted as the initial intercept of the least squares regression. However, the following shift coefficients do not necessarily represent the change that took place at the given structural change. For this reason, the reader is referred to Figures 5.1 through 5.8, which plot the estimated Model 1 and Model 2 for each of the sixteen franchises, respectively.

Model 1 and Model 2 indicate similar competitive balance preferences to that of Lee & Fort (2008), in that the most common statistically significant uncertainty of outcome measure of attendance is *Windiff* (PU). The coefficient for PU is significant at the 5% level or higher for four teams in Model 1 (Chicago Cubs, Cincinnati Reds, Los Angeles Dodgers, and Philadelphia Phillies) and four teams in Model 2 (Chicago Cubs, Houston Astros, Los Angeles Dodgers, and Philadelphia Phillies). The negative direction of the coefficients is as expected for all of these teams with respect to the predictions of the UOH (or, an *increase* in attendance with a closer pennant race). There is a significant estimated effect of *Tail Likelihood* (GU) only for Boston, Cincinnati and Detroit, with the sign of the coefficient *reversed* from UOH expectations for Boston and Cincinnati. The estimated coefficient for *Corr* (CSU) is significant only for Boston (5% level) and Houston (1% level). The sign on this coefficient is in the expected direction for the Red Sox, but in the opposite direction that would be predicted by the UOH for the Astros. Finally, in Model 2, the estimated coefficient for *CBR* is statistically significant only for the Chicago White Sox and Detroit Tigers at the 1% level. Coefficients for balance measures and win percent can be found in Tables 5.17 and 5.19 for Models 1 and 2, respectively.

It is interesting to see the differential effects of balance across markets. It seems likely that much of this is related to the fact that uncertainty at the league level mediates the aggregate “hope” for individual fans, as found in Lee and Fort (2008). In other words, the fact that the pennant race is tighter means that more fans are rooting for their favorite team(s) with a chance at the playoffs for a longer period in the regular season. Therefore, each of these teams likely sees an increase in attendance from the increase in quality and playoff chances, rather than purely from a direct relationship to uncertainty. This is not to say that the uncertainty itself does not create further excitement, and interactive effects should prove instructive in shorter term cross-sectional models. Further evaluation of this mediating hypothesis is recommended within a statistical framework that can test for direct and indirect effects.

Finally, the values of the measures of fit are relatively high for the models fitted, which is common in this sort of time series modeling. Lee and Fort (2008) note that the time trend likely accounts for omitted variables such as ticket prices and population changes; however, this should not impact the competitive balance coefficient estimates, as the significance of the trend variable would simply be transferred to the significance of the structural variables—such as market size and ticket price—if we were to include them in the model. Certainly these structural variables are of interest, and this is a shortcoming of the simplistic approach used here for long-term attendance. Unfortunately, there is very little consistency in the economic data for such a long period of analysis—especially for individual market areas—and any subsequent short-term analysis of fan behavior that includes these variables would be a welcome complement to the current investigation. Over such a long period, the structure of urban sprawl also likely has had an effect on the definition of markets for professional sports leagues, making the inclusion of these factors even more difficult.

A further analysis of the economic implications (gained/lost fans and cost of attendance) of fluctuations in league balance measures indicate that while some coefficients are statistically significant, the practical implications of such changes for team gate revenues tend to be minimal. This result echoes the conclusions from Lee and Fort (2008) for the league aggregate approach in Major League Baseball (see Tables 5.20, 5.21 and 5.22 for GU, CSU and PU, respectively). For the coefficients of each of the uncertainty measures, I apply a variant of the 'Incremental Approach' first described in Lee and Fort (2008), and initially revisited here in Chapter 4. To reiterate, for PU, the Incremental Approach involves decreasing the average number of games separating the playoff races by a single game. For the 2009 season, the average difference in the National League playoff races was about 5.35 games (0.033 in win percent for a 162 game season), and I reduce the difference to 4.35 games (now 0.027, a reduction of 0.006 in *Windiff*) to assess impacts on attendance for each team.

For GU and CSU, I take a more abstract approach to the incremental estimates. For the Incremental Approach I use the average season-to-season change in each measure. In the case of the GU measure, in 2009 the value was 0.094 for the AL, with an average historical yearly change of 0.115 (in absolute value) and a "historically most balanced" value of 0.815. For the NL, 2009 *Tail Likelihood* was at 0.472, with an average historical yearly change of 0.143 (in absolute value) and a "historically most balanced" value of 1.081.

Finally, the CSU measure for 2009 was 0.703 and 0.449 for the AL and NL, respectively, indicating that in the AL the same teams have been more dominant against their counterparts in recent years than those in the NL over theirs. I apply a similar Incremental Approach here as for GU. For the American League, the average change in CSU over the course of our series is 0.201 (in absolute value), with a minimum historical value of -0.197. In the National League, the average change from year to year has been 0.215, with a minimum historical value of -0.536. The results of these estimates for each team and the accompanying balance input can be found in Tables 5.20, 5.21 and 5.22 for GU, CSU and PU, respectively.

Beginning with the Boston Red Sox (2009 TAPG of 37,811), Model 1 indicates that an improvement in GU using the Incremental Approach is associated with a change of about 325 fans per game (0.86%) for the Red Sox. It is important to keep in mind that the coefficient for GU is reversed from the predictions of Rottenberg's UOH, indicating a *decrease* in attendance with closer game uncertainty. However, the model unsurprisingly reveals that Red Sox fans tend to have a seemingly appropriate aversion to teams dominating over time, given their rivalry with the historically dominant New York Yankees. The Incremental Approach for improving CSU is associated with an increase of 389 (1.03%) fans per game, still rather small overall.

For the Chicago Cubs, we find Model 1 estimates a significant coefficient for Playoff Uncertainty. Continuing with the Incremental Approach, the model estimates an increase of about 194 fans per game, (0.49% for a 2009 TAPG of 39,610). For Model 2, the coefficient estimate for PU is about 37% less, indicating an even smaller effect of *Windiff*.

I also find significant effects of both PU and GU for the Cincinnati Reds. With a 2009 *TAPG* of 21,579, the estimated attendance changes are 69 fans (0.32%) for an incremental change in PU, and a change of 156 (0.39%) fans for the incremental change in GU. While the coefficient for PU is in the expected direction for the UOH, the coefficient on GU indicates a *decrease* in fans with an improvement in game uncertainty.

For the Detroit Tigers *Tail Likelihood* coefficient (2009 *TAPG* of 31,693), using the average change in *TL*, I find a change in *TAPG* of about 506 fans per game (or 1.60%). The direction of the coefficient indicates an increase in fans with an improvement in game uncertainty.

Model 1 estimates a statistically significant effect of CSU, while Model 2 indicates a significant effect of PU on Astros attendance. Using the Incremental Approach for the CSU coefficient, there is a predicted *decrease* of 1,162 (3.73% of a 2009 TAPG of 31,124) fans per game using the average yearly improvement in CSU. Keep in mind that these apparent fan preferences indicate a reversal in sign from the expectations of UOH, as we would expect dynasties to negatively affect uncertainty of outcome and. Considering the Houston Astros are not a historic perennial powerhouse, these results are somewhat surprising. There may be issues with this shorter series at play here, similar to those affecting the balance coefficients in the league level National Hockey League model from Chapter 4, though the homogeneous version of Model 1 does not confirm this speculation. For Playoff Uncertainty (using the coefficient in Model 1 to remain consistent), implementing the Incremental Approach indicates an increase of 298 fans per game (0.96%). This result is consistent with the Uncertainty of Outcome Hypothesis.

The attendance effect of Playoff Uncertainty is shown to be statistically significant for the Los Angeles Dodgers—not to be confused with the Brooklyn Dodgers—in Model 1 as well. Using the Incremental Approach, a one game improvement in the closeness of the playoff race is associated with an increase of about 445 fans per game (0.96% of a 2009 TAPG of 46,440). In Model 2, the coefficient is also statistically significant, indicating a similar increase in fans per game associated with the associated improvement in *Windiff*.

Finally**,** for Philadelphia, I find statistically significant coefficients for PU. The elasticity estimates indicate that reducing the 2009 playoff standings by a single game would increase Phillies attendance by 267 fans per game (0.60% of a 2009 *TAPG* of 44,453) for Model 1. For each of the balance measures across all models, it seems that the practical implications of changes in the balance measures with respect to attendance levels are small at best.

Very few of the team attendance levels in this analysis revealed significant effects of competitive balance as measured by *Windiff*, *Tail Likelihood*, *Corr*, or *CBR*. These findings confirm some of the findings in aggregated approaches by Lee and Fort (2008) and Krautmann and Hadley (2006). While Lee and Fort (2008) find evidence of an attendance effect only for Playoff Uncertainty, the current research provides further evidence for the possibility that fans in some places are also sensitive to both Game Uncertainty (as in Soebbing, 2008) and Consecutive Season Uncertainty (as in Krautmann et al., 2008).

These results suggest that while some fans show a preference for more balance, others seem to prefer less, and many have little response with respect to the decision to attend a baseball game (holding constant team quality). This has interesting implications for the UOH and the conclusions made by Major League Baseball's Blue Ribbon Panel that fans invariably prefer uncertain outcomes to relatively known ones. However, this does not mean that the UOH is invalidated. It very well could be that MLB has managed certain balance elements well enough that its effect at the extremes is not detectable in these models with respect to fan decisions to attend games (Lee and Fort, 2008). There is also the possibility that teams adjust ticket prices in season based on the balance of the league and the team's current standing. The estimations presented here do not fully account for this sort of dynamic pricing behavior. And I do find significant effects of balance on certain teams in the league. Certainly, the effects of balance on television contracts and viewership are an important consideration in sports league fan behavior (see Alavay, Gaskell, Leach and Szymanski, 2006; Buriamo and Simmons, 2008; Tainsky, 2010).

In addition, if a team is consistently finishing in the bottom half of the standings, we would expect much of the variation in attendance levels to be caught through the *Win Percent* measure in the model. For example, if only a single team were finishing very low in consecutive years, while the rest of the league is very balanced, we may expect to only see effects of *quality* in this single team's attendance record, as there is little uncertainty as to whether or not they will prosper over the rest of the teams in the league. Under this scenario, there may still be little variation in the balance measure for the league. Because the league is highly balanced overall in this hypothetical situation, there could be a net increase in the aggregated attendance for MLB despite the loss of fans in the flailing team's market. This is one important advantage to understanding balance effects at both the aggregated and disaggregated level. At the league level, it very well may be beneficial to have "designated" losing teams and winning teams in order to provide a net gain in revenues, as long as the low-level teams are sustainable at their revenue levels. As a whole, the analysis here as well as in Lee and Fort (2008) and Meehan et al. (2007) seems to indicate that the relationship between Playoff Uncertainty in baseball and attendance at the league level is related to balance through a larger number of teams with higher win percent, rather than directly related to the interest in the uncertainty itself. Hope and expectation may be a better characterization of this phenomenon. Most likely, the New York Yankees will attract more in revenues than the Kansas City Royals with a World Series win. Switching the performances of the Yankees and Royals for prolonged periods may result in a net decrease in revenues and attendance for Major League Baseball, given the relative market sizes of these two teams. Fort and Quirk (2010) discuss this theoretical issue for single game ticket leagues in more detail.

Since we expect fans to first care about their own team success with balance as a secondary component to attendance (El-Hodiri and Quirk, 1971), these results are not particularly surprising. On average a low-level team with a better chance of winning each of its games would indicate an improvement in both GU *and* home team win percent. Based on the UOH, we would expect this to increase attendance levels for that team due to both an increase in uncertainty and an increase in home team quality. However, this simplistic model seems to account the change to win percent alone for a majority of franchises. For inferior clubs, once fans give up on their team's playoff prospects, they may turn to preferring absolute quality of play on the field rather than relative quality (Meehan et al., 2007). After all, a Kansas City Royals and Pittsburgh Pirates matchup may not sound very appealing to many fans, despite the relative competitiveness of the two franchises. Conversely, a Royals and Yankees matchup may well attract significant Royals (and local Yankee) fans due to the absolute quality of the visiting team. Fans of other teams may prefer to see their home team win every game.

Recent work by Davis (2009) and Meehan et al. (2007) have begun to investigate these preferences in more detail in shorter term cross-sectional analyses.

Additionally, we may not expect a close pennant race to increase attendance for a team not involved in that pennant race for most of the season. When many teams are close to winning a pennant, there seems little reason to believe that there would be an attendance increase for those teams not involved in that race. A team within the pennant race could experience higher attendance levels if they are both very good and barely holding off a competitor, and the aggregate of many of these teams may be net beneficial for aggregate MLB attendance. Lee and Fort (2008) mention this phenomenon in their aggregate approach, as much of the PU effect could be coming only from those few teams involved in the pennant race. Therefore, at the team level, much of the excitement found in close pennant races may be accounted for by the inclusion of win percent when that team is in fact entrenched in the race for the playoffs.

These effects of the inclusion of win percent in the model could also be the case for CSU, as fans of the continually dominant team would be predicted to continue to attend at high levels, while fans of the continually losing team may cease to attend at all. In this investigation, I find little pattern with respect to *home team* quality characteristics for those franchises with a significant coefficient for any of the competitive balance measures. However, I was unable to include the Yankees attendance series in our analysis because of concerns over its time series properties. Interestingly, the Boston Red Sox are the only long-tenured team to show a preference for improvement in Consecutive Season Uncertainty, indicating a possible effect of the Yankees dynasty on the Red Sox revenue potential. This is true even when controlling for the quality of the

Red Sox, indicating that fans in Boston may be especially sensitive to Yankee dominance. In a related fashion, it seems reasonable to expect Yankee fans to show preferences for low CSU, given the history of Yankee Dynasties over the past 100 years. When the Yankees go on the road, this could increase attendance by fans who value absolute quality, as opposed to relative quality of the two competing teams. Ultimately, it could be optimal for the league to have a consistently dominant New York Yankees team when attempting to maximize revenues across the league.

The evidence here suggests that the prediction of El-Hodiri and Quirk (1971)—that the optimal probability of winning for a given home team is somewhere between 0.5 and 1—may need more consideration, and may differ across markets and certain time points *within* a season depending on the playoff race. As mentioned earlier, recent work has been headed in this direction (Meehan et al., 2007). Variability in fan preferences is important to both team and league managers with respect to ticket pricing and league policy, respectively. The simplistic model discussed here would be well served with the addition of further analysis—accounting for exogenous breaks, of course—of varying fan preferences at the game level in order to assess how the predictions of the UOH differ across markets and absolute quality of visiting teams and the implications of this with respect to league organization. Extending the work here to this consideration is a planned next step for empirical research.

5.5 Breakpoint Regression Results

The breakpoints estimated from Model 1 and Model 2 coincide with significant events not only in U.S history, but also league and individual team history. The following subsections illustrate specific time lines of significant events near breakpoints for each of the franchises in the analysis. Much of the historical information provided comes from extensive searches through Wikipedia (in a general sense for links to reputable sources), USA Today and The New York Times. The size and direction of each structural change in both levels and trends can be gleaned from Figures 5.1 to 5.8.

5.5.1 Baltimore Orioles

The Baltimore Orioles have common breakpoints of 1974 and 1991 in both Models 1 and 2. In 1973 and 1974, Baltimore made the playoffs only to lose the AL Pennant to the Oakland Athletics in both seasons. This success may explain some of the upward attendance level shifts and trend changes during the 1970s through 1991. The season following 1991 brought forth another massive uptick in attendance for the Orioles, as Camden Yards opened in 1992, immediately following the 1991 AL MVP Award of Cal Ripken, Jr. Since this massive peak, Orioles attendance has been trending sharply downward.

5.5.2 Boston Red Sox

The 1918 Boston break point estimated in Model 1 occurs near the end of World War I, and this seems to be the most likely explanation for the structural change at this time. Similarly, the 1945 break occurs at the end of World War II, a finding common to many of the teams analyzed here. In both models, the Boston Red Sox have a breakpoint estimated for the year 1966. This structural shift seems relatively straight forward, as there is an enormous jump in attendance following the 1966 season. In 1967, the Red

Sox were in a 4-team race for the AL Pennant almost to the final game, riding Carl Yastrzemski's Triple Crown to the top of the standings. It seems that this extraordinary year had a longer-term impact on attendance than one would initially expect, though there could be other causes of this large change that I am unaware of. The final estimated break occurs in 1993 for Model 1. This is shown as a slight downward blip in attendance in Figure 5.1; however, there is a rapid recovery just after the shift. Given the labor strife in the 1994/1995 season, this finding seems to support the findings of Schmidt and Berri (2002) that strikes cause short-term effects in fan interest.

5.5.3 Chicago Cubs

In 1917, the Cubs hired William Veeck, Sr. (father of Bill Veeck) who brought the team 3 pennants (1918, 1929 and 1932). Looking at Figure 5.1, we can see a sharp upward trend during this time, with a large drop off just after the 1932 season. Given the fact that the Cubs won the NL pennant in that season, it seems that the city of Chicago was particularly susceptible to the Great Depression, indicated by this large downward attendance shift. Cook County significantly cut back on government employed workers, and nearly went bankrupt. In addition, the neighboring city of Gary, Indiana and its steel industry were hit particularly hard after the crash in 1929. It is not surprising that the Cubs would see the effects of these events in their attendance levels despite their success on the field in those years immediately preceding the 1932 season.

Each of the two models indicate breaks in the 1950's (1955 in Model 1 and 1950 in Model 2). Each of these breaks is associated with a downward shift in attendance during this period. However, Model 1 indicates an upward trend after this negative level shift for Cubs attendance, while Model 2 indicates a negative trend following the downward level shift in 1950. The 1950's were a bad time for the Cubs franchise, and marked a time when even players on the team had little confidence in the team's potential (player/manager Phil Cavarretta was fired after publicly admitting the team would not finish above 5th place in 1954 (Goldstein. 2010)).

Finally, the Cubs franchise also has breakpoints estimated in 1967 in Model 2 and in 1983 for both models. These final two breakpoints indicate a large upward level shift in attendance for both breaks (Figure 5.5). The 1967 season marked a year in which the Cubs rebounded from a 103 loss season. Again in 1984, the Cubs had a strong squad, winning their first pennant since 1945.

5.5.4 Chicago White Sox

Though the White Sox have a structural shift estimated for the 1927 season, it is difficult to attribute this completely to the Great Depression given its relatively early onset. Outside of this explanation, it is unclear why Chicago's American League team saw such a change. The Depression effect hypothesis seems reasonable, given the similar downward shift found in the Chicago Cubs model. Like the Cubs and many other teams, the White Sox also experienced a large upward jump in attendance following World War II in 1945, according to Model 1.

The White Sox also have breaks in 1975 and 1993. The years surrounding the 1975 breakpoint were of significant turmoil for the White Sox franchise. The notoriously innovative Bill Veeck purchased the team in 1975 after the Seattle Pilots lawsuits that almost moved the storied franchise to the West Coast. Veeck put the team in shorts in

1976 and held open tryouts in 1978, only adding to the marketing gimmicks he is known well for. As I will discuss later, Bill Veeck had a tendency to make an appearance at other breakpoints in franchise histories as well. At this particular break, there is a large sudden increase in attendance that persists as a trend with significant variability through 2009. However, in Model 2 there is a breakpoint estimated for the 1993 season, indicating a possible effect of the work stoppage in the following seasons. While the White Sox eventually recovered, they seem to have been hit harder by the strike than other teams included in this analysis.

5.5.5 Cincinnati Reds

Both of the models discussed here estimate the same break dates for the Cincinnati Reds: 1945 (as in most other long-tenured teams near the end of WWII) and 1969. In 1969, Hamilton County agreed to build a new stadium to keep the Reds from moving to San Diego. The following year is known as the start of the “Big Red Machine” and the hiring of manager Sparky Anderson in 1970—a year in which the Reds lost to the Baltimore Orioles in the World Series after a very successful season. The 1978 and 1979 seasons saw the dismantling of the popular “Big Red Machine”, and it is easy to see a dramatic downward spike in attendance just after this season. However, the models did not estimate any structural shifts during this time, indicating that the Reds recovered relatively quickly in subsequent seasons.

5.5.6 Cleveland Indians

For the Cleveland Indians, Models 1 and 2 estimate essentially the same breaks within the attendance series. The 1945/1946 change coincides with many of the other teams seeing a large spike in attendance after the end of World War II. Looking at the true attendance data, it seems that there was an enormous shift upward following the end of WWII before attendance quickly regressed to low levels for Cleveland *following* the reign of Bill Veeck (who bought the team in 1946 and sold it in 1949) and a World Series title. During his short tenure as owner of the Cleveland Indians, Veeck broke the AL color barrier by signing Larry Doby in 1947 and Satchel Paige in 1948, concurrently moving the team into Cleveland Municipal Stadium full time (and winning the World Series in 1948). While the stadium was not new at the time, the Indians had been playing the majority of their games at League Park, with a capacity of just over 21,000. Municipal stadium had a capacity of 78,000 for Indians games. Veeck's proclamation that attendance levels were dwindling for his own team seems to be a reasonable concern for the years following his tenure as owner, but it is unclear why such a large attendance increase was not sustained by Cleveland as it was for many of the other teams who saw a similar increase after World War II (especially apparent in the National League).

Indians attendance did not begin to trend slowly trend upward until the break estimated in 1963/1964. The upward trend is surprising, given that the era from 1960 through 1990 was a dismal time for the Indians in which the team did not finish above 3rd place in any season during that span. This period in Indians history even sparked the making of a series of disparaging comedies about the ineptitude of the franchise. Finally, the beginning of the 1990s sparked another enormous uptick in attendance for the Indians

(1991/1992 break date). This coincides with the opening of the brand new Jacobs Field and a wildly successful Indians franchise featuring the likes of Manny Ramirez, Jim Thome and Albert Belle. This success was short-lived, however, as attendance again regressed quickly as the 21st century progressed through its first decade.

5.5.7 Detroit Tigers

It is well-known that the manufacturing industry in Detroit was hit hard by the depression, and it is no surprise that the Tigers saw the effects of this as indicated by a breakpoint estimated in 1929. However, this downward shift was found only in Model 1, and does not seem to have been sustained for long afterward. While there was a slight recovery in attendance after the end of the Depression Era, the Tigers saw a large shift upward with the end of WWII. Both models estimate a breakpoint in the range of 1967 to 1969 for the Tigers. The 1967 break coincides with one of the closest AL Pennant races in history; however, the Tigers were unable to hold off the Boston Red Sox. Detroit's baseball mainstay continued to have solid draws in spite of this, as attendance increased steadily until shortly before the player strike in the early 1990s.

According to Model 1, 1989 signaled a large downward shift in attendance levels (a shift for Model 2 was estimated for 1991, with a confidence interval spanning back to 1989). Tigers attendance has recovered nicely and has seen a generally upward trend since the work stoppage. Tigers attendance was particularly volatile through the 1990s and 2000s, as Detroit lost 103 games in 1989—marking one of the worst seasons in franchise history—and continued their futility throughout much of the decade. Following a miraculous 95 win season in 2006, and subsequent World Series birth, attendance rebounded dramatically. Unfortunately, the break point regression model restricts the estimation of breakpoints within a certain time period of each endpoint, so the effects of these later events would need to be estimated in another fashion or when more data is available for those seasons well after 2009.

5.5.8 Houston Astros

Model 1 and 2 estimate vastly different breakpoints for the Houston Astros' attendance series. The Model 1 break (1973) does not seem to coincide with any significant team events, but indicates a downward shift followed by an upward trend in attendance. In Model 2, structural changes are estimated not to have occurred until much later in the franchise's history. After the 1997 season, this regression indicates a massive upward shift in attendance for the Astros, coinciding with a very successful run of 6 playoff appearances from 1997 through 2005 and the opening of their new stadium in 2000 (then named Enron Field).

5.5.9 Los Angeles Dodgers

For the Los Angeles Dodgers, Models 1 and 2 estimate a large structural shift in 1974. For the first part of the Dodgers' 1958 move to Los Angeles, the team experienced a general downward trend in attendance; however, in 1974, this changed dramatically. The 1973 season signaled a very large upward shift in attendance, followed by a gradual trend through the 2009 season. The 1973 season began the 8 year tenure of a Dodgers' star infield that would stay together through the 1981 season, reaching 2 World Series during that time.

5.5.10 Milwaukee Brewers

The breaks estimated in the Milwaukee Brewers attendance series differ across Models 1 and 2. Model 1 finds two breaks—one in 1983 and one in 1993—while Model 2 estimates breaks for only the 1990 season. In Model 1, the 1983 break identifies what seems to be a slight downward shift in attendance levels. This is a strange event considering the Brewers reached their first and only World Series in 1982 (a feat they have not achieved since that year). The team was relatively successful from the 1978 season through this time, while those seasons after 1982 had mixed results. With most of the teams in this analysis, appearing in the World Series has often been associated with a large upward shift in attendance, but Milwaukee was particularly poor after its World Series loss in ’82.

As with many of the teams in this analysis, the BP Method estimates that the Brewers experienced a downward shift near the 1994-95 work stoppage (in 1993), followed by a rapid recovery through the 2009 season. In Model 1, the trend after the player strike is relatively consistent with the exception of a large spike in the data, likely due to the opening of Miller Park in 2001. However, Model 2 indicates a significant break—a downward shift—just after the opening of the stadium. Taken together, these findings seem to lend support to the idea of the rather *short-lived* honeymoon effect of a new stadium.

5.5.11 New York Mets

The models for the New York Mets estimate two common breakpoints for 1975 and 1993. Both breaks are associated with a downward shift in attendance, the second of which occurs after a period of success for the Mets franchise in the 1980's. The 1993 season was abysmal for the Mets, a year in which they lost 103 games and experienced a very large downward shift after the 1993 season. This shift may have been enhanced by the strike shortened seasons of 1994 and 1995, after which the team has experienced an upward trend in attendance levels through the 2009 season.

5.5.12 Oakland Athletics

For the Oakland Athletics, I find two similar breaks in each model in 1981 and 1993. These both coincide with the major labor disputes in Major League Baseball. Interestingly, these breaks shift in opposite directions: upward following the 1981 work stoppage, and then downward near the 1994 player strike. In addition, the 1993 season represented a difficult year for the A's, as they finished last in the American League and experienced a downward shift. The Athletics do not seem to recover from the attendance decrease following the breakpoint in 1994 until the turn of the century and the reign of Billy Beane as general manager.

The sharp trend from the mid-1980's through the end of the decade coincides with a significant speculation made by Lee and Fort (2008), who found a large break in the aggregate American League attendance estimation. The 1987 season marked the beginning of the "Bash Brothers Era" in Oakland, and the American League saw a very large increase in home run hitting during that year. Oakland reached the playoffs four out of the five seasons from 1988 to 1992, sweeping their cross-town rivals—the San Francisco Giants—in the infamous 1989 "Earthquake Series". The end of this run coincides with the steep drop-off as indicated by the structural break in 1993.

5.5.13 Philadelphia Phillies

Both models for the Philadelphia Phillies indicate breaks at 1945 and 1970 in the attendance series. In addition, Model 1 estimates a third break following the 1930 season. The first two estimated breaks, at 1930 and 1945, are concurrent with the previously discussed historical events of the Great Depression and World War II. There is a large level shift in attendance after the 1970 season: the final season the team was housed in Connie Mack Stadium. In 1971, the Phillies moved to Veteran's Stadium, where they remained until the opening of Citizen's Bank Park in 2004. However, the honeymoon effect does not seem to be apparent for the move to Veteran's Stadium, and the Phillies sustained relatively high levels of attendance through the entirety of their stay there.

5.5.14 Pittsburgh Pirates

The Pittsburg Pirates models have common breakpoints in 1927 preceding the Great Depression, near the end of World War II (1945/1946) and in 1961. Model 1 estimates an addition break for the team in 1987. The structural change in 1927 just prior to the Great Depression indicates a significant shift downward in attendance levels. Pittsburgh's steel industry was hit particularly hard; however, the fact that this drop occurs before this historical event makes it difficult to make confident conclusions regarding this break. The final *common* breakpoint for the Pirates falls in 1961, a year after winning the World Series and just as Roberto Clemente rose to prominence for the team.

Finally, Model 1 estimates a break in 1987. While Lee and Fort (2008) found a shift for AL attendance in 1987, this shift was absent for the NL. Perhaps the upward shift in attendance may be explained by the emergence of Barry Bonds (a rookie in 1986). While Bonds was a very good player in his early years, he did not reach the epic performance he is most well-known for until later in his career (and in fact did not hit 30 or more home runs until his 5^{th} season in Major League Baseball). This leaves room for another explanation.

5.5.15 San Francisco Giants

Both models for the San Francisco Giants estimated similar breaks in 1975. While the Giants experienced a gradual attendance decline after its move to San Francisco in 1958, the BP procedure estimates an upward shift followed by an increasing attendance trend after the 1975 season. The team was sold to Bob Lurie the in 1976, saving them from a move to Toronto and possibly reenergizing fan interest for the team afterward. While the 1970's were not particularly successful for the Giants on the field, perhaps remaining in San Francisco had restored fan confidence in the franchise as the hometown team for the city's residents.

5.5.16 St. Louis Cardinals

For the St. Louis Cardinals, both Model 1 and Model 2 estimate significant breakpoints for the post-WWII years (1945). They also share a similar breakpoint at 1981/1982, indicating a possible effect of the labor stoppage of 1981 and subsequent restructuring of the playoffs for that season. Interestingly, there is a large upward attendance shift after the 1981 work stoppage for the Cardinals, which is sustained along with a strong trend upward through 2009. In addition to the 1981 strike, St. Louis acquired shortstop legend Ozzie Smith just before the 1982 season, and went on to win the World Series that year.

I also find a breakpoint estimated at 1964 for Model 1. The 1964 break follows the World Series Championship won by the Cardinals that year. Figure 5.4 exhibits a large shift upward in attendance that only slowly decreased to the 1981 strike season, at which point it jumped up significantly. It's also important to note that in 1966, the Cardinals moved to Busch Memorial Stadium. A recent World Series victory and a new stadium could very well have created a perfect storm for a large sudden increase in attendance levels in the mid-1960s. While this break is not found for Model 2, an additional structural shift is estimated for the 1921 season. However, there does not seem to be any significant reasonable explanation for this break, and likely has to do with the predicted negative trend near the beginning of the Cardinals attendance series for Model 2.

5.6 Summary and Conclusions

In this chapter, I evaluate the time series behavior of franchise attendance in Major League Baseball and its relationship to Uncertainty of Outcome as described by Rottenberg. All in all, the analysis here finds scant evidence of any large influence of uncertainty of outcome as it pertains to attracting fans to the ballpark. While a few teams were found to have significant effects of certain uncertainty measures—with PU being the most common, as in Lee and Fort (2008)—the models presented here tend to indicate that fans are less worried about balance throughout the league and more interested in whether or not their home team will be able to compete in the given season.

Despite the statistical significance of the estimated outcome uncertainty coefficients, the economic significance tends to be minimal. Marginal alterations in outcome uncertainty can improve team revenues in MLB by at most one percent (excluding the strange case of the Houston Astros, for which further evaluation is suggested). While leagues may have managed balance well enough that it does not affect attendance numbers for teams, it seems that it would be difficult for league balance to become truly detrimental to league survival based on the results here.

Again, while large historical events like World War II had significant influences on franchise attendance, most shifts or fluctuations in the number of fans at each game tend to be most related to team performance, new stadiums and generalized increases in interest in professional baseball over time. There is additional evidence that some teams experienced more harm by work stoppages than others; however, they tend to be minimal across the entire league. For those series which are found to be non-stationary, a further cross-sectional analysis using other time series and differencing methods is recommended. In addition, as with the league-level analysis, a further evaluation of the impact of sellouts on possibly downward biased coefficient estimates for a few teams would be complementary to this analysis (for example, the Boston Red Sox and Chicago Cubs).

TABLE 5.1: MLB Franchise TAPG by Decade

Team	1900's	1910's	1920's	1930's	1940's	1950's	1960's	1970's	1980's	1990's	2000's	1901-2009
ATL							16,960	10,570	16,531	36,685	32,194	23,356
BAL						11,952	12,228	13,685	23,676	41,716	30,997	23,073
BOS	6,033	6,172	4,285	6,329	12,328	14,684	14,300	22,230	24,863	29,560	34,919	16,064
CHC	6,045	5,223	10,529	11,300	11,565	11,235	11,008	16,942	21,629	29,329	37,460	15,749
CHW	6,578	7,312	8,119	5,378	9,257	14,518	13,445	13,948	18,641	25,705	27,066	13,698
CIN	4,241	3,709	6,178	5,696	7,936	9,693	11,169	26,647	21,261	26,735	25,732	13,631
CLE	4,072	4,950	7,169	6,385	14,091	15,907	9,402	10,517	12,898	31,611	28,506	13,312
DET	3,628	6,020	9,888	9,390	15,224	15,284	15,832	18,461	24,032	19,140	28,024	15,097
HOU							16,182	15,340	20,858	23,479	34,812	22,326
KCR							11,005	17,391	27,551	21,761	19,456	21,234
LAD						25,260	27,135	30,385	39,416	38,330	42,589	35,209
LAA							11,476	15,445	31,550	26,319	36,453	24,420
MIL								13,803	22,409	19,891	29,183	21,184
MIN							16,359	11,285	18,822	21,290	24,604	18,368
MON							14,970	15,520	22,873	17,112	10,287	17,223
NYM							19,969	20,811	26,079	24,942	37,066	26,015
NYY	4,857	4,727	13,665	11,820	18,494	20,872	16,537	19,591	28,537	28,949	46,743	19,938
OAK							9,849	9,507	20,243	22,644	24,113	18,685
PHI	3,482	4,305	3,508	3,033	6,907	11,934	11,019	23,780	26,354	26,276	32,151	13,982
PIT	4,652	3,793	8,341	4,814	10,394	11,443	12,519	15,688	14,418	20,208	22,065	11,731
SDN							6,333	13,361	19,756	23,015	30,538	21,294
SEA								12,594	12,418	28,025	36,044	24,323
SFG						17,498	17,459	11,024	16,745	23,050	38,478	21,203
STL	3,703	3,319	6,233	5,193	10,170	12,935	17,376	18,507	28,985	32,804	40,362	16,442
TEX								14,043	17,635	31,804	29,539	23,740
TOR								19,410	26,636	40,632	24,696	29,632
A.L.	4,809	4,997	7,796	6,445	11,235	13,360	12,606	14,824	22,015	27,892	29,160	14,189
N.L.	4,366	4,203	7,248	6,686	10,478	13,348	15,578	18,215	22,897	27,794	31,304	14,833

TABLE 5.2: MLB Decade Averages for All Balance Measures

Measure	***1900's***	***1910's***	***1920's***	***1930's***	***1940's***	***1950's***	***1960's***	***1970's***	***1980's***	***1990's***	***2000's***	***Overall***
A.L. TL	0.038	0.045	0.064	0.018	0.103	0.055	0.166	0.267	0.364	0.395	0.167	0.154
A.L. CSU	0.499	0.458	0.628	0.747	0.616	0.742	0.638	0.558	0.433	0.337	0.560	0.568
A.L. PU	0.027	0.051	0.050	0.072	0.045	0.040	0.047	0.041	0.035	0.045	0.038	0.045
A.L. CBR	0.763	0.806	0.894	0.901	0.882	0.864	0.790	0.744	0.795	0.818	0.817	0.826
N.L. TL	0.006	0.101	0.090	0.072	0.047	0.146	0.148	0.294	0.393	0.339	0.543	0.200
N.L. CSU	0.690	0.396	0.690	0.685	0.631	0.693	0.494	0.603	0.298	0.178	0.429	0.520
N.L. PU	0.082	0.062	0.032	0.029	0.043	0.038	0.030	0.040	0.038	0.038	0.033	0.042
N.L. CBR	0.733	0.706	0.804	0.800	0.821	0.875	0.818	0.820	0.860	0.857	0.857	0.815

TABLE 5.3: MLB Win Percent by Decade 1901-2009

Team	1900's	1910's	1920's	1930's	1940's	1950's	1960's	1970's	1980's	1990's	2000's	Overall
ATL							0.517	0.450	0.457	0.595	0.551	0.513
BAL						0.436	0.565	0.590	0.512	0.512	0.431	0.513
BOS	0.514	0.569	0.386	0.461	0.550	0.528	0.475	0.556	0.525	0.523	0.568	0.514
CHC	0.600	0.546	0.523	0.576	0.475	0.434	0.456	0.487	0.471	0.476	0.499	0.502
CHW	0.550	0.529	0.474	0.443	0.460	0.545	0.528	0.468	0.485	0.525	0.529	0.503
CIN	0.473	0.470	0.518	0.432	0.496	0.481	0.536	0.592	0.499	0.520	0.463	0.499
CLE	0.516	0.488	0.511	0.534	0.518	0.585	0.486	0.460	0.455	0.531	0.504	0.508
DET	0.509	0.525	0.489	0.531	0.537	0.476	0.546	0.490	0.535	0.452	0.450	0.503
HOU							0.428	0.492	0.522	0.523	0.514	0.498
KCR							0.423	0.528	0.529	0.468	0.415	0.483
LAD						0.513	0.545	0.565	0.526	0.513	0.532	0.536
LAA							0.470	0.484	0.500	0.475	0.556	0.498
MIL								0.458	0.514	0.478	0.457	0.476
MIN							0.540	0.505	0.468	0.463	0.532	0.501
MON							0.321	0.464	0.518	0.499	0.454	0.483
NYM							0.381	0.473	0.523	0.494	0.504	0.478
NYY	0.491	0.466	0.606	0.629	0.602	0.620	0.549	0.555	0.547	0.548	0.596	0.567
OAK							0.523	0.520	0.512	0.497	0.550	0.521
PHI	0.473	0.508	0.369	0.379	0.378	0.495	0.473	0.503	0.500	0.471	0.525	0.462
PIT	0.634	0.488	0.568	0.529	0.486	0.398	0.528	0.568	0.469	0.498	0.421	0.507
SDN							0.321	0.415	0.486	0.487	0.474	0.461
SEA								0.386	0.429	0.493	0.517	0.471
SFG						0.529	0.560	0.493	0.493	0.508	0.528	0.517
STL	0.382	0.433	0.533	0.588	0.615	0.502	0.550	0.495	0.528	0.488	0.564	0.518
TEX								0.477	0.461	0.519	0.479	0.484
TOR								0.343	0.522	0.515	0.497	0.496

TABLE 5.4: MLB Average Games Back From Playoffs by Era

Team	AL/NL (1901-1968)	Div. Era (1969-1993)	WC Era (1994-2009)
ATL	16.83	18.48	2.38
BAL	18.63	8.56	18.13
BOS	20.93	10.48	4.06
CHC	17.65	16.64	11.16
CHW	19.50	15.72	7.28
CIN	21.83	8.26	11.16
CLE	16.94	23.58	6.47
DET	17.86	14.02	20.13
HOU	29.86	14.44	4.75
KCR		11.02	20.94
LAD	9.23	8.64	4.38
LAA	23.50	15.98	7.19
MIL		17.13	15.06
MIN	13.75	14.54	10.59
MON		15.96	15.68
NYM	41.21	14.74	9.16
NYY	9.54	10.40	0.38
OAK	21.00	10.32	8.38
PHI	29.05	14.76	10.28
PIT	17.13	9.80	19.31
SDN		23.02	11.72
SEA		24.15	9.94
SFG	7.00	14.74	6.44
STL	17.48	12.44	5.00
TEX		16.93	11.79
TOR		14.82	14.19

TABLE 5.5: MLB Franchise Playoff Appearances by Era

Team	AL/NL (01-68)	Div. Era (69-93)	WC Era (94-09)	Total	% of Seasons
ATL	0	5	12	17	38.6%
BAL	1	7	2	10	17.9%
BOS	8	4	9	21	19.3%
CHC	10	2	4	16	14.7%
CHW	5	2	4	11	10.1%
CIN	4	8	2	14	12.8%
CLE	3	0	8	11	10.1%
DET	8	3	1	12	11.0%
HOU	0	2	6	8	16.7%
KCR		6	0	6	14.6%
LAD	4	6	7	17	32.7%
LAA	0	3	6	9	18.4%
MIL		2	1	3	7.5%
MIN	1	4	5	10	20.4%
MON		0	1	1	2.8%
NYM	0	4	3	7	14.6%
NYY	29	4	15	48	44.9%
OAK	0	10	5	15	35.7%
PHI	2	6	3	11	10.1%
PIT	7	9	0	16	14.7%
SDN		1	4	5	12.2%
SEA		0	4	4	12.1%
SFG	1	3	4	8	15.4%
STL	12	4	8	24	22.0%
TEX		0	4	4	10.5%
TOR		5	0	5	15.2%

TABLE 5.6: MLB Franchise ADF and PP Tests (Unadjusted)

Team		**ATL**	**BAL**	**BOS**	**CHC**	**CHW**	**CIN**	**CLE**
T (seasons)		44	56	109	109	109	109	109
ADF (p)	Constant	-1.772 (1)	-1.189 (0)	0.558 (6)	-0.015 (3)	-0.251 (7)	-1.696 (0)	-1.960 (0)
ADF (p)	Trend	-2.757 (1)	-1.171 (0)	-2.234 (6)	-1.826 (3)	-4.747 (1)***	-3.494 (3)**	-3.096 (1)
P-P (l)	Constant	-1.496 (3)	-1.204 (3)	-0.397 (4)	-0.390 (4)	-1.879 (4)	-1.613 (4)	-2.110 (4)
P-P (l)	Trend	-2.354 (3)	-1.290 (3)	-3.230 (4)*	-2.268 (4)	-4.220 (4)***	-3.535 (4)**	-2.922 (4)

Team		**DET**	**HOU**	**KCR**	**LAD**	**LAA**	**MIL**	**MIN**
T (seasons)		109	48	41	52	49	40	49
ADF (p)	Constant	-1.028 (5)	-0.394 (7)	-2.139 (0)	-0.745 (7)	-1.393 (0)	-1.849 (0)	-2.014 (5)
ADF (p)	Trend	-5.318 (1)***	-2.482 (7)	-2.023 (0)	-2.532 (3)	-2.430 (0)	-3.283 (0)*	-3.192 (5)
P-P (l)	Constant	-1.953 (4)	-1.973 (3)	-2.112 (3)	-1.823 (3)	-1.283 (3)	-1.439 (3)	-1.785 (3)
P-P (l)	Trend	-4.770 (4)***	-3.289 (3)*	-1.950 (3)	-3.446 (3)*	-2.424 (3)	-3.225 (3)*	-2.618 (3)

Team		**MON**	**NYM**	**NYY**	**OAK**	**PHI**	**PIT**	**SD**
T (seasons)		36	48	107	42	109	109	41
ADF (p)	Constant	-2.214 (0)	-1.239 (7)	-0.945 (0)	-1.778 (4)	-0.200 (2)	-0.896 (7)	-1.421 (5)
ADF (p)	Trend	-2.374 (0)	-3.625 (6)**	-2.605 (0)	-3.003 (3)	-2.953 (0)	-5.448 (4)***	-3.239 (0)*
P-P (l)	Constant	-2.269 (3)	-2.095 (3)	-0.934 (4)	-2.025 (3)	-0.276 (4)	-2.434 (4)	-2.195 (3)
P-P (l)	Trend	-2.392 (3)	-2.535 (3)	-2.781 (4)	-2.154 (3)	-2.960 (4)	-5.135 (4)***	-3.248 (3)*

Team		**SEA**	**SF**	**STL**	**TEX**	**TOR**
T (seasons)		33	52	109	38	33
ADF (p)	Constant	-2.527 (6)	-1.445 (0)	-0.323 (1)	-1.475 (5)	-2.576 (7)
ADF (p)	Trend	-1.585 (6)	-2.730 (7)	-3.722 (0)**	-1.282 (8)	-2.667 (7)
P-P (l)	Constant	-1.074 (3)	-1.286 (3)	-0.184 (4)	-1.946 (3)	-1.498 (3)
P-P (l)	Trend	-1.862 (3)	-2.481 (3)	-3.571 (4)**	-2.281 (3)	-1.338 (3)

Data unadjusted for strikes. *p:* the number of lags; *l*: lag truncation.
***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 5.7: MLB Franchise Two-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
ATL	8	1982, 1990	0.164, 4.956***	-4.884	λ = (0.39, 0.57)
BAL	8	1978, 1990	0.113, 5.311***	-6.662***	λ = (0.45, 0.66)
BOS	4	1944, 1959	4.240***, -4.416***	-6.115***	λ = (0.40, 0.54)
CHC	3	1951, 1985	-4.151***, 4.154***	-5.692**	λ = (0.47, 0.78)
CHW	3	1950, 1976	-1.038, 0.211	-6.5254***	λ = (0.46, 0.70)
CIN	6	1960, 1970	-2.413**, 4.137***	-6.447***	λ = (0.55, 0.64)
CLE	8	1959, 1991	-0.502, 5.627***	-6.333***	λ = (0.54, 0.83)
DET	8	1981, 1996	2.342**, -0.240	-6.332***	λ = (0.74, 0.88)
HOU	8	1981, 1994	0.037, 5.545***	-6.136**	λ = (0.42, 0.69)
KCR	8	1987, 2002	-6.735***, 1.134	-5.216	λ = (0.46, 0.83)
LAD	8	1978, 1991	5.841***, 3.174***	-7.201***	λ = (0.40, 0.65)
LAA	7	1986, 2001	0.545, 3.683***	-4.480	λ = (0.53, 0.84)
MIL	7	1982, 1999	-5.646***, 7.029***	-6.587***	λ = (0.33, 0.75)
MIN	6	1982, 1995	5.056***, -4.012***	-5.853**	λ = (0.45, 0.71)
MON	5	1982, 1992	-0.363, 5.262***	-6.587***	λ = (0.39, 0.67)
NYM	6	1982, 1997	1.471, -2.312**	-4.861	λ = (0.44, 0.75)
NYY	2	1961, 1994	-1.207, 3.653***	-4.649	λ = (0.55, 0.86)
OAK	7	1987, 1996	5.514***, 4.786***	-6.736***	λ = (0.48, 0.69)
PHI	7	1972, 1992	4.429***, -4.859***	-6.010**	λ = (0.66, 0.84)
PIT	5	1945, 1986	3.994***, 2.140**	-6.991***	λ = (0.41, 0.79)
SD	4	1991, 2004	-5.200***, -0.084	-6.224**	λ = (0.56, 0.88)
SEA	8	1990, 1994	-0.523, 7.304***	-9.114***	λ = (0.42, 0.55)
SF	7	1970, 1984	-2.979***, 5.628***	-6.089**	λ = (0.25, 0.52)
STL	8	1927, 1983	-2.680***, 5.876***	-6.195***	λ = (0.25, 0.76)
TEX	5	1984, 1993	-2.520**, -8.091***	-7.405***	λ = (0.34, 0.58)
TOR	8	1990, 2004	4.085***, 4.089***	-7.039***	λ = (0.42, 0.85)

Data unadjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See Lee and Strazicich (2003) Table 2 for critical values. ***, ** = significant at 99% and 95% critical levels, respectively.

TABLE 5.8: MLB Franchise One-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
ATL	8	1989	4.251***	-4.388*	λ = 0.55
CHC	2	1955	-2.368**	-5.207***	λ = 0.50
HOU	7	1994	4.800***	-5.454***	λ = 0.69
KCR	7	1990	-4.535***	-4.481*	λ = 0.54
LAA	8	1982	-0.967	-4.352*	λ = 0.45
MIN	6	1976	-0.676	-4.731**	λ = 0.33
NYM	6	1997	-1.799*	-4.715**	λ = 0.75
NYY	2	1994	3.292***	-4.247*	λ = 0.86
PHI	5	1949	-1.824*	-4.1000	λ = 0.45
SD	8	1980	3.184***	-5.338***	λ = 0.20
SF	7	1984	5.775***	-6.022***	λ = 0.52

Data unadjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 5.9: MLB Franchise ADF and PP Tests (Adjusted)

Team		**ATL**	**BAL**	**BOS**	**CHC**	**CHW**	**CIN**	**CLE**
T (*seasons*)		44	56	109	109	109	109	109
ADF (*p*)	Constant	-1.749 (1)	-1.174 (0)	0.610 (6)	0.048 (3)	-2.525 (7)	-1.628 (0)	-1.944 (0)
ADF (*p*)	Trend	-2.656 (1)	-1.119 (0)	-2.194 (6)	-1.775 (3)	-4.833 (1)***	-3.521 (3)**	-3.004 (1)
P-P (*l*)	Constant	-1.479 (3)	-1.203 (3)	-0.376 (4)	-0.330 (4)	-1.807 (4)	-1.604 (4)	-2.108 (4)
P-P (*l*)	Trend	-2.290 (3)	-1.270 (3)	-3.153 (4)*	-2.203 (4)	-4.124 (4)***	-3.522 (4)**	-2.935 (4)

Team		**DET**	**HOU**	**KCR**	**LAD**	**LAA**	**MIL**	**MIN**
T (*seasons*)		109	48	41	52	49	40	49
ADF (*p*)	Constant	-1.019 (5)	-0.401 (7)	-2.089 (0)	-0.742 (7)	-1.355 (0)	-1.672 (0)	-1.688 (4)
ADF (*p*)	Trend	-5.350 (1)***	-2.651 (7)	-1.967 (0)	-2.475 (3)	-2.281 (0)	-2.923 (0)	-2.846 (4)
P-P (*l*)	Constant	-1.943 (4)	-1.905 (3)	-2.083 (3)	-1.806 (3)	-1.291 (3)	-1.336 (3)	-1.676 (3)
P-P (*l*)	Trend	-4.789 (4)***	-3.229 (3)*	-1.917 (3)	-3.431 (3)*	-2.315 (3)	-2.898 (3)	-2.544 (3)

Team		**MON**	**NYM**	**NYY**	**OAK**	**PHI**	**PIT**	**SD**
T (*seasons*)		36	48	107	42	109	109	41
ADF (*p*)	Constant	-1.974 (0)	-2.684 (1)*	-0.886 (0)	-2.354 (1)	-0.524 (0)	-0.385 (8)	-1.743 (5)
ADF (*p*)	Trend	-2.236 (2)	-3.204 (1)*	-2.536 (0)	-2.533 (1)	-2.904 (0)	-5.588 (2)***	-2.308 (5)
P-P (*l*)	Constant	-2.078 (3)	-2.087 (3)	-0.896 (4)	-1.935 (3)	-0.198 (4)	-2.304 (4)	-2.128 (3)
P-P (*l*)	Trend	-2.218 (3)	-2.541 (3)	-2.732 (4)	-2.052 (3)	-2.892 (4)	-4.927 (4)***	-2.890 (3)

Team		**SEA**	**SF**	**STL**	**TEX**	**TOR**
T (*seasons*)		33	52	109	38	33
ADF (*p*)	Constant	-3.105 (6)**	-1.395 (0)	0.226 (3)	-1.847 (0)	-1.624 (1)
ADF (*p*)	Trend	-1.518 (6)	-2.702 (7)	-3.482 (0)**	-1.450 (0)	-1.481 (1)
P-P (*l*)	Constant	-1.030 (3)	-1.260 (3)	-0.063 (4)	-1.843 (3)	-1.504 (3)
P-P (*l*)	Trend	-1.515 (3)	-2.476 (3)	-3.320 (4)*	-1.347 (3)	-1.345 (3)

Data adjusted for strikes. *p:* the number of lags; *l*: lag truncation.

***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 5.10: MLB Franchise Two-Break LM Test (Adjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
ATL	2	1985, 1994	0.947, 0.550	-5.198	λ = (0.45, 0.66)
BAL	8	1978, 1990	0.391, 5.365***	-6.740***	λ = (0.45, 0.66)
BOS	4	1944, 1959	4.147***, -4.261***	-5.973**	λ = (0.40, 0.54)
CHC	2	1955, 1986	-2.373**, 1.452	-5.524*	λ = (0.50, 0.79)
CHW	1	1931, 1967	1.271, -1.250	-6.214**	λ = (0.28, 0.61)
CIN	4	1960, 1970	-2.274**, 3.842***	-6.852***	λ = (0.55, 0.64)
CLE	6	1959, 1991	-0.534, 4.771***	-5.471*	λ = (0.54, 0.83)
DET	1	1981, 1996	2.411**, -0.284	-6.343**	λ = (0.74, 0.88)
HOU	1	1972, 1998	-3.004***, 2.663**	-5.254	λ = (0.23, 0.77)
KCR	6	1988, 1999	-6.358***, 0.857	-5.558*	λ = (0.49, 0.76)
LAD	8	1980, 1991	3.469***, 5.141***	-6.611***	λ = (0.44, 0.65)
LAA	5	1983, 2001	2.096**, 2.858***	-4.376	λ = (0.45, 0.84)
MIL	6	1980, 2000	2.573**, -6.512***	-7.454***	λ = (0.28, 0.78)
MIN	6	1982, 1995	4.921***, -3.945***	-5.525*	λ = (0.45, 0.71)
MON	4	1980, 1986	1.661*, 1.245	-5.591*	λ = (0.33, 0.50)
NYM	6	1982, 1997	1.547, 2.844***	-4.716	λ = (0.44, 0.75)
NYY	2	1961, 1998	-2.199**, 1.994**	-4.582	λ = (0.55, 0.90)
OAK	7	1982, 1986	0.517, 4.771***	-7.524***	λ = (0.36, 0.45)
PHI	7	1972, 1992	4.569***, -5.042***	-6.215**	λ = (0.66, 0.84)
PIT	5	1944, 1986	4.831***, 0.917	-6.943***	λ = (0.40, 0.79)
SD	4	1990, 2005	-5.086***, 0.082	-5.879**	λ = (0.54, 0.90)
SEA	0	1989, 2002	6.049***, -4.796***	-6.391**	λ = (0.39, 0.79)
SF	8	1972, 1984	-2.416**, 5.457***	-6.086**	λ = (0.29, 0.52)
STL	8	1927, 1983	-2.797***, 6.104***	-6.423***	λ = (0.25, 0.76)
TEX	5	1982, 1996	-3.740***, 0.246	-4.941	λ = (0.29, 0.66)
TOR	4	1987, 1998	5.405***, -6.140***	-7.230***	λ = (0.33, 0.67)

Data adjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 5.11: MLB Franchise One-Break LM Test (Adjusted)

Team	$\hat{\mathbf{k}}$	$\hat{\mathbf{T}}_{\mathbf{b}}$	$\hat{\mathbf{t}}_{\gamma j}$	**Test Statistic**	**Critical Value Break Points**
ATL	2	1991	2.785***	-4.295*	λ = 0.59
CHC	2	1955	-2.318**	-5.162***	λ = 0.50
CLE	6	1991	3.564***	-4.576**	λ = 0.83
HOU	7	1995	3.941***	-4.600**	λ = 0.71
KCR	0	1979	-1.940*	-3.086	λ = 0.27
LAA	8	1982	-1.207	-4.448*	λ = 0.45
MIN	6	1976	-0.366	-4.320*	λ =0.33
MON	8	1976	0.708	-4.149	λ = 0.22
NYM	8	1969	-2.262**	-4.636**	λ = 0.17
NYY	2	1962	-1.464	-4.098	λ = 0.56
TEX	6	1991	3.046***	-4.948**	λ = 0.53

NOTE: $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. Data adjusted for strikes. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 5.12: MLB Franchise Model 1 Break Point Test Results (Heterogeneous)

Team	*$SupF_t(1)$*	*$SupF_t(2)$*	*$SupF_t(3)$*	*$SupF_t(4)$*	*$SupF_t(5)$*	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
BAL	214.05[a]	179.72[a]				214.05[a]	250.21[a]	80.80[a]				**2**
BOS	61.22[a]	131.84[a]	96.00[a]	105.81[a]	75.32[a]	131.84[a]	188.02[a]	117.74[a]	29.84[a]	29.84[a]		**4**
CHC	156.74[a]	138.53[a]	106.57[a]	114.65[a]	86.77[a]	156.74[a]	203.72[a]	27.39[a]	31.20[a]	9.41		**3**
CHW	17.26[a]	15.83[a]	21.54[a]	26.52[a]	23.81[a]	26.52[a]	52.29[a]	43.92[a]	43.92[a]	13.38[c]		**2**
CIN	157.01[a]	102.66[a]	84.40[a]	82.63[a]	70.28[a]	157.01[a]	157.01[a]	32.19[a]	31.04[a]	31.06[a]	5.36	**2**
CLE	56.08[a]	44.08[a]	47.56[a]	44.56[a]	39.10[a]	56.08[a]	85.86[a]	15.78[b]	35.29[a]	12.22	7.81	**3**
DET	21.76[a]	20.58[a]	30.89[a]	27.69[a]	24.29[a]	30.89[a]	53.33[a]	14.52[b]	28.64[a]	16.26[b]		**4**
HOU	16.92[a]	12.19[a]				16.92[a]	16.97[a]	5.68				**1**
LAD	38.44[a]	34.76[a]				38.44[a]	48.38[a]	8.64				**1**
MIL	12.08[b]	14.10[a]				14.10[a]	19.63[a]	17.85[a]				**2**
NYM	34.32[a]	54.72[a]				54.72[a]	76.18[a]	40.54[a]				**2**
OAK	35.31[a]	21.95[a]				35.31[a]	35.31[a]	11.40[b]				**2**
PHI	86.27[a]	72.57[a]	57.35[a]	50.96[a]	45.75[a]	86.27[a]	100.45[a]	51.10[a]	51.10[a]	34.97[a]	10.78	**3**
PIT	15.95[a]	38.05[a]	30.98[a]	32.45[a]	24.67[a]	38.05[a]	57.67[a]	62.30[a]	51.30[a]	45.76[a]		**4**
SDN	7.98	9.50[c]				9.50[c]	12.27[b]	10.99[b]				**0**
SFG	96.07[a]	53.18[a]				96.07[a]	96.07[a]	3.47				**1**
STL	160.13[a]	151.07[a]	137.00[a]	108.22[a]	83.68[a]	160.13[a]	205.03[a]	47.16[a]	17.05[b]	6.02		**3**

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE 5.13: MLB Franchise Model 1 Estimated Break Dates (Heterogeneous)

Team	T_1	T_2	T_3	T_4	*Team*	T_1	T_2	T_3	T_4
BAL	**1974** [73, 75]	**1991** [90, 92]			***LAD***	**1974** [73, 76]			
BOS	**1918** [17, 20]	**1945** [44, 46]	**1966** [65, 67]	**1993** [92, 95]	***MIL***	**1983** [82, 85]	**1993** [90, 94]		
CHC	**1932** [30, 33]	**1955** [54, 58]	**1983** [82, 90]		***NYM***	**1975** [74, 76]	**1993** [90, 94]		
CHW	**1945** [42, 46]	**1975** [73, 76]			***OAK***	**1981** [80, 82]	**1993** [92, 95]		
CIN	**1945** [43, 46]	**1969** [68, 70]			***PHI***	**1930** [24, 31]	**1945** [44, 46]	**1970** [69, 71]	
CLE	**1946** [44, 47]	**1964** [63, 66]	**1992** [90, 93]		***PIT***	**1927** [25, 28]	**1946** [43, 47]	**1961** [56, 63]	**1987** [84, 89]
DET	**1929** [27, 40]	**1945** [43, 46]	**1967** [66, 69]	**1989** [84, 90]	***SFG***	**1975** [74, 76]			
HOU	**1973** [71, 75]				***STL***	**1945** [44, 46]	**1964** [62, 65]	**1981** [80, 83]	

*Brackets denote 90% confidence interval for break date

TABLE 5.14: MLB Franchise Model 2 Break Point Test Results (Heterogeneous)

Team	*$SupF_t(1)$*	*$SupF_t(2)$*	*$SupF_t(3)$*	*$SupF_t(4)$*	*$SupF_t(5)$*	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
BAL	197.39[a]	149.94[a]				197.39[a]	208.75[a]	39.28[a]				**2**
BOS	79.52[a]	156.08[a]	114.26[a]	95.55[a]	52.17[a]	156.08[a]	197.44[a]	46.05[a]	8.90	8.90		**2**
CHC	189.70[a]	147.00[a]	109.03[a]	113.78[a]	100.49[a]	189.70[a]	220.64[a]	15.75[b]	20.95[a]	20.61[a]		**4**
CHW	34.99[a]	39.81[a]	26.81[a]	26.88[a]	22.06[a]	39.81[a]	50.36[a]	46.49[a]	23.53[a]	23.53[a]		**2**
CIN	150.13[a]	97.41[a]	86.30[a]	75.68[a]	47.77[a]	150.13[a]	150.13[a]	30.65[a]	29.69[a]	12.57		**2**
CLE	63.61[a]	52.30[a]	53.33[a]	46.00[a]	39.22[a]	63.61[a]	86.11[a]	40.73[a]	24.16[a]	12.61	12.61	**3**
DET	20.85[a]	38.09[a]	32.21[a]	26.00[a]	19.36[a]	38.09[a]	48.21[a]	14.76[b]	12.29	7.08		**3**
HOU	20.60[a]	13.05[a]				20.60[a]	20.60[a]	4.59				**1**
LAD	42.67[a]	38.48[a]				42.67[a]	53.57[a]	10.32				**1**
MIL	12.28[b]	17.53[a]				17.53[a]	24.41[a]	4.13				**1**
NYM	34.02[a]	48.85[a]				48.85[a]	68.01[a]	35.35[a]				**2**
OAK	36.14[a]	26.67[a]				36.14[a]	37.12[a]	15.60[a]				**2**
PHI	97.84[a]	68.20[a]	57.50[a]	49.21[a]	45.21[a]	97.84[a]	99.26[a]	63.11[a]	63.11[a]	35.37[a]	9.75	**2**
PIT	46.73[a]	39.11[a]	32.43[a]	35.55[a]	18.67[a]	46.73[a]	63.17[a]	48.39[a]	48.39[a]	46.21[a]		**3**
SDN	8.67	10.46[c]				10.46[c]	13.51[b]	9.31[c]				**0**
SFG	86.32[a]	45.80[a]				86.32[a]	86.32[a]	3.97				**1**
STL	187.42[a]	151.52[a]	139.97[a]	112.68[a]	70.19[a]	187.42[a]	209.48[a]	31.07[a]	22.46[a]	16.47[b]		**3**

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE 5.15: MLB Franchise Model 2 Estimated Break Dates (Heterogeneous)

Team	T_1	T_2	T_3	T_4
BAL	**1973** [72, 74]	**1991** [90, 92]		
BOS	**1945** [44, 46]	**1966** [65, 67]		
CHC	**1932** [30, 33]	**1950** [49, 52]	**1967** [66, 68]	**1983** [82, 88]
CHW	**1927** [26, 28]	**1993** [81, 94]		
CIN	**1945** [43, 46]	**1969** [68, 70]		
CLE	**1945** [42, 46]	**1963** [62, 65]	**1991** [89, 92]	
DET	**1946** [45, 47]	**1969** [68, 72]	**1991** [82, 92]	
HOU	**1997** [96, 99]			
LAD	**1974** [73, 75]			
MIL	**1990** [85, 91]			
NYM	**1975** [74, 76]	**1993** [92, 94]		
OAK	**1981** [80, 82]	**1993** [92, 95]		
PHI	**1945** [38, 46]	**1970** [69, 71]		
PIT	**1927** [26, 28]	**1945** [43, 46]	**1961** [59, 62]	
SFG	**1975** [74, 76]			
STL	**1921** [19, 25]	**1945** [44, 46]	**1982** [81, 84]	

*Brackets denote 90% confidence interval for break date

TABLE 5.16: MLB Franchise Model 1 (Heterogeneous) Breakpoint Regression Results

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5
BAL	-204	2077	1225	-26700	-1237	84764				
t-value	*(-1.75)*[c]	*(0.69)*	*(8.90)*[a]	*(-4.28)*[a]	*(-9.24)*[a]	*(10.32)*[a]				
BOS	-273	3039	109	-2009	-310	26286	447	-16389	653	-39416
t-value	*(-2.50)*[b]	*(1.69)*[c]	*(2.35)*[b]	*(-1.21)*	*(-4.41)*[a]	*(5.56)*[a]	*(9.84)*[a]	*(-3.97)*[a]	*(6.66)*[a]	*(-3.98)*[a]
CHC	403	-14086	487	-24063	301	-20001	611	-40652		
t-value	*(7.09)*[a]	*(-5.19)*[a]	*(5.96)*[a]	*(-5.12)*[a]	*(5.24)*[a]	*(-4.78)*[a]	*(7.84)*[a]	*(-5.42)*[a]		
CHW	49	-8267	-130	6361	325	-22701				
t-value	*(1.05)*	*(-2.73)*[a]	*(-1.71)*[c]	*(1.24)*	*(5.56)*[a]	*(-3.88)*[a]				
CIN	38	-7064	4	-1453	142	1133				
t-value	*(1.09)*	*(-3.13)*[a]	*(0.04)*	*(-0.31)*	*(3.59)*[a]	*(0.24)*				
CLE	91	-9668	-1040	58480	264	-21410	-849	104045		
t-value	*(2.07)*[b]	*(-3.02)*[a]	*(-6.36)*[a]	*(5.71)*[a]	*(3.17)*[a]	*(-2.94)*[a]	*(-4.58)*[a]	*(5.27)*[a]		
DET	382	-17136	176	-14823	-439	23042	218	-15110	976	-90325
t-value	*(5.47)*[a]	*(-6.64)*[a]	*(1.23)*	*(-2.51)*[b]	*(-4.81)*[a]	*(4.21)*[a]	*(2.39)*[b]	*(-1.98)*[c]	*(8.52)*[a]	*(-7.84)*[a]
HOU	92	-952	661	-13594						
t-value	*(0.22)*	*(-0.16)*	*(8.87)*[a]	*(-1.84)*[b]						
LAD	-180	8012	210	12408						
t-value	*(-1.20)*	*(1.50)*	*(3.98)*[a]	*(2.17)*[b]						
MIL	1138	-1390	167	7335	1346	-27724				
t-value	*(4.18)*[a]	*(-0.23)*	*(0.44)*	*(0.81)*	*(6.55)*[a]	*(-3.30)*[a]				
NYM	-571	-3916	1032	-34387	1581	-67034				
t-value	*(-2.08)*[b]	*(-1.28)*	*(5.96)*[a]	*(-6.31)*[a]	*(7.91)*[a]	*(-7.82)*[a]				
OAK	221	-11109	1034	-16529	312	-9027				
t-value	*(1.05)*	*(-2.63)*[b]	*(4.17)*[a]	*(-3.12)*[a]	*(1.88)*[c]	*(-1.40)*				
PHI	144	-12260	469	-25518	-57	-830	213	-7983		
t-value	*(1.45)*	*(-3.43)*[a]	*(2.19)*[b]	*(-2.91)*[a]	*(-0.56)*	*(-0.13)*	*(4.05)*[a]	*(-1.50)*		
PIT	238	-13545	311	-20816	-183	10885	180	-15082	191	-11002
t-value	*(3.15)*[a]	*(-5.05)*[a]	*(3.09)*[a]	*(-4.68)*[a]	*(-1.25)*	*(1.41)*	*(2.75)*[a]	*(-2.73)*[a]	*(1.82)*[c]	*(-1.03)*
SFG	-642	-3553	835	-27287						
t-value	*(-3.63)*[a]	*(-0.56)*	*(11.54)*[a]	*(-5.07)*[a]						
STL	-70	-4857	-40	3558	-100	1485	462	-20641		
t-value	*(-1.83)*[c]	*(-2.74)*[a]	*(-0.43)*	*(0.62)*	*(-0.92)*	*(1.76)*[c]	*(8.62)*[a]	*(-4.01)*[a]		

a. Significant at the 99% critical level. b. Significant at the 95% critical level. c. Significant at the 90% critical level. α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE 5.17: MLB Franchise Model 1 (Heterogeneous) Regression Coefficients

Team	***TL***	***CSU***	***PU***	***W%***	$\bar{R}^2$ (R^2)
BAL	2066	1059	21525	19037	0.964
t-value	*(0.99)*	*(0.64)*	*(1.37)*	*(3.15)*[a]	*(0.970)*
BOS	-2959	-1949	-1592	13481	0.974
t-value	*(-2.22)*[b]	*(-2.22)*[b]	*(-0.27)*	*(4.59)*[a]	*(0.977)*
CHC	1008	321	-30218	29134	0.941
t-value	*(0.68)*	*(0.36)*	*(-3.26)*[a]	*(7.52)*[a]	*(0.947)*
CHW	3699	-1422	3095	29418	0.831
t-value	*(1.54)*	*(-0.91)*	*(0.27)*	*(6.13)*[a]	*(0.845)*
CIN	-3465	376	-19632	25238	0.923
t-value	*(-2.21)*[b]	*(0.42)*	*(-1.99)*[b]	*(6.36)*[a]	*(0.930)*
CLE	1069	2622	-8773	24129	0.893
t-value	*(0.41)*	*(1.52)*	*(-0.75)*	*(4.23)*[a]	*(0.904)*
DET	5386	-1034	-701	35046	0.894
t-value	*(2.62)*[b]	*(-0.78)*	*(-0.08)*	*(9.21)*[a]	*(0.907)*
HOU	679	5403	-48255	33875	0.766
t-value	*(0.22)*	*(2.77)*[a]	*(-1.71)*[c]	*(2.42)*[b]	*(0.800)*
LAD	2934	-950	-71092	40454	0.842
t-value	*(1.50)*	*(-0.65)*	*(-3.51)*[a]	*(4.34)*[a]	*(0.863)*
MIL	-2038	-3176	6475	24473	0.794
t-value	*(-0.73)*	*(-1.19)*	*(0.20)*	*(2.04)*[b]	*(0.841)*
NYM	-157	3045	-27969	69400	0.870
t-value	*(-0.06)*	*(1.62)*	*(-1.10)*	*(9.17)*[a]	*(0.895)*
OAK	-3671	-4609	-35819	46882	0.886
t-value	*(-1.38)*	*(-1.99)* [c]	*(-1.49)*	*(7.49)*[a]	*(0.911)*
PHI	-151	-925	-36253	36026	0.908
t-value	*(-0.07)*	*(-0.77)*	*(-2.68)*[a]	*(6.94)*[a]	*(0.917)*
PIT	1717	1102	-17650	28571	0.872
t-value	*(1.16)*	*(1.26)*	*(-1.91)*[c]	*(7.43)*[a]	*(0.888)*
SFG	110	1545	-39149	46152	0.867
t-value	*(0.04)*	*(0.83)*	*(-1.60)*	*(4.35)*[a]	*(0.885)*
STL	1622	1405	-4703	21090	0.971
t-value	*(1.24)*	*(1.77)*[c]	*(-0.58)*	*(5.57)*[a]	*(0.974)*

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE 5.18: MLB Franchise Model 2 (Heterogeneous) Breakpoint Regression Results

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5
BAL	-234	7925	1259	-22091	-1251	90986				
t-value	*(-1.53)*	*(0.63)*	*(9.22)*[a]	*(-2.09)*[b]	*(-10.96)* [a]	*(6.93)*[a]				
BOS	72	3227	-412	35800	402	-9802				
t-value	*(2.12)*[b]	*(0.54)*	*(-4.57)*[a]	*(3.43)*[a]	*(14.67)*[a]	*(-1.84)*[c]				
CHC	336	-15542	711	-35967	-144	3045	91	-6753	620	-45077
t-value	*(6.57)*[a]	*(-3.36)*[a]	*(6.91)*[a]	*(-5.51)*[a]	*(-1.29)*	*(0.32)*	*(0.77)*	*(-0.65)*	*(11.15)*[a]	*(-5.86)*[a]
CHW	-115	-38524	351	-55113	631	-86550				
t-value	*(-1.00)*	*(-4.94)*[a]	*(10.57)*[a]	*(-5.44)*[a]	*(3.44)*[a]	*(-4.27)*[a]				
CIN	51	-5760	-40	2648	125	3213				
t-value	*(1.33)*	*(-1.18)*	*(-0.48)*	*(0.34)*	*(3.13)*[a]	*(0.50)*				
CLE	127	-5181	-1009	62396	273	-17042	-765	100555		
t-value	*(2.24)*[b]	*(-0.57)*	*(-5.90)*[a]	*(3.75)*[a]	*(3.25)*[a]	*(-1.79)*[c]	*(-4.53)*[a]	*(5.04)*[a]		
DET	48	-36345	-140	-18841	185	-33934	814	-97172		
t-value	*(0.93)*	*(-4.78)*[a]	*(-1.37)*	*(-1.52)*	*(1.88)*[c]	*(-3.75)*[a]	*(7.75)*[a]	*(-7.50)*[a]		
HOU	240	21135	228	31208						
t-value	*(2.68)*[a]	*(1.10)*	*(0.60)*[a]	*(1.09)*						
LAD	-211	22408	242	26228						
t-value	*(-1.29)*	*(1.64)*	*(4.64)*[a]	*(1.97)* [c]						
MIL	736	16134	1099	-193						
t-value	*(3.06)*[a]	*(0.57)*	*(6.26)*[a]	*(-0.01)*						
NYM	-500	27644	1037	-1279	1666	-37161				
t-value	*(-1.91)*[c]	*(1.59)*	*(6.06)* [a]	*(-0.07)*	*(8.81)*[a]	*(-2.02)*[c]				
OAK	140	-3875	1159	-11568	274	-41				
t-value	*(0.63)*	*(-0.18)*	*(4.43)* [a]	*(-0.55)*	*(1.70)*[c]	*(-0.00)*				
PHI	90	-11957	-50	-1783	219	-8932				
t-value	*(1.74)*[c]	*(-1.56)*	*(-0.50)*	*(-0.16)*	*(4.29)*[a]	*(-0.99)*				
PIT	262	-18176	219	-21897	-97	1840	340	-30548		
t-value	*(3.34)*[a]	*(-3.41)*[a]	*(1.91)*[c]	*(-3.15)*[a]	*(-0.68)*	*(0.22)*	*(11.28)*[a]	*(-5.11)*[a]		
SFG	-697	10022	838	-14069						
t-value	*(-3.68)*[a]	*(0.63)*	*(12.62)*[a]	*(-0.94)*						
STL	-184	-498	-116	283	265	-8756	453	-15885		
t-value	*(-1.77)*[c]	*(-0.10)*	*(-1.54)*	*(0.05)*	*(6.88)*[a]	*(-1.32)*	*(7.44)*[a]	*(-1.94)*[c]		

a. Significant at the 99% critical level. b. Significant at the 95% critical level. c. Significant at the 90% critical level. α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE 5.19: MLB Franchise Model 2 (Heterogeneous) Regression Coefficients

Team	***PU***	***CBR***	***W%***	$\bar{R}^2$ (R^2)
BAL	-21237	-5085	18197	0.964
t-value	*(1.35)*	*(-0.37)*	*(3.11)*[a]	*(0.970)*
BOS	-4808	-5108	11623	0.968
t-value	*(-0.78)*	*(-0.74)*	*(4.27)*[a]	*(0.971)*
CHC	-19173	6037	25636	0.957
t-value	*(-2.55)*[b]	*(1.09)*	*(7.49)*[a]	*(0.962)*
CHW	-4094	40971	27271	0.820
t-value	*(-0.36)*	*(4.08)*[a]	*(5.53)*[a]	*(0.834)*
CIN	-16774	-3006	26421	0.921
t-value	*(-1.85)*[c]	*(-0.46)*	*(6.58)*[a]	*(0.927)*
CLE	-5674	-5430	25575	0.894
t-value	*(-0.51)*	*(-0.48)*	*(4.59)*[a]	*(0.904)*
DET	-3000	29924	34157	0.887
t-value	*(-0.33)*	*(3.12)*[a]	*(9.12)*[a]	*(0.898)*
HOU	-60458	-22605	28296	0.757
t-value	*(-2.14)*[b]	*(-0.97)*	*(2.10)*[b]	*(0.788)*

Team	***PU***	***CBR***	***W%***	$\bar{R}^2$ (R^2)
LAD	-75596	-12501	34271	0.838
t-value	*(-3.74)*[a]	*(-0.89)*	*(3.90)*[a]	*(0.857)*
MIL	16502	-34007	40496	0.757
t-value	*(0.51)*	*(-0.96)*	*(3.41)*[a]	*(0.795)*
NYM	-28589	-38510	70678	0.874
t-value	*(-1.15)*	*(-1.71)*[c]	*(9.30)*[a]	*(0.895)*
OAK	-28352	-10151	41588	0.872
t-value	*(-1.17)*	*(-0.39)*	*(6.45)*[a]	*(0.897)*
PHI	-26087	1436	32824	0.907
t-value	*(-2.21)*[b]	*(0.16)*	*(6.39)*[a]	*(0.914)*
PIT	-17072	4323	31520	0.861
t-value	*(-1.92)*[c]	*(0.65)*	*(8.40)*[a]	*(0.874)*
SFG	-36766	-16714	48973	0.921
t-value	*(-1.52)*	*(-0.97)*	*(5.16)*[a]	*(0.934)*
STL	-8596	-3688	22413	0.964
t-value	*(-0.99)*	*(-0.61)*	*(5.44)*[a]	*(0.967)*

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE 5.20: MLB Franchise Economic Implications of Game Uncertainty

	BOS	***CIN***	***DET***
2009 TAPG	37,811	21,579	31,693
2009 GU	0.094	0.472	0.094
GU Coef. Est.[a]	-2,959*	-3,465*	5,386*
Elasticity	*0.007*	*0.043*	*0.013*
ΔGU[b]	0.115	0.143	0.115
Inc. Factor	*122.92%*	*30.30%*	*122.92%*
ΔTAPG	***-325.3***[d]	***-281.1***	506.4
% ΔTAPG	***-0.86%***	***-1.30%***	*1.60%*
Rev. Per Attend[c]	$81.61	$36.19	$51.26
Δ Game Rev.	***-$26,550***	***-$10,174***	$25,959

a. Coefficient taken from Model 1 and follow the approach of Lee and Fort (2008, pp. 291).
b. All measure changes imply an improvement in balance.
c. Revenue per attendee data come from Team Marketing Report Fan Cost Index (2009).
d. ***Bold Italic*** font indicates disagreement with Rottenberg's Uncertainty of Outcome Hypothesis.
Coefficients found to be *statistically* significant in Model 1 are indicated with an asterisk (*).

TABLE 5.21: MLB Franchise Economic Implications of Consecutive Season Uncertainty

	BOS	***HOU***
2009 TAPG	37,811	31,124
2009 CSU	0.703	0.449
CSU Coef. Est.[a]	-1,949*	5,403*
Elasticity	*0.036*	*0.078*
ΔCSU[b]	-0.201	-0.215
Inc. Factor	*28.59%*	*47.88%*
ΔTAPG	389.2	***-1,162.4***
% ΔTAPG	*1.03%*	***-3.73%***
Rev. Per Attend[c]	$81.61	$52.48
Δ Game Rev.	$31,762	***-$61,003***

a. Coefficient taken from Model 1 and follow the approach of Lee and Fort (2008, pp. 291).
b. All measure changes imply an improvement in balance.
c. Revenue per attendee data come from Team Marketing Report Fan Cost Index (2009).
d. ***Bold Italic*** font indicates disagreement with Rottenberg's Uncertainty of Outcome Hypothesis.
Coefficients found to be *statistically* significant in Model 1 are indicated with an asterisk (*).

TABLE 5.22: MLB Franchise Economic Implications of Playoff Uncertainty

	CHC	***CIN***	***LAD***	***PHI***
2009 TAPG	39,610	21,579	46,440	44,453
2009 PU	0.033	0.033	0.033	0.033
PU Coef. Est.[a]	-30,218*	-19,632*	-71,902*	-36,253*
Elasticity	*0.026*	*0.017*	*0.051*	*0.032*
ΔPU[b]	-0.006	-0.006	-0.006	-0.006
Inc. Factor	*18.79%*	*18.79%*	*18.79%*	*18.79%*
ΔTAPG	193.5	68.9	445.0	267.3
% ΔTAPG	*0.49%*	*0.32%*	*0.96%*	*0.60%*
Rev. Per Attend[c]	$76.25	$36.19	$55.41	$54.98
Δ Game Rev.	$14,755	$2,495	$24,657	$14,695

a. Coefficient taken from Model 1 and follow the approach of Lee and Fort (2008, pp. 291).
b. All measure changes imply an improvement in balance.
c. Revenue per attendee data come from Team Marketing Report Fan Cost Index (2009).
Coefficients found to be *statistically* significant in Model 1 are indicated with an asterisk (*).

FIGURE 5.1: Fitted MLB TAPG for BAL, BOS, CHA and CHN (Model 1, Heterogeneous)

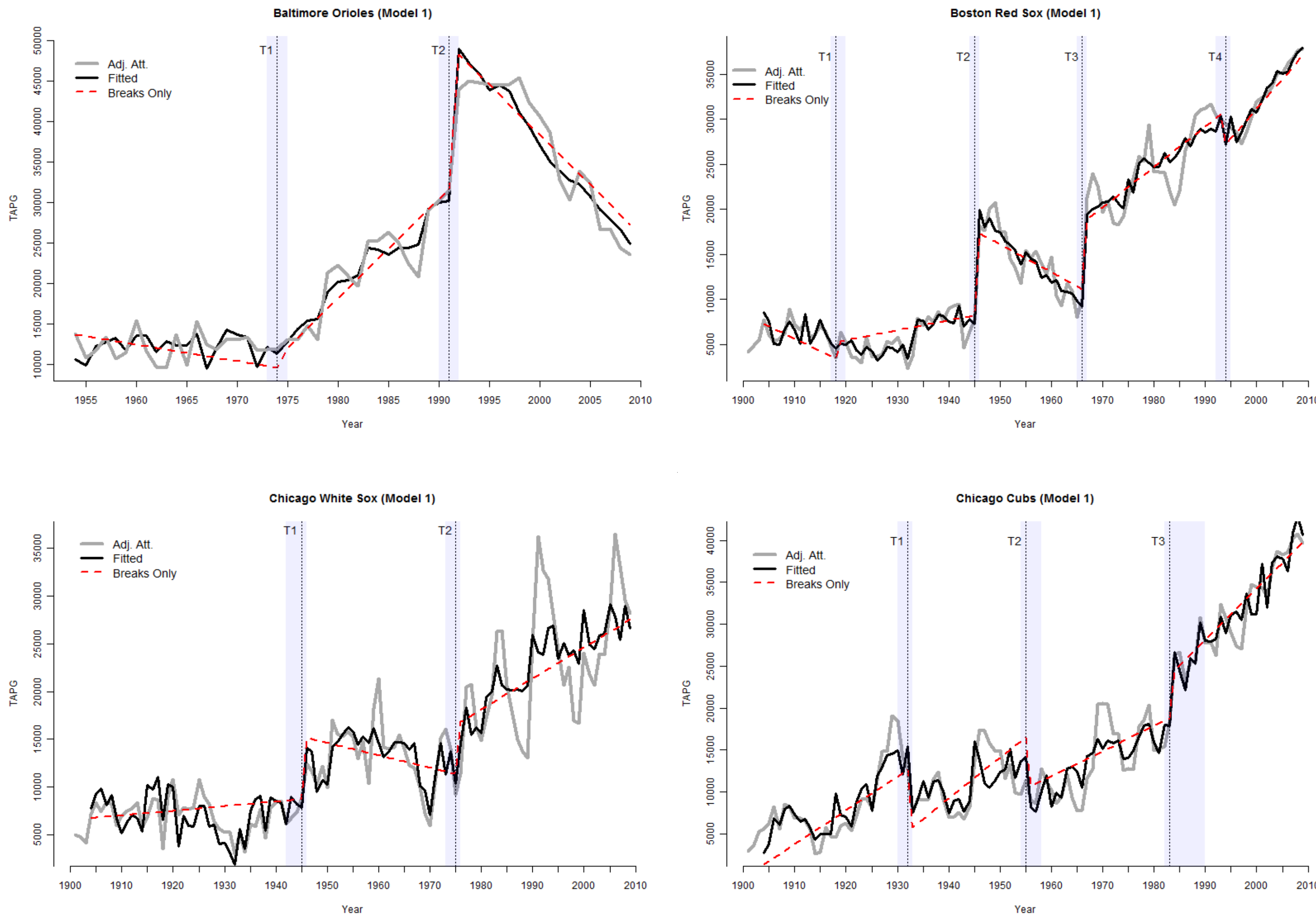


FIGURE 5.2: Fitted MLB TAPG for CIN, CLE, DET and HOU (Model 1, Heterogeneous)

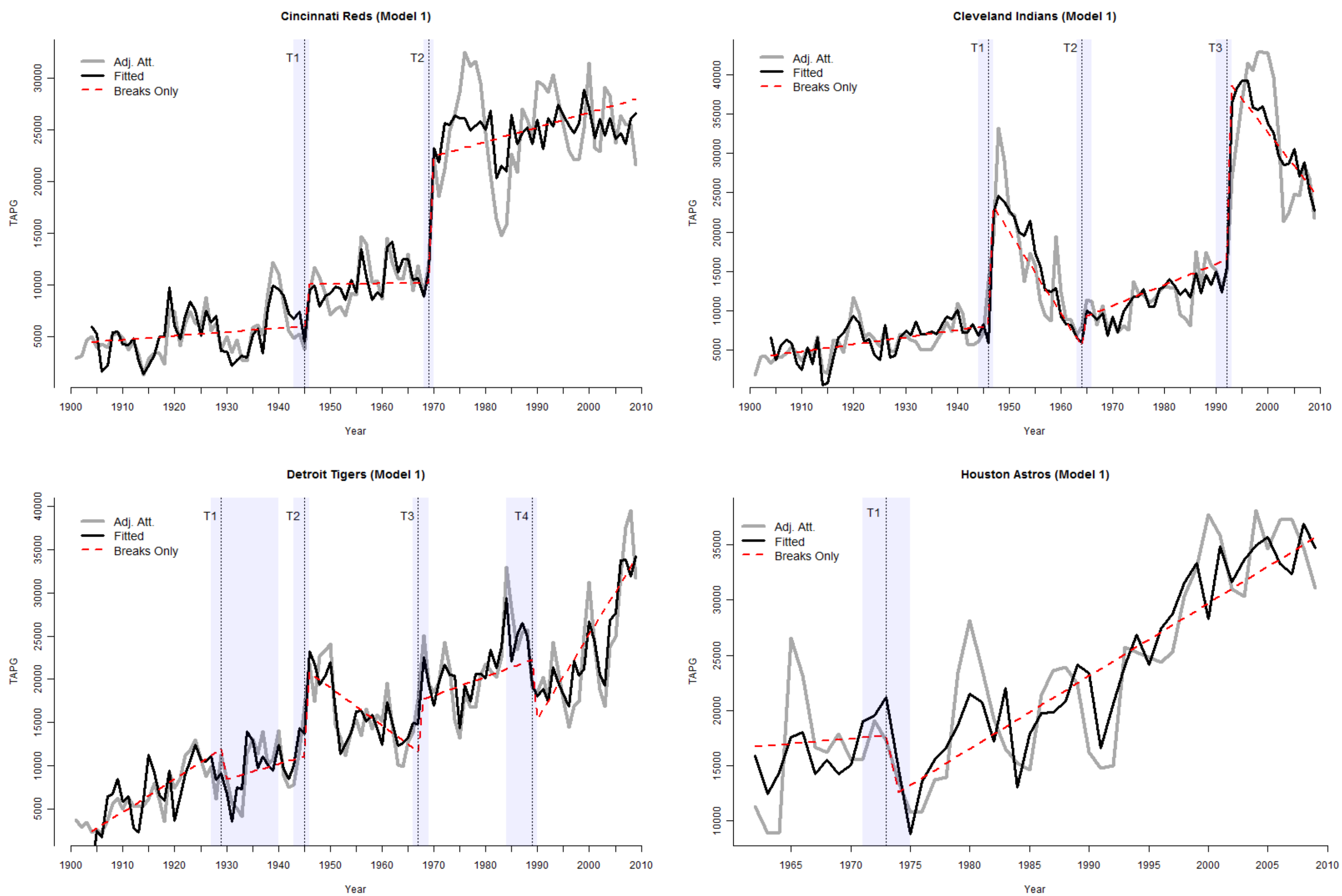


FIGURE 5.3: Fitted MLB TAPG for LAD, MIL, NYM and OAK (Model 1, Heterogeneous)

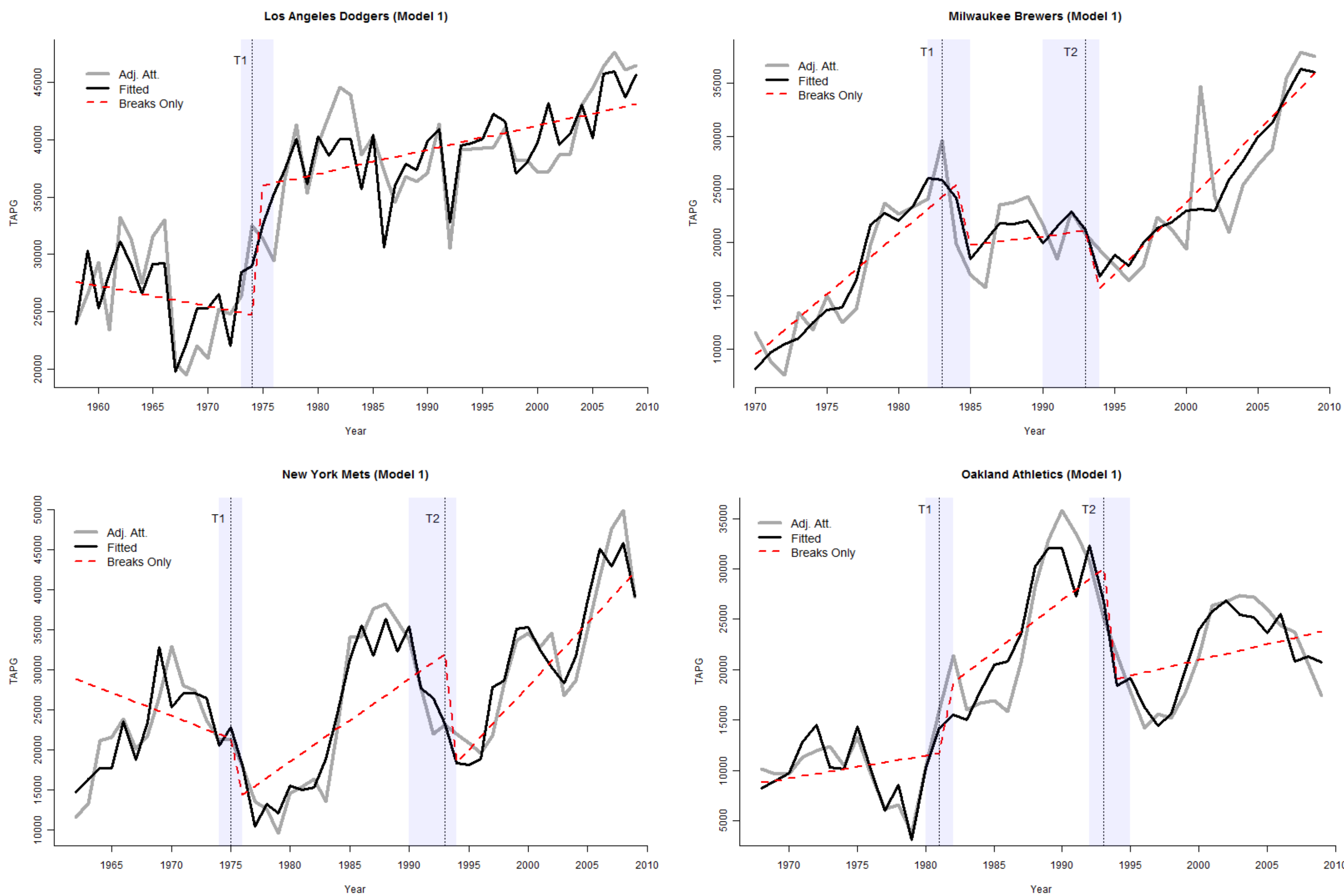


FIGURE 5.4: Fitted MLB TAPG for PHI, PIT, SFG and STL (Model 1, Heterogeneous)

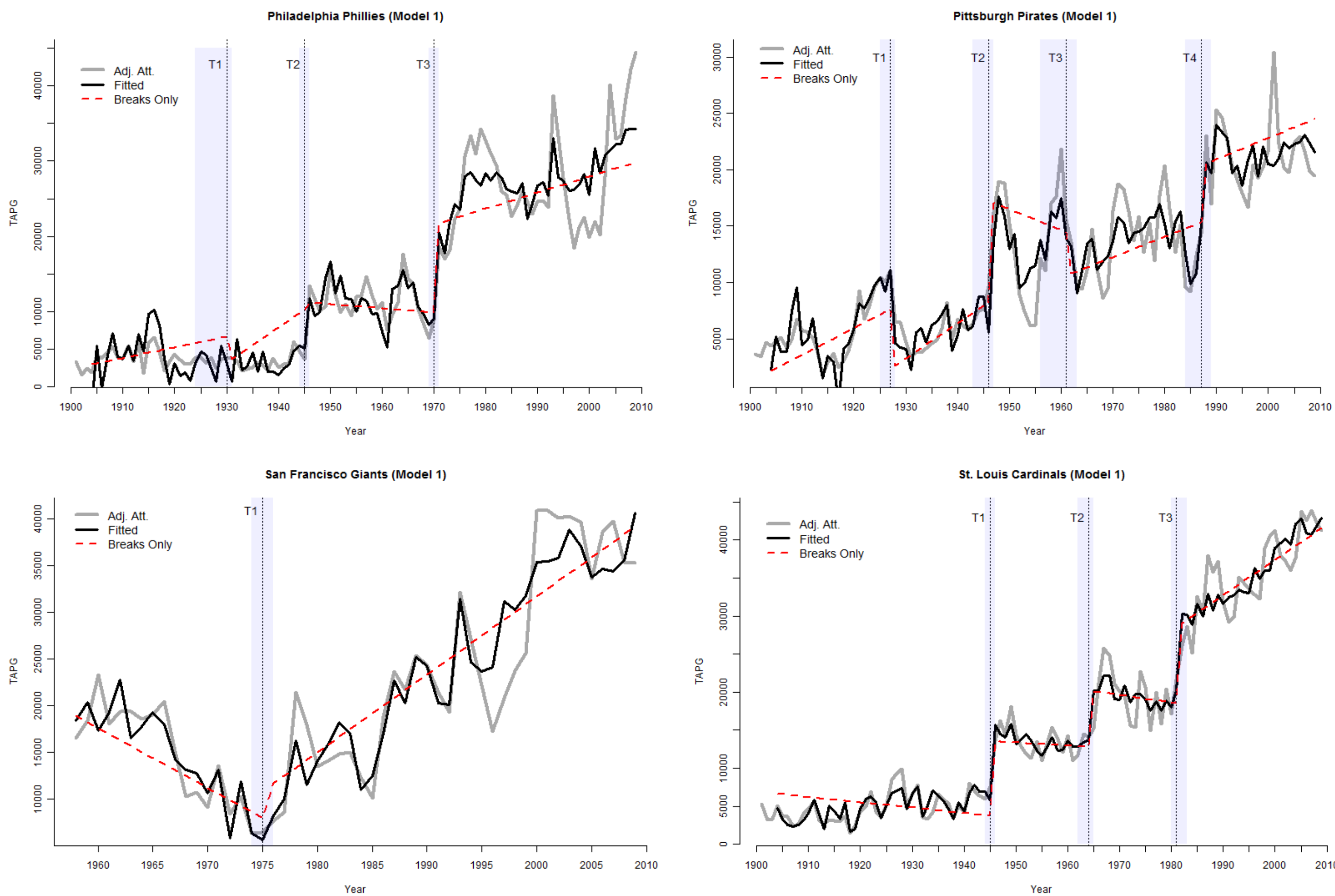


FIGURE 5.5: Fitted MLB TAPG for BAL, BOS, CHA and CHN (Model 2, Heterogeneous)

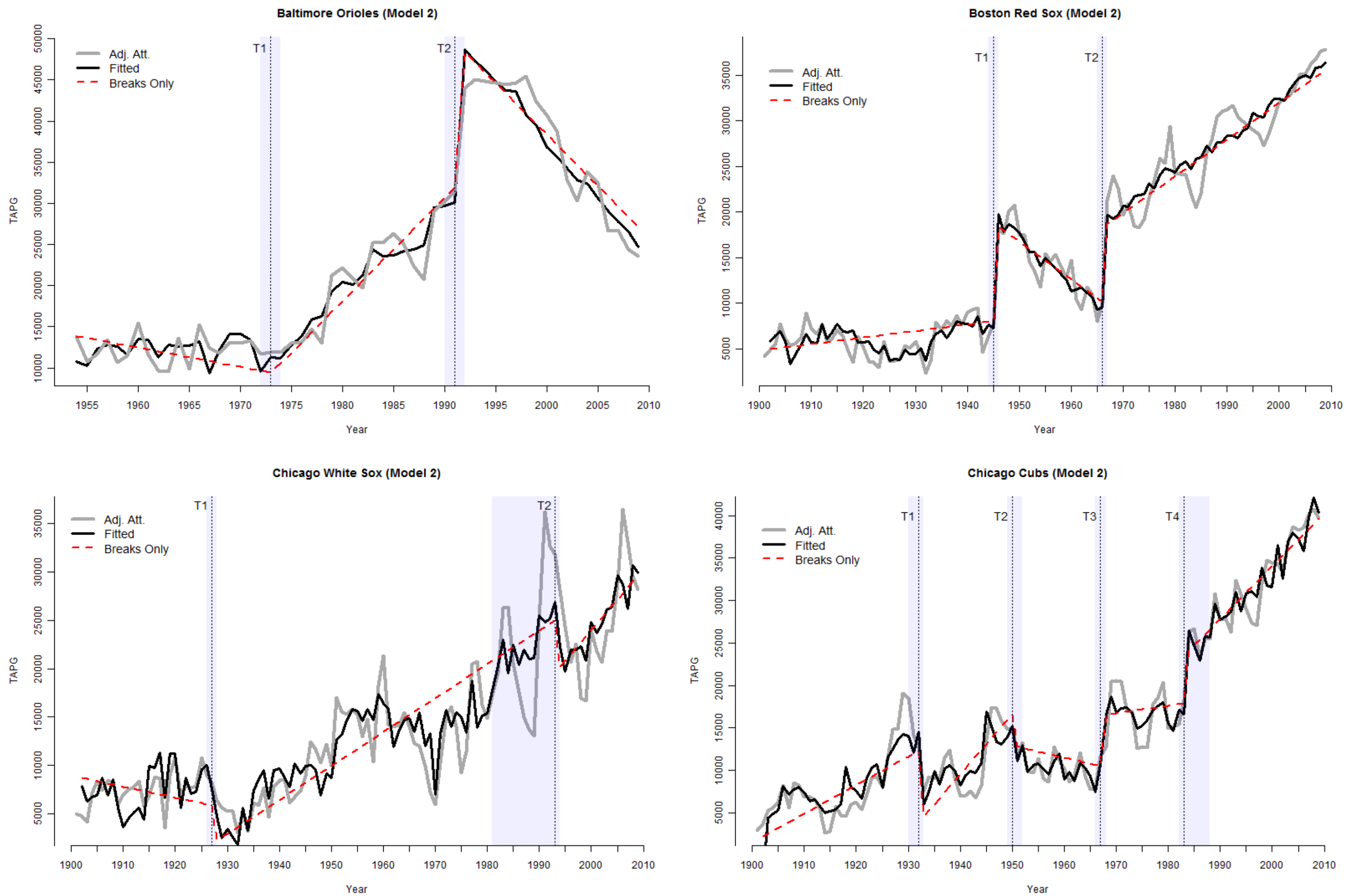


FIGURE 5.6: Fitted MLB TAPG for CIN, CLE, DET and HOU (Model 2, Heterogeneous)

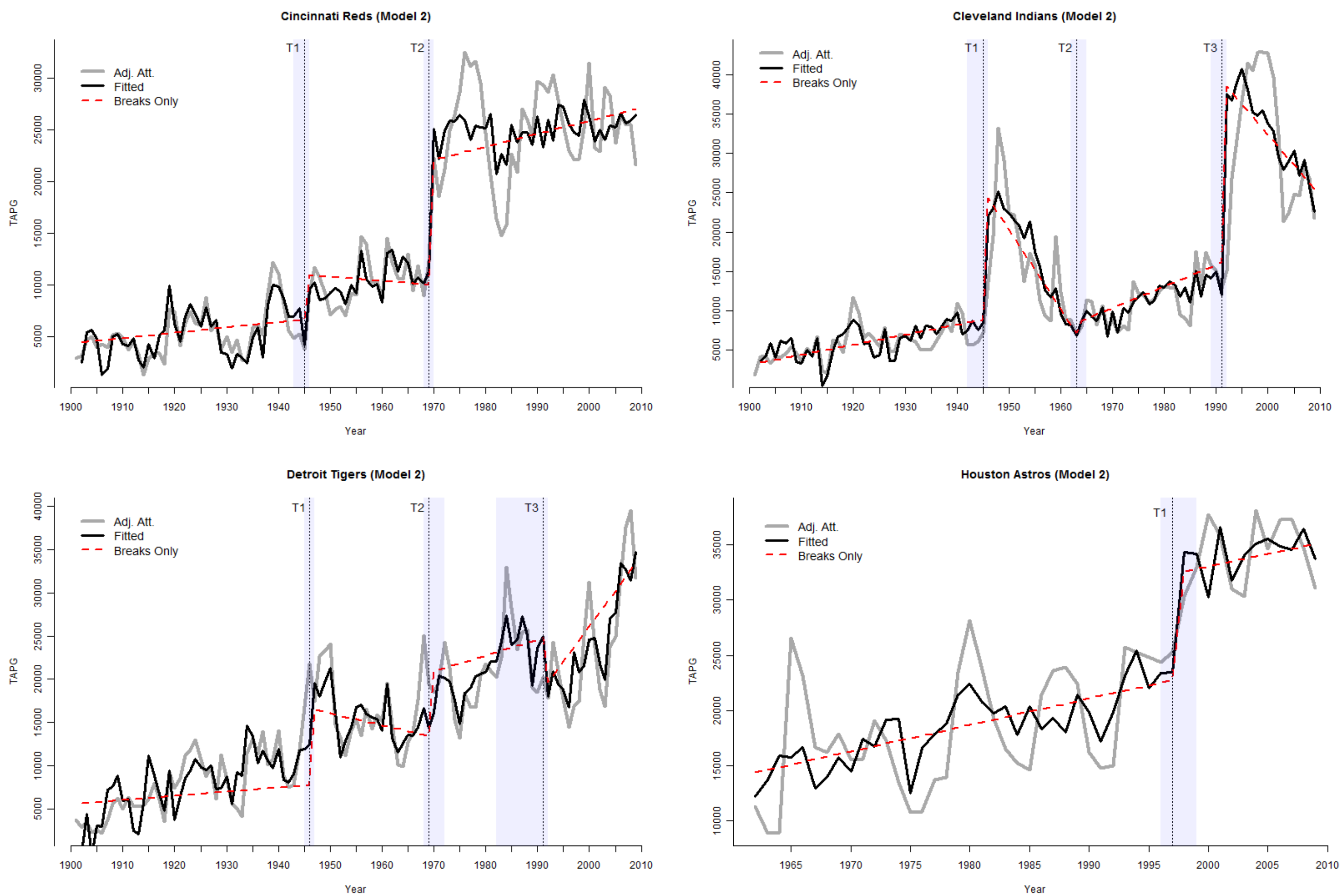


FIGURE 5.7: Fitted MLB TAPG for LAD, MIL, NYM, OAK (Model 2, Heterogeneous)

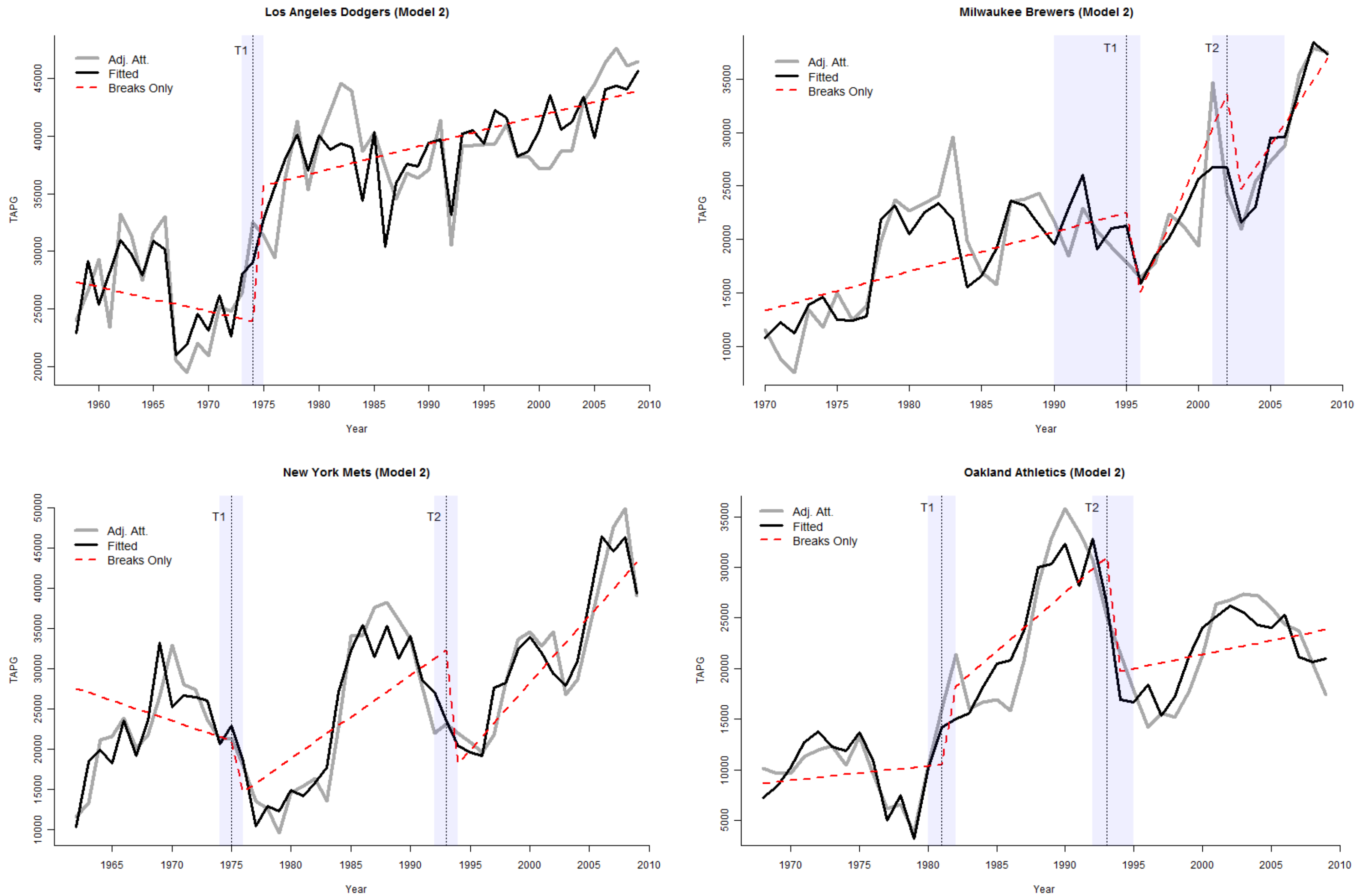
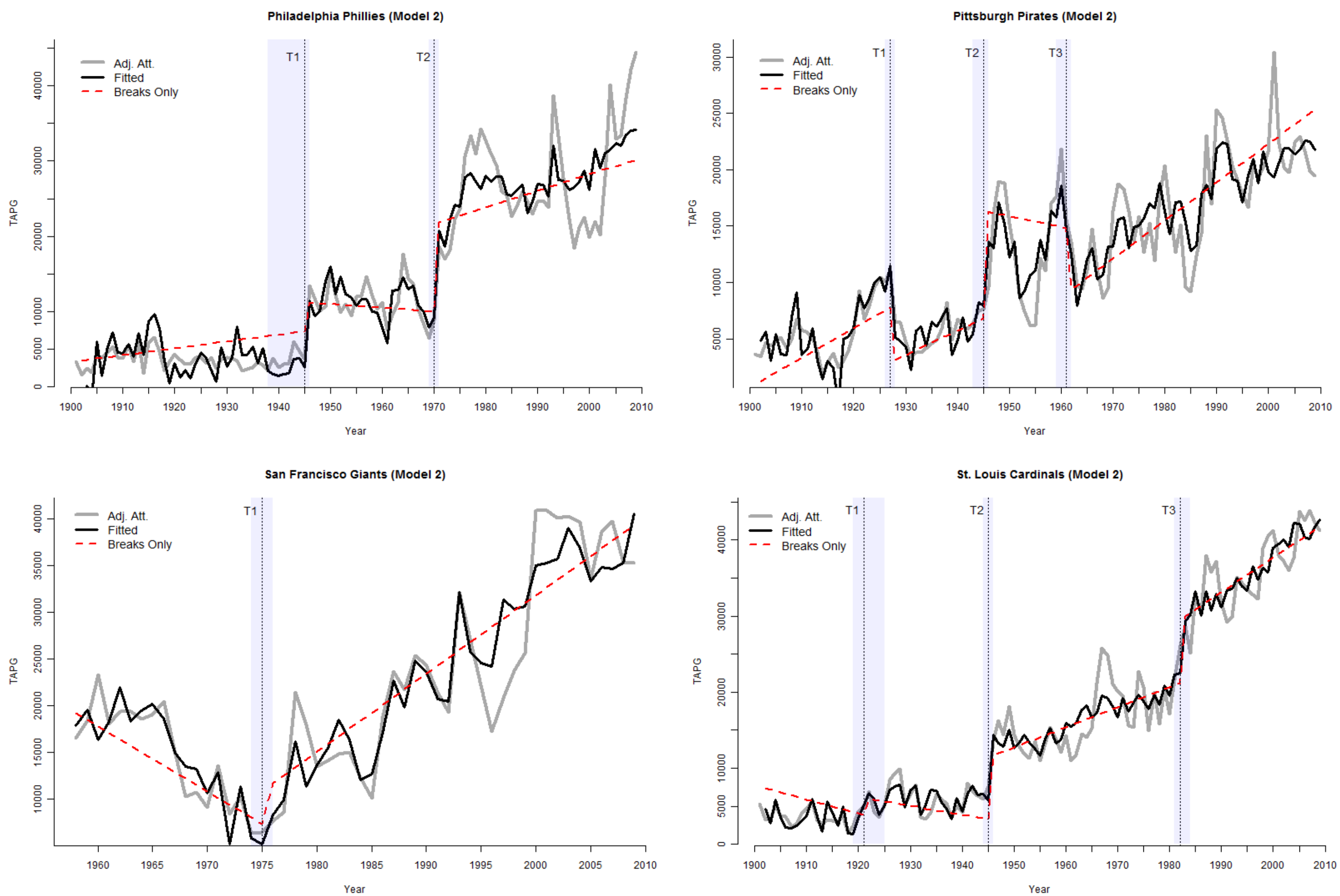


FIGURE 5.8: Fitted MLB TAPG for PHI, PIT, SFG and STL (Model 2, Heterogeneous)



CHAPTER 6

National Basketball Association Franchises

6.1 Justification

As with Major League Baseball, understanding the intricacies of the effects of uncertainty on franchise level attendance can help to inform those results at the league level for the NBA. In addition, research regarding franchise-level estimation of attendance in the NBA has been relatively sparse, especially compared to its baseball counterpart. Finally, a full estimation of all possible teams in all four major leagues can add to our understanding of fan substitution between sports, specifically using diverging attendance shifts for same-market teams in different leagues. Analysis of NFL and NHL will follow in Chapter 7 and Chapter 8, respectively. Whether or not same market teams in different sports are competitors with one another is surely an important issue with respect to not only demand at the league and team level, but may have implications for competition and antitrust research in sport (Winfree, 2009a, 2009b). Therefore, this section evaluates structural change and the importance of uncertainty of outcome variables on team-level data in the NBA. Data for analysis of teams in the NBA were used for the aggregate league-level investigation, and therefore come from the same sources with only a few exceptions. The reader is referred to earlier sections for a general description of this data. For the NBA franchise-level analysis here, I again use *TAPG* as defined in the analysis of MLB franchises (Chapter 5).

6.2 Data and Methods

For the team-level analysis, the BP model is defined exactly as in the Model 1 MLB franchise attendance analysis:

$$z_t = \{1, t\},\ x_t = \{TL, WinDiff, Corr, W\%\}, \text{ and } (q=2; p=4)$$

for each team in each league. Again, I estimate an ancillary model as above with an additional lagged win percent variable (NBA Model B). Given the lack of coherent application of CBR in the regression models, I neglect to include this measure for the NBA (and subsequent leagues at the franchise level). Models with both heterogeneous and homogeneous variance are estimated; however, I continue with a full discussion of only the heterogeneous error variance models. The latter are provided in Appendix B.

The requirement of lags of particular length again comes into play, leaving only some teams subject to the analysis performed here. For example, this consideration excludes the Baltimore Bullets/Wizards from analysis, despite the relatively short relocation distance. However, one NBA team that moved within the last 5 years with a length meeting the requirements for the breakpoint methodology preceding the move is included in the initial unit root analysis (Seattle Supersonics). With this single exception, for those franchises that have relocated I begin the attendance series in the first year of the most recent location using the same parameters as in the MLB franchise level analysis. I will continue with modeling only current franchises found to be stationary in the preliminary analysis of unit-roots and unit-roots with breakpoints.

There are a few additional considerations for the franchise-level data in the NBA. For the adjusted series, the individual franchises are imputed just as the league-level NBA attendance in Chapter 4. To reiterate, I take a weighted average of the years just before and just following years in which a labor dispute takes place (for the NBA, 1998-99). Only National Basketball Association attendance (rather than ABA attendance) is included in the regression estimations. This consideration ultimately excludes the Indiana Pacers and San Antonio Spurs (Dallas Chaparrals) from the analysis despite the fact that these franchises opened for business in 1967. As with MLB franchises in the previous chapter, teams that move from one location to another are considered a new franchise at the new location.

The NBA contains twelve (12) individual franchises with attendance series of sufficient length (40 years) for the breakpoint analysis. Descriptive statistics regarding TAPG and win percent for each of the franchises can be found in Table 6.1.

6.3 Unit Root Results

Turning to the unit root results, nine of twelve unadjusted attendance series were found to be stationary or stationary with breakpoints. Tables 6.2 through 6.7 present the unit root results for the unadjusted and adjusted data. Stationary series include the Atlanta Hawks, Boston Celtics, Cleveland Cavaliers, Detroit Pistons, New York Knicks, Philadelphia 76ers, Phoenix Suns, Portland Trailblazers, and Seattle Supersonics (pre-Oklahoma City Thunder, treated as a current franchise for this analysis). In addition, ADF and PP tests indicate some evidence of the Los Angeles Lakers attendance series being stationary without breaks; however, the DFGLS test did not indicate evidence for rejection of a unit root for this series (available upon further request). Therefore, I proceed with treating only those found to be stationary with breaks above as stationary data for the BP Method, the results of which are presented in the following sections. Given the similarity between the adjusted and unadjusted results, I limit discussion and regression estimation with only the adjusted data from this point forward.

6.4 Uncertainty of Outcome Results

Results of influence of uncertainty of outcome were mixed across franchises analyzed in this chapter. This is the case both for the direction and size of the effect, and there is again little evidence for comprehensive confirmation of Rottenberg's UOH. This section discusses those franchises with statistically significant coefficients (Table 6.11) estimated for the uncertainty measures as well as the economic significance of these estimated effects (Table 6.12). To summarize, none of the estimated coefficients for the realizations of outcome uncertainty included in these models were universally in favor of Rottenberg's UOH. While Atlanta and Philadelphia both had statistically significant coefficients for GU, Atlanta's fans tend to prefer less balance (Table 6.11). In both instances, the manipulation in *Tail Likelihood* described in Chapter 4 did not change team revenues by more than 2.35% for either team (Table 6.12).

For PU, both Cleveland and New York were found to have significant effects of the *WinDiff* measure. However, the direction of the effect again differs across the two franchises. While Cleveland fans seem to have a revealed preference for tighter playoff races, Knicks fans have tended to enjoy larger gaps between playoff and non-playoff teams. This could indicate a propensity for New York fans to attend in years where they have been a sure playoff contender. For the case of PU, the one game change in the playoff race did not affect either team's revenues by more than 1.2% per game.

Lastly, three teams were found to have significant effects of CSU: Cleveland, Philadelphia and Seattle. Fans of the former Seattle Supersonics tended to avoid attending games when balance was better. On the other hand, Cleveland fans tend to be most sensitive to overall balance changes in the league, preferring more Playoff Uncertainty and Consecutive Season Uncertainty. As you can see in Table 6.12, the change in CSU applied here had a much larger influence on revenues than the change in the other two measures, increasing revenues for teams by as much as 4.45%. All in all, evidence for the UOH is again mixed for franchises in the NBA.

6.5 Breakpoint Regression Results

The following subsections of this chapter individually discuss the breakpoints estimated in each of the franchises considered in the NBA. Common breaks include those following stadium and arena moves. Championships have tended to have larger effects than attributed to just regular season success, resulting in further sustained upward shifts in attendance for many teams. Not surprisingly, a number of NBA teams saw attendance shifts in the 1980s, which was found in the aggregate analysis as well. Further details of franchise breaks follow, and a time plot of each team can be found in Figures 6.1 through 6.3.

6.5.1 Atlanta Hawks

Both of the estimated breaks—upward shifts—for the Atlanta Hawks coincide with the start of exciting and relatively successful teams. In 1985, a young team starring Spud Webb and Dominique Wilkins won 50 or more games in four consecutive seasons, while in 1995 there was another run of 50-plus win seasons. However, there may be more to the shift in 1985, as Ted Turner had the team play a number of games in New Orleans in the 1984-85 season. Similar to the Atlanta Braves, the Hawks' market encompassed much of the South. Turner's attempt at reaching westward seems to have been relatively successful given the increase in attendance during this time.

6.5.2 Boston Celtics

The 1960-61 season began a steeper upward trend for the Celtics, which also marked the beginning of coach Red Auerbach and star Bill Russell's run of Championships. In addition, the Celtic fielded the first all-black starting lineup during this time, perhaps capturing a minority demographic in the Boston market. The second break occurred in 1973 and coincides with and upward shift in attendance following a year in which Boston won 68 games, followed by an NBA Championship the following season. Lastly, the Celtics experienced another upward shift in the 1994-95 season, followed by a slight downward trend. This likely has to do with moving out of the Boston Garden and expanded seating in a new venue.

6.5.3 Cleveland Cavaliers

Only a single break was found for the Cavaliers, realized as a very large upward shift after the 1984-85 season. The team returned to the playoffs in 1985 after a somewhat dismal run of seasons, and continued its success through the early 1990s as well. As can be seen in Figure 6.1, the team saw a downward trend following this success up until they drafted LeBron James. However, it seems that the changes in attendance during this time can be chalked up to simple win percent and/or balance measures rather than any exogenous break in attendance trends.

6.5.4 Detroit Pistons

Not surprisingly, the Detroit Pistons also experience a large upward shift during a time of high attendance and the opening of a new arena (The Palace of Auburn Hills). Attendance nearly tripled from this large shift. As any astute NBA fan would note, Isiah Thomas was drafted in 1981 and was the spark of a run of very successful Pistons teams in the 1980s, culminating with back-to-back NBA Championships in 1989 and 1990. The combination of these two factors seemed to have vaulted the success of Detroit to a new level.

6.5.5 New York Knicks

The 1968-69 season was the first time the Knicks had seen the playoffs since 1953. They followed this up with an NBA Championship in 1969, which coincides with the large upward shift in attendance during this time. While attendance trended downward after this peak, it again shifted up once the team won a division title in 1988, the first for the franchise in 18 years.

6.5.6 Philadelphia 76ers

The 76ers experienced an upward shift in attendance after drafting superstar Allen Iverson, with some ensuing success. While the team never won a title, Iverson was arguably one of the most exciting players in the game at the time. This seems to be the best explanation for the upward shift after the 1998-99 season for the Sixers.

6.5.7 Phoenix Suns

The Phoenix Suns are another team that experienced a shift in attendance concurrent with both a move to a new arena (America West Arena, now US Airways Center) as well as the arrival of a team superstar. Charles Barkley arrived in Phoenix in 1993 and immediately won the league Most Valuable Player Award. Consistent with past research on arena honeymoon effects, attendance has trended downward since the opening of the new arena that season.

6.5.8 Portland Trailblazers

After a steep upward trend in attendance for the Portland Trailblazers, things leveled off following the 1979-80 season. The Blazers may be a team particularly affected by the censoring issue mentioned earlier, as their 1977 NBA Championship began a sellout streak of 814 consecutive games. This ended in 1995 when they moved to a new, higher capacity facility. As would be expected, the team experienced a large upward shift after the 1994-95 season when they moved to the 20,000 seat Rose Garden.

6.5.9 Seattle Supersonics

Finally, the Seattle Supersonics seemed to have some devastating effects of a terrible 1980-81 as their start player, Gus Williams, sat out the season because of a contract dispute. The team experienced a massive downward shift in attendance during this time—cutting attendance to nearly a third of its previous levels. While the team saw an upward trend afterward, until the years just before a move to Oklahoma City, attendance levels never recovered to those before the 1981-82 season.

6.7 Summary and Conclusions

All in all—as with the previous two chapters—the evidence for fan interest in uncertainty of outcome continues to be mixed at best. While the economic influence of balance measures seems to be larger on average in the NBA—namely for CSU—the direction of the effect varies across teams and the type of uncertainty evaluated. This leaves us with an interesting picture of sports leagues and calls for further evaluation. While some franchises seem to have incentives to encourage balance, others have experienced positive attendance changes in years when balance is *lower*. Cleveland and Philadelphia stand out as teams with fans that prefer more balance across the different measures of uncertainty, while Atlanta, New York and Seattle tend to have fans interested in less balance depending on the measure considered. This echoes the league level findings for basketball, in which fans prefer balance in different directions depending on the type of uncertainty realization considered. While fans tend to like close game play (TL) and turnover from year to year (CSU), there seems to be some preference for having an overly dominant team in each season (PU). While this of course has important implications for marketing to fans, it again alludes to the importance of understanding how decisions come about as a league. Unlike MLB, teams in the NBA tend to experience shifts more related to championship wins than historical events. Nearly all of the upward breaks found in the franchise level data in the NBA can be reasonably explained by league championships or the building of new stadiums. As would be expected from the league-level analysis, the 1980's were a particularly prosperous time for the NBA, as it grew across both smaller and larger markets.

TABLE 6.1: NBA Franchise TAPG and W% by Decade

Team	1950's	1960's	1970's	1980's	1990's	2000's	Overall
ATL TAPG		4,597	6,889	10,450	13,481	14,740	11,066
ATL W%		0.585	0.465	0.537	0.553	0.399	0.493
BOS TAPG	5,665	6,479	10,888	14,911	16,071	16,969	11,690
BOS W%	0.623	0.679	0.615	0.711	0.454	0.542	0.599
CHI TAPG		4,807	9,914	12,587	21,268	20,742	15,099
CHI W%		0.410	0.523	0.479	0.644	0.416	0.506
CLE TAPG			7,895	9,568	16,928	18,063	13,113
CLE W%			0.416	0.404	0.534	0.518	0.468
DET TAPG	3,392	3,913	6,815	16,903	19,260	20,352	12,910
DET W%	0.416	0.390	0.448	0.568	0.503	0.588	0.495
LAL TAPG		9,014	13,665	15,962	16,299	18,953	14,778
LAL W%		0.580	0.609	0.724	0.620	0.634	0.634
MIL TAPG		6,988	9,930	11,856	15,743	16,155	13,115
MIL W%		0.506	0.592	0.631	0.418	0.463	0.525
NYK TAPG	6,520	10,275	16,787	13,603	19,178	19,182	14,114
NYK W%	0.530	0.429	0.533	0.463	0.613	0.399	0.496
PHI TAPG		5,570	9,969	13,490	14,597	17,342	12,616
PHI W%		0.627	0.490	0.645	0.390	0.493	0.523
PHO TAPG		5,395	8,970	11,836	18,076	17,535	13,690
PHO W%		0.336	0.520	0.534	0.633	0.600	0.561
POR TAPG			9,997	12,707	16,642	18,392	14,434
POR W%			0.439	0.565	0.631	0.506	0.535
SEA TAPG		5,617	13,300	12,098	15,556	15,483	13,421
SEA W%		0.323	0.497	0.516	0.643	0.478	0.523

TABLE 6.2: NBA Franchise ADF and PP Tests (Unadjusted)

Team		**ATL**	**BOS**	**CHI**	**CLE**	**DET**	**LAL**
T (*seasons*)		*42*	*61*	*44*	*40*	*53*	*50*
ADF (*p*)	Constant	-1.442 (1)	-0.744 (1)	-1.763 (1)	-1.513 (1)	-1.234 (1)	-2.967 (1)**
ADF (*p*)	Trend	-3.136 (1)	-2.602 (1)	-2.107 (1)	-2.639 (1)	-1.834 (1)	-3.737 (1)**
P-P (*l*)	Constant	-1.471 (3)	-1.189 (3)	-1.567 (3)	-1.566 (3)	-1.147 (3)	-3.018 (3)**
P-P (*l*)	Trend	-3.190 (3)	-3.277 (3)*	-2.357 (3)	-2.511 (3)	-1.896 (3)	-3.392 (3)*

Team		**MIL**	**NYK**	**PHI**	**PHO**	**POR**	**SEA**
T (*seasons*)		*42*	*61*	*47*	*42*	*40*	*41*
ADF (*p*)	Constant	-1.604 (1)	-1.686 (1)	-2.628 (1)*	-1.395 (1)	-1.634 (1)	-2.982 (1)**
ADF (*p*)	Trend	-1.877 (1)	-3.105 (3)	-3.268 (1)*	-2.035 (1)	-2.635 (1)	-2.753 (1)
P-P (*l*)	Constant	-2.558 (3)	-1.482 (3)	-2.255 (3)	-2.095 (3)	-1.699 (3)	-2.701 (3)*
P-P (*l*)	Trend	-3.083 (3)	-2.058 (3)	-2.404 (3)	-2.334 (3)	-2.739 (3)	-2.486 (3)

***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 6.3: NBA Franchise Two-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	**Test Statistic**	**Critical Value Break Points**
ATL	3	1984/85, 2001/02	3.815***, -3.621***	-5.940**	λ = (0.40, 0.81)
BOS	0	1959/60, 1980/81	-2.934***, -0.645	-5.941**	λ = (0.18, 0.52)
CHI	3	1978/79, 1994/95	3.055***, -1.560	-5.042	λ = (0.30, 0.66)
CLE	6	1990/91, 1996/97	2.288**, -2.427**	-5.608*	λ = (0.53, 0.68)
DET	6	1979/80, 1996/97	5.585***, -5.281***	-6.307**	λ = (0.43, 0.75)
LAL	7	1972/73, 1983/84	-5.666***, 4.761***	-5.534*	λ = (0.26, 0.48)
MIL	0	1983/84, 1990/91	-1.868*, -0.823	-4.759	λ = (0.38, 0.55)
NYK	5	1962/63, 1979/80	4.044***, -3.653***	-5.750**	λ = (0.23, 0.51)
PHI	2	1981/82, 1998/99	-5.274***, 3.546***	-6.006**	λ = (0.40, 0.77)
PHO	8	1981/82, 1990/91	-4.804***, 5.926***	-7.419***	λ = (0.33, 0.55)
POR	8	1987/88, 1993/94	-3.769***, 4.578***	-5.824**	λ = (0.45, 0.60)
SEA	8	1980/81, 1991/92	-7.290***, 6.968***	-7.379***	λ = (0.34, 0.61)

Data adjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 6.4: NBA Franchise One-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	**Test Statistic**	**Critical Value Break Points**
ATL	3	1993/94	-0.500	-4.9849**	λ = 0.62
BOS	0	1973/74	-0.377	-5.002**	λ = 0.41
CHI	8	1992/93	2.624***	-4.163	λ = 0.61
CLE	7	1989/90	2.845***	-6.374***	λ = 0.50
DET	6	1982/83	3.892***	-5.162***	λ = 0.49
LAL	7	1982/83	-3.692***	-4.028	λ = 0.46
MIL	0	1998/99	-1.945*	-3.602	λ = 0.74
NYK	5	1989/90	0.232	-4.941**	λ = 0.67
PHI	7	1973/74	3.209***	-4.380*	λ = 0.23
POR	7	1987/88	-2.566**	-4.725**	λ = 0.45

NOTE: $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2.
See J. Lee and Strazicich (2003) Table 2 for critical values. Data adjusted for strikes.
***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 6.5: NBA Franchise ADF and PP Tests (Adjusted)

Team		**ATL**	**BOS**	**CHI**	**CLE**	**DET**	**LAL**
T (*seasons*)		*42*	*61*	*44*	*40*	*53*	*50*
ADF (*p*)	Constant	-1.605 (1)	-0.739 (1)	-1.762 (1)	-1.505 (1)	-1.235 (1)	-2.965 (1)**
ADF (*p*)	Trend	-3.536 (1)*	-2.579 (1)	-2.090 (1)	-2.633 (1)	-1.837 (1)	-3.727 (1)**
P-P (*l*)	Constant	-1.466 (3)	-1.188 (3)	-1.566 (3)	-1.562 (3)	-1.147 (3)	-3.012 (3)**
P-P (*l*)	Trend	-2.945 (3)	-3.281 (3)*	-2.337 (3)	-2.501 (3)	-1.895 (3)	-3.384 (3)*

Team		**MIL**	**NYK**	**PHI**	**PHO**	**POR**	**SEA**
T (*seasons*)		*42*	*61*	*47*	*42*	*40*	*41*
ADF (*p*)	Constant	-1.604 (1)	-1.686 (1)	-2.632 (1)*	-1.395 (1)	-1.624 (1)	-3.008 (1)**
ADF (*p*)	Trend	-1.862 (1)	-3.105 (3)	-3.281 (1)*	-2.035 (1)	-2.563 (1)	-2.785 (1)
P-P (*l*)	Constant	-2.558 (3)	-1.482 (3)	-2.256 (3)	-2.095 (3)	-1.702 (3)	-2.707 (3)*
P-P (*l*)	Trend	-3.078 (3)	-2.058 (3)	-2.406 (3)	-2.332 (3)	-2.695 (3)	-2.491 (3)

***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 6.6: NBA Franchise Two-Break LM Test (Adjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	**Test Statistic**	**Critical Value Break Points**
ATL	7	1980/81, 1986/87	3.266***, -5.317***	-6.331***	λ = (0.31, 0.45)
BOS	0	1959/60, 1980/81	-2.969***, -0.664	-5.983**	λ = (0.18, 0.52)
CHI	8	1982/83, 1999/00	3.519***, -5.465***	-5.049	λ = (0.39, 0.77)
CLE	6	1989/90, 2003/04	2.266**, -1.132	-5.659*	λ = (0.50, 0.85)
DET	6	1979/80, 1996/97	5.554***, -5.245***	-6.270**	λ = (0.43, 0.75)
LAL	7	1972/73, 1983/84	-5.717***, 4.846***	-5.578*	λ = (0.26, 0.48)
MIL	0	1983/84, 1990/91	-1.884*, -0.803	-4.778	λ = (0.38, 0.55)
NYK	5	1962/63, 1979/80	4.044***, -3.653***	-5.750**	λ = (0.23, 0.51)
PHI	2	1981/82, 1998/99	-5.319***, 3.572***	-6.043**	λ = (0.40, 0.77)
PHO	8	1981/82, 1990/91	-4.783***, 5.897***	-7.382***	λ = (0.33, 0.55)
POR	7	1985/86, 1993/94	-2.970***, 4.493***	-5.888**	λ = (0.40, 0.60)
SEA	8	1980/81, 1991/92	-7.883***, 7.551***	-7.978***	λ = (0.34, 0.61)

Data adjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 6.7: NBA Franchise One-Break LM Test (Adjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
BOS	0	1973/74	-0.393	-5.021**	λ = 0.41
CHI	8	1992/93	2.633**	-4.176	λ = 0.61
CLE	7	1989/90	2.908***	-6.269***	λ = 0.50
DET	6	1982/83	3.892***	-5.155***	λ = 0.49
LAL	7	1982/83	-3.900***	-4.247*	λ = 0.49
MIL	0	1998/99	-1.866*	-3.573	λ = 0.74
NYK	5	1989/90	0.232	-4.941**	λ = 0.67
PHI	7	1973/74	3.210***	-4.395*	λ = 0.23
POR	7	1987/88	-2.498**	-4.713**	λ = 0.45

NOTE: $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2.
See J. Lee and Strazicich (2003) Table 2 for critical values. Data adjusted for strikes.
***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 6.8: NBA Franchise Model Break Point Sequential Test Results (Heterogeneous)

Team	*$SupF_t(1)$*	*$SupF_t(2)$*	*$SupF_t(3)$*	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*Breaks*
ATL	15.02***	20.72***		20.72***	28.85***	17.13***		**2**
BOS	58.65***	42.82***	42.05***	58.65***	86.77***	14.56**	13.26**	**3**
CLE	32.57***	26.36***	32.57***	36.70***	10.73**			**1**
DET	49.87***	36.61***		49.87***	50.97***	7.68		**1**
NYK	100.08***	100.78***	76.56***	100.78***	133.06***	19.54***	5.01	**2**
PHI	37.19***	23.29***		37.19***	37.19***	6.53		**1**
PHO	124.07***	74.07***		124.07***	124.07***	2.88		**1**
POR	84.54***	75.29***		84.54***	104.82***	144.85***		**2**
SEA	89.50***	46.44***		89.50***	89.50***	2.43		**1**

"***" Significant at the 99% critical level
"**" Significant at the 95% critical level
"*" Significant at the 90% critical level

TABLE 6.9: NBA Franchise Model Break Dates (Heterogeneous)

Team	T_1	T_2	T_3
ATL	**1985-86** [84-85, 86-87]	**1995-96** [94-95, 98-99]	
BOS	**1960-61** [59-60, 61-62]	**1973-74** [70-71, 74-75]	**1994-95** [89-90, 95-96]
CLE	**1984-85** [83-84, 85-86]		
DET	**1982-83** [80-81, 83-84]		
NYK	**1968-69** [66-67, 69-70]	**1987-88** [86-87, 90-91]	
PHI	**1998-99** [97-98, 99-00]		
PHO	**1991-92** [90-91, 92-93]		
POR	**1979-80** [78-79, 80-81]	**1994-95** [93-94, 95-96]	
SEA	**1981-82** [80-81, 82-83]		

*Brackets denote 90% confidence interval for break date

TABLE 6.10: NBA Franchise Model Breakpoint Regression Results (Heterogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4
ATL	253.59	2797.64	-140.97	14249.91	14.23	13213.29		
t-value	*(4.10)****	*(2.33)***	*(-1.29)*	*(4.75)****	*(0.15)*	*(3.45)****		
BOS	27.21	1503.04	365.84	-3531.57	208.41	2998.18	-68.86	17961.97
t-value	*(0.36)*	*(2.07)***	*(6.14)****	*(-2.49)***	*(6.04)****	*(1.89)**	*(-1.28)*	*(6.33)****
CLE	87.93	4492.79	152.00	9125.38				
t-value	*(0.88)*	*(2.72)****	*(3.50)****	*(4.04)****				
DET	294.56	-1703.76	55.29	12808.46				
t-value	*(5.00)****	*(-0.89)*	*(1.15)*	*(4.49)****				
NYK	436.48	-2268.58	-329.75	19554.25	139.22	6860.07		
t-value	*(8.07)****	*(-1.35)*	*(-5.12)****	*(7.02)****	*(2.79)****	*(2.12)***		
PHI	395.76	157.85	-432.78	32042.24				
t-value	*(15.92)****	*(0.11)*	*(-3.07)****	*(5.22)****				
PHO	324.41	3032.93	-113.51	18344.77				
t-value	*(9.75)****	*(3.10)****	*(-2.68)***	*(9.44)****				
POR	625.30	2524.33	-30.00	7716.57	-116.66	17878.52		
t-value	*(5.34)****	*(2.26)***	*(-0.54)*	*(4.85)****	*(-2.01)***	*(7.16)****		
SEA	790.74	-364.77	296.49	-2071.08				
t-value	*(9.62)****	*(-0.26)*	*(8.56)****	*(-0.99)*				

*** Significant at the 99% critical level

** Significant at the 95% critical level

* Significant at the 90% critical level

α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE 6.11: NBA Franchise Model Balance and W% Coefficients (Heterogeneous)

Team	*TL*	*PU*	*CSU*	*W%*	$\bar{R}^2$ (R^2)
ATL	-4561.71	2662.63	-1964.98	6181.94	0.919
t-value	*(-2.11)***	*(0.37)*	*(-1.47)*	*(3.54)****	*(0.937)*
BOS	1385.24	3416.26	-310.26	5434.97	0.972
t-value	*(1.38)*	*(0.79)*	*(-0.62)*	*(5.37)****	*(0.977)*
CLE	-766.02	-20683.06	-5123.60	14837.77	0.933
t-value	*(-0.28)*	*(-2.22)***	*(-2.85)****	*(7.31)****	*(0.945)*
DET	-5071.77	2021.47	-483.54	9426.68	0.940
t-value	*(-1.61)*	*(0.21)*	*(-0.30)*	*(4.02)****	*(0.948)*
NYK	2530.10	15057.65	635.27	7278.62	0.945
t-value	*(1.75)**	*(2.32)***	*(0.83)*	*(3.92)****	*(0.953)*
PHI	5392.75	4301.21	-3694.38	9095.13	0.919
t-value	*(2.42)***	*(0.51)*	*(-3.02)****	*(6.73)****	*(0.932)*
PHO	-155.63	7636.85	-939.51	6010.38	0.964
t-value	*(-0.10)*	*(1.47)*	*(-0.96)*	*(4.91)****	*(0.970)*
POR	-2121.08	9198.59	96.64	8499.86	0.958
t-value	*(-1.24)*	*(1.63)*	*(0.09)*	*(6.07)****	*(0.968)*
SEA	571.04	-10282.88	2564.20	12442.80	0.893
t-value	*(0.27)*	*(-1.35)*	*(1.99)***	*(7.00)****	*(0.911)*

*** Significant at the 99% critical level
** Significant at the 95% critical level
* Significant at the 90% critical level

TABLE 6.12: NBA Franchise Level Economic Implications

	Game Uncertainty		Playoff Uncertainty		Consecutive Season Uncertainty		
Team	***ATL***	***PHI***	***CLE***	***NYK***	***CLE***	***PHI***	***SEA***
2009 TAPG	16,546	14,225	20,562	19,501	20,562	14,225	13,355 (***2007***)
2009 Variable	0.030	0.030	0.073	0.073	0.550	0.550	0.285 (***2007***)
Coef. Est.[a]	-4,562	5,393	-20,683	15,058	-5,124	-3,694	2,564
Elasticity	0.008	0.011	0.073	0.056	0.137	0.143	0.055
ΔVariable[b]	0.064	0.064	0.012	0.012	0.171	0.171	0.171
Inc. Factor	213.3%	213.3%	16.4%	16.4%	31.1%	31.1%	60.0%
ΔTAPG	*-2823*[d]	334	246	*-179*	876	633	*-441*
% ΔTAPG	*-1.71%*	2.35%	1.20%	*-0.92%*	4.26%	4.45%	*-3.30%*
Rev. Per Attend[c]	$73.78	$67.47	$72.47	$102.79	$72.47	$67.47	$57.46 (***2007$***)
Δ Game Rev.	*-$20,828*	$22,521	$17,842	*-$18,410*	$63,491	$42,682	*-$25,323* (***2007$***)

a. Coefficient taken from model with heterogeneous errors across regimes and follow the approach of Lee and Fort (2008, pp. 291).
b. All measure changes imply an *improvement* in balance.
c. Revenue per attendee data come from Team Marketing Report Fan Cost Index (2009).
d. *Italic* font indicates disagreement with Rottenberg's Uncertainty of Outcome Hypothesis.

FIGURE 6.1: Fitted NBA TAPG for ATL, BOS, CLE and DET (Heterogeneous)

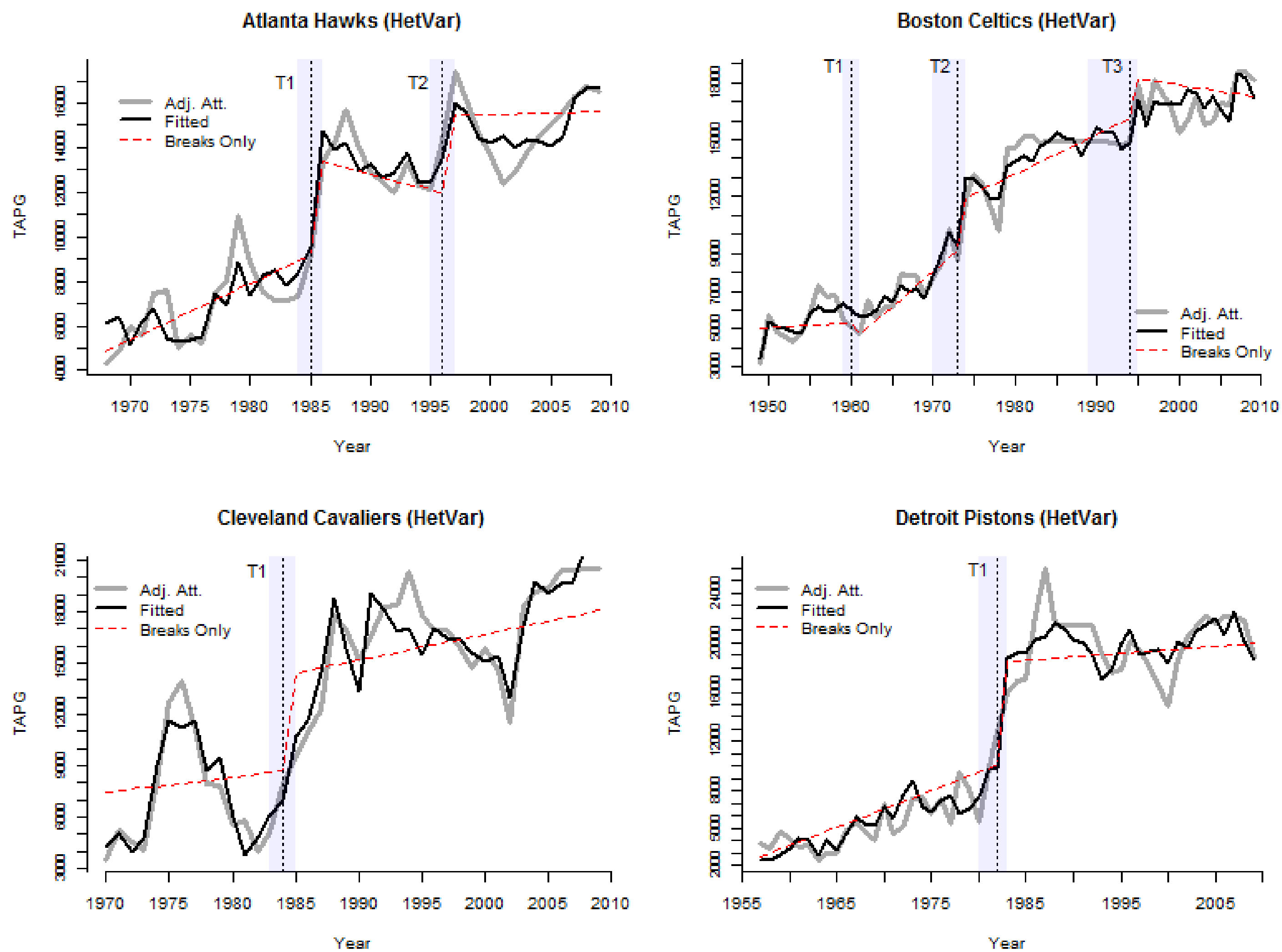


FIGURE 6.2: Fitted NBA TAPG for NYK, PHI, PHO and POR (Heterogeneous)

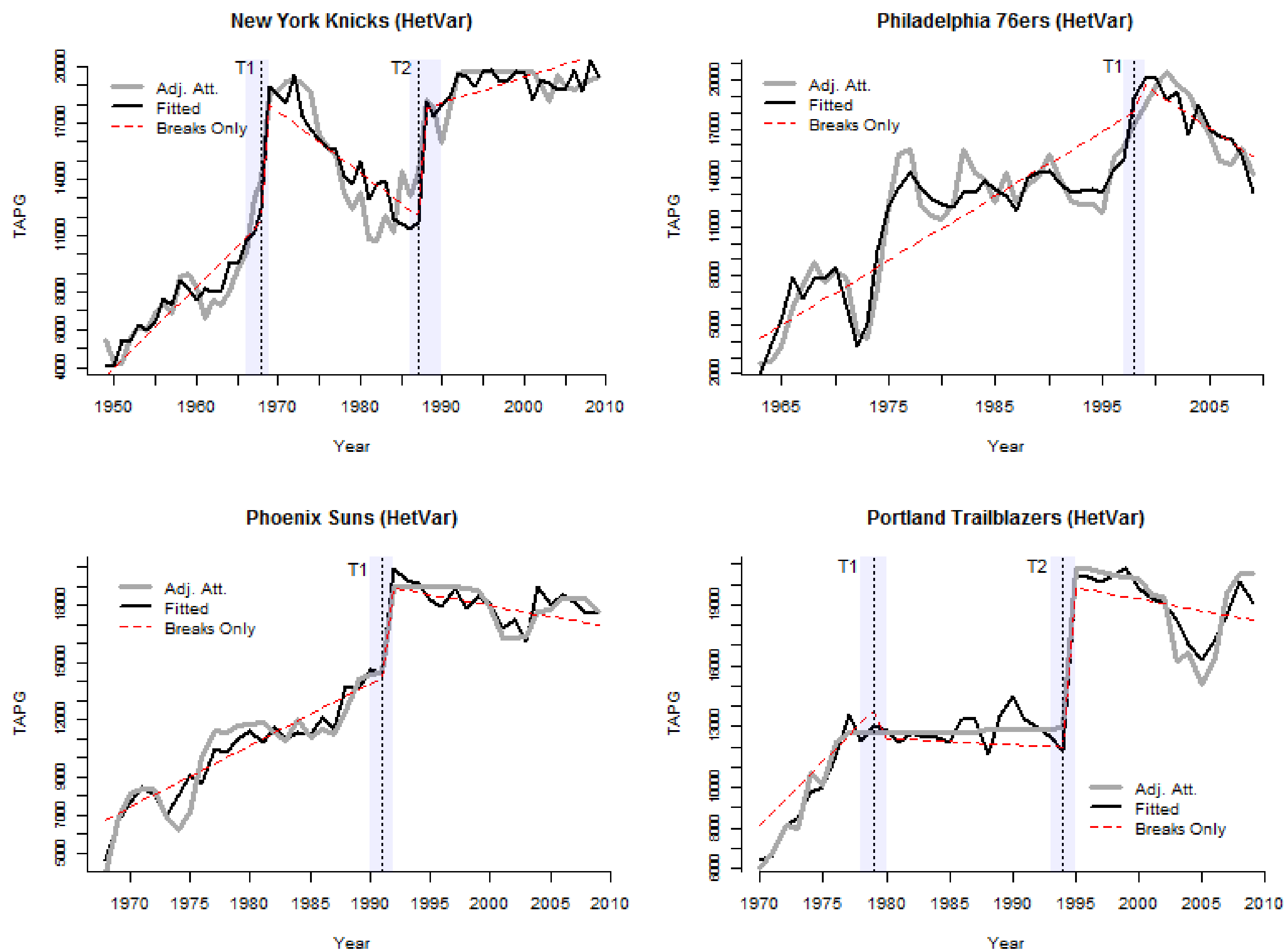
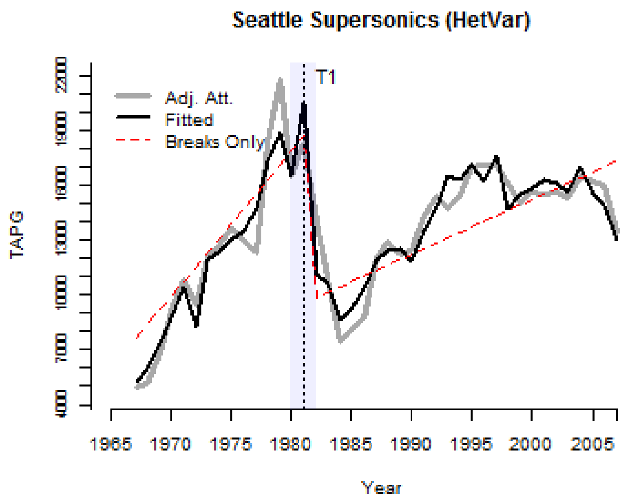


FIGURE 6.3: Fitted NBA TAPG for SEA (Heterogeneous)



CHAPTER 7

National Football League Franchises

7.1 Introduction/Justification

As with the NBA, understanding the behavior of individual franchise attendance in the National Football League can help to understand the break locations and fan behaviors at the league level. Given the lack of significant effects of competitive balance on attendance levels found throughout the history of the NFL, we must further evaluate whether this is an aggregate effect (increases for some teams, and decreases for others) or a result due to actual lack of interest in uncertainty as a whole. As a preview, individual those franchises with statistically significant balance effects have fans with preferences almost exclusively *for* uncertainty of outcome. Additionally, teams experienced similar large increases in attendance that seem to be related to structural changes in the way the game was played (for example, increases in use of the forward pass and offense). These and other linkages will be discussed in Section 7.5 in more detail.

7.2 Data and Methods

The methods used here are identical to those used in Chapters 5 and 6 (NFL Model B reports results from an ancillary regression including lagged win percent as a predictor). Results from additional models (error variance considerations) are exhibited in Appendix C. In addition to the league-level NFL data treatment in Chapter 4, there are various unique data considerations for a number of franchises. First, the number of home games in each season changes for teams early on in league history (as in the NBA). Therefore, the number of home games for each team was collected individually from Pro-Football Reference (2010) to ensure accurate calculation of TAPG. Data for the 1992 and 1998 seasons at the team level are imputed due to unavailability, while only 15 games were played in 1987 and only 9 in 1982 due to labor issues. The adjusted data impute the years containing work stoppages as with the league-level data; however, imputations for the 1992 and 1998 seasons are included in both the adjusted and unadjusted franchise attendance series.

As with the NBA, rival American Football League (AFL) and All-American Football Conference (AAFC) team attendance numbers are excluded from this analysis. Those teams which merged with the NFL from the AFL or AAFC are only used for years in which they participated in the NFL. For example, the Miami Dolphins' attendance series spans from 1970 through 2009, despite their 10-year tenure in the 1960's with the AFL. However, in the lagged win percent models—presented in Appendix C—each of these teams has their previous year's AFL or AAFC win percent as the *t-1* win percent in the model for the first time point in the NFL series. Similarly, for those teams whom played the previous season in a different location, the win percent for the team in that location is used as the *t-1* win percent for the first year in their respective new home. The first year of existence of each team is not used in the lagged win percent models, and the regression estimation begins with the second year in existence (and the *t-1* win percent from the inaugural season as a covariate). Finally, teams in the NFL with a history of temporarily leveraging the Los Angeles market are also excluded (i.e. Rams and Raiders).

Some years for specific teams are missing reported attendance numbers at each of the sources listed here: the Chicago Bears (1961 and 1962), Green Bay Packers (1952), New York Giants (1953 and 1958), Philadelphia Eagles (1938), Pittsburgh Steelers (1938, 1944, 1951, 1952, 1953, 1957 and 1965) and Washington Redskins (1938, 1939, 1951, 1957, 1960, 1962 and 1965). For those missing seasons which have a preceding and following year attendance number reported, a similar weighted average approach is taken as with the 1992 and 1998 seasons. However, for those teams with multiple consecutive missing data (Bears 1961-62, Steelers 1951-53 and Redskins 1938-39), an alternative approach is taken in which a simple linear trend is calculated through those seasons.

The Pittsburg Steelers require additional consideration for their early years. Along with significant missing early attendance data, the Steelers spent two separate seasons merged with the Philadelphia Eagles (1943, nicknamed the “Steagles”) and the Chicago Cardinals (1944, nicknamed “Card-Pitt” or “Carpets”). In these seasons—while the Steelers’ played home games at Forbes Field in Pittsburgh—the teams played some home games at Shibe Park in Philadelphia (4 games) and Wrigley Field and Comiskey Park in Chicago (1 and 2 home games, respectively). In 1943, only two home games were played at Forbes Field, while three were played there in 1944. For the 1943 season, TAPG for the Steelers is calculated using only those games played at Forbes Field (and only those at Shibe Park for the Eagles). However, data for Forbes in 1944 was unavailable; therefore, the 1944 TAPG reported is the average attendance for the three games played in Chicago in the unadjusted data. For the adjusted data, a weighted average of the years before and after the season—as well as the Chicago-based attendance numbers—are included for 1944.

The NFL contains twenty (20) individual franchises with attendance series of sufficient length (40 years) for the breakpoint analysis. Descriptive statistics regarding TAPG and win percent for each of the franchises in each league can be found in Table 7.1.

7.3 Unit Root Results

Of the twenty NFL teams considered, fifteen were found to be stationary or stationary with breakpoints (Tables 7.2 through 7.7), including the Atlanta Falcons, Buffalo Bills, Chicago Bears, Cincinnati Bengals, Denver Broncos, Detroit Lions, Kansas City Chiefs, Miami Dolphins, Minnesota Vikings, New York Giants, Philadelphia Eagles, Pittsburg Steelers, San Diego Chargers, San Francisco 49ers, and Washington Redskins. There was some discrepancy for the unit root analyses on the adjusted and unadjusted data, with the LM-1 unit root test indicating rejection of a unit root with a single break for the New York Jets. However, given that no other test rejected the presence of a unit root for the Jets series (adjusted or unadjusted) I proceed as treating the franchise attendance series as non-stationary, and do not apply the BP procedure here.

Finally, the BP procedure ultimately estimates no breaks in the Buffalo Bills and San Diego Chargers attendance series. Therefore, no subsequent breakpoint regressions are estimated for these franchises as the preliminary unit root tests do not indicate stationarity without breaks. Most likely, the breaks indicated from the LM tests were too small in size for the BP Procedure to estimate them as significant structural changes (as with San Diego Padres series in Chapter 5). Further investigation into these attendance series is recommended for future work in addition to those franchises for which a unit root is not rejected with or without breaks.

7.4 Uncertainty of Outcome Results

Results of the influence of uncertainty of outcome were again mixed across franchises analyzed in the NFL as with the previously discussed leagues. Interestingly, a number of teams in the NFL were found to have significant effects of outcome uncertainty, despite the null finding at the league level (Table 7.11). This exhibits the importance of understanding the variation in fan preferences across markets in individual leagues in order to shed light on collective decision-making by team owners, rather than the net effect across teams as a whole. While the net effects of UOH tend to be insignificant for the league, owners in different markets will have different incentives for balance based on the results of the models presented here. For example, fans of Atlanta, Denver, Miami and Minnesota tend to prefer closer distributions of win percent in the league as implied by the franchise-level regression models. However, the owner of the Washington Redskins seems to have some small incentive to *avoid* creating a balanced league in some respects (Table 7.12).

For PU, however, only three teams were found to have significant effects of *Windiff*: Denver, Miami and Minnesota. The direction of the coefficient for Miami and Minnesota is switched from that of the Game Uncertainty variable for each team, indicating disagreement with Rottenberg's UOH. Unlike evaluation of most other effects of uncertainty of outcome on attendance, revenue changes for Miami do not seem to be trivial with a one game improvement in the playoff race, resulting in nearly a 7.5% decrease in revenues per game. For Denver and Minnesota, the magnitude of the effect is much smaller (both below 3% of revenues in either direction).

Finally, CSU has statistically significant attendance effects for Kansas City, Philadelphia and Washington, with the coefficient estimate for Kansas City in disagreement with Rottenberg's UOH. The change in preference for Washington seems to indicate that while fans prefer a wider spread of win percent in season, they do enjoy significant turnover across seasons. Again, the economic significance of this variable is relatively small for those fans that enjoy turnover; however, the change in Chiefs revenues is somewhat non-trivial at 3.52% (or a decrease of about $265,000 per game with the marginal improvement in CSU).

7.5 Breakpoint Regression Results

Similar to the aggregate NFL analysis, individual teams also saw attendance shifts during the rise of the quarterback during the 1980s. Those teams which claimed a star quarterback their own—like the Miami Dolphins' Dan Marino—saw large shifts. It seems that the change of play style was truly exciting for fans as a whole. Other attendance shifts seem to be tied to increases in stadium capacity and sustained team success or failure. The following sections discuss the structural change for each of the NFL franchises under analysis here, and the reader is referred to Figures 7.1 through 7.4 for visual inspection of these attendance changes.

7.5.1 Atlanta Falcons

Beginning discussion of NFL franchises, the Atlanta Falcons experience a single upward shift in 1989 followed by a positive trend, after experiencing a declining trend throughout most of the team's history. The Falcons acquired Deion Sanders in 1989 and moved to the Georgia Dome in 1992. The exciting—and often mouthy—Sanders and new stadium seem to have attracted extra fans to the gate for the team.

7.5.2 Chicago Bears

As with the Falcons, the historic Chicago Bears franchise has only a single estimated attendance break throughout its history, corresponding to a change in the trend in 1948. While the team experience positive trends in attendance throughout its history, the trend leveled off a bit after this season. This is likely due to the team's decline in success after a dominating decade in the 1940s.

7.5.3 Cincinnati Bengals

After the merger of the AFL and NFL, the Cincinnati Bengals saw a sharp decreasing attendance trend until their first breakpoint in 1979. Following this season Bengals attendance changes course, trending upward until the next break in 1991 at which point it shifts down and continues its upward path. The Bengals made two Super Bowl appearances in the 1980s, losing to the San Francisco 49ers both times. However, the end of 1990-91 season marked the death of Paul Brown and 14 consecutive losing seasons. Despite this, the team—just as the NFL as a whole—experienced upward trending attendance through much of the 1990s and early 21st century.

7.5.4 Denver Broncos

The 1982 season marked the end of a large upswing in Broncos attendance at Mile High Stadium. After a small downward shift, attendance has slowly increased through today for Denver. The team likely hit a point of near sellouts during this period, as John Elway arrived in 1982 to lead successful Broncos teams for nearly two decades.

7.5.5 Detroit Lions

While it is rather unbelievable in this day and age, the Detroit Lions were a very successful team in the 1950s. After the 1951 season the team experienced a large upward attendance shift likely due to back-to-back NFL Championships in 1952 and 1953. While Detroit's attendance has generally trended upward following this large shift, the team has experienced significant volatility in gate attendance, as can be seen in Figure 7.2.

7.5.6 Kansas City Chiefs

The Kansas City Chiefs generally experienced a negative trend in attendance after the AFL-NFL merge, but this seemed to change with the hiring of coach Marty Schottenheimer in 1988. During this time, the team saw a large positive break in attendance followed by a string of sustained success on the field and 155 consecutive sellouts from 1991 through 2009. The team's Arrowhead Stadium seems to have had a short honeymoon effect when it opened in 1972, though the BP Procedure was unable to estimate breakpoints so close to the ends of the attendance series.

7.5.7 Miami Dolphins

As mentioned in the aggregate NFL analysis, pass-happy offenses seem to have excited fans about football. The Miami Dolphins, led by Dan Marino beginning in 1983, were arguably the most prominent passing team in the NFL during the 1980s and into the 1990s. In 1983 the team experienced an upward shift followed by a slight positive trend through the next break in 1995, another positive attendance change. Interestingly, there do not seem to be any large effects of the opening of Joe Robbie Stadium in 1987, though the team did experience a small spike near this time. Marino broke multiple career passing records in 1995, including total yards, touchdowns and completions. After the 1995 season attendance trended downward with a string of mediocre Dolphins teams.

7.5.8 Minnesota Vikings

With a move to the Hubert H. Humphrey Metrodome in 1981, the Minnesota Vikings saw an increase of about 12,000 fans per game. The Metrodome increased stadium capacity compared to the Vikings old home and the team saw a relatively flat trend following the shift. A second shift of about the same size came after the 1996 season. This is best explained by a record-breaking 1998 (just outside the estimated confidence interval) team that featured Randy Moss, Chris Carter and Randal Cunningham.

7.5.9 New York Giants

The New York Giants are well known to have played in the "Greatest Game Ever Played" in 1958 against the Baltimore Colts. This game was one of six NFL Championship appearances for the team from 1956 through 1963. The 1956 Championship was the only game won by the Giants, and the team had an enormous increase in attendance following this season. The 1958 game is often credited with increasing interest in the NFL, as it was the first aired nationally on NBC. It seems, however, that the Giants experienced substantial increased interest just before this game was even played.

7.5.10 Philadelphia Eagles

Just as the Giants saw a huge increase in fans after their championship win, the Philadelphia Eagles experienced a positive shift in attendance after their 1960 NFL Championship. The team managed to sustain this level of attendance until a smaller downward shift in 1981 after losing to Oakland in the Super Bowl.

7.5.11 Pittsburg Steelers

With the exception of two small downward shifts in 1955 and 1986, the Pittsburgh Steelers have enjoyed a relatively consistent upward slope in gate attendance since the 1930s. The team had significant struggles during the 1950s and mid-to-late 1980s until the hiring of Bill Cowher in 1992. These prolonged periods of on-field disappointment seem to have affected fan interest in the team.

7.5.12 San Francisco 49ers

The San Francisco 49ers model indicates a very large shift downward in 1960, followed by a somewhat consistent upward trend through today. The formation of the AFL in 1960 may have had a significant impact on the team's interest, as it had initially been the only major professional football team west of Dallas. With the formation of the AFL, two teams were added in California, one of which was just across the bay in Oakland. This competition cut 49ers attendance nearly in half for a period up until the AFL-NFL merger.

7.5.13 Washington Redskins

Finally, the Washington Redskins have experienced two significant upward attendance shifts throughout franchise history. The first occurred in 1962, the year just after the opening of RFK Stadium. IN this same year, the federal government warned the ownership of the team to desegregate. Ultimately, the team became the last NFL franchise to integrate in 1962. The combination of a new stadium and attraction of African American consumers likely explain much of this break. Another arena move sparked a large shift upward (1995) in attendance when the team left RFK for Jack Kent Cooke Stadium (now FedEx Field) in 1997. Not only did attendance shift upward, but since this time has been followed by a very steep upward trend through the 2009 season.

7.6 Summary and Conclusions

Unlike the league aggregate analysis regarding the NFL, I find a number of statistically significant effects of uncertainty of outcome at the team level. Surprisingly, there is an apparent overwhelming interest in *more* balance (with few exceptions) for those fans that are found to care about the three measures used here. Fans of the Washington Redskins are perhaps the most curious, as they tend to prefer more balance across seasons while enjoying less in-season uncertainty. This could be a result of the long-standing rivalry with the Dallas Cowboys who have in the past been able to sustain successful dynasties. It may be that fans generally enjoy unbalanced competition within the season, with the exception of their heated rival. As with the apparent Red Sox preferences, more empirical research is suggested for directly assessing fan preferences with respect to rivalries.

Overall, this evidence tends to point against the "canceling out" effect of preferences across the league, where some fans prefer more balance while others prefer less. However, what this could indicate is an issue in the analysis of coefficients at the league level. Given that only seven teams show any significant effect of the three balance measures on attendance, this aggregate effect may not be large enough to mean a significant effect at the league level with possible censoring issues over the long period. Therefore, the results here indicate that further analysis using censored regression techniques may be more enlightening with respect to coefficient estimates. Nevertheless, the size and location of break points in attendance series found here are rather interesting, and seem to be associated with similar events as found in the NBA. Finally, further evaluation of the occurrence of breaks and increases in trends are recommended with respect to structural changes in offensive play in the league through panel estimations at the team level.

TABLE 7.1: NFL Franchise TAPG and W% by Decade

Team	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s	Overall
ATL TAPG				55,018	50,847	42,244	53,871	65,771	53,350
ATL W%				0.216	0.424	0.385	0.450	0.472	0.413
BUF TAPG					55,071	64,038	73,617	68,673	65,350
BUF W%					0.359	0.454	0.644	0.413	0.467
CHI TAPG	24,609	33,645	42,509	46,430	48,854	57,770	58,970	61,658	47,974
CHI W%	0.754	0.753	0.593	0.511	0.417	0.594	0.456	0.506	0.573
CIN TAPG					51,886	51,709	51,212	61,985	54,198
CIN W%					0.521	0.542	0.325	0.428	0.454
DAL TAPG				45,119	60,361	57,720	64,745	66,019	58,793
DAL W%				0.492	0.729	0.526	0.631	0.512	0.578
DEN TAPG					58,979	73,412	72,762	75,374	70,132
DEN W%					0.534	0.598	0.587	0.581	0.575
DET TAPG	20,448	21,722	48,625	51,498	59,186	59,055	67,572	62,364	50,301
DET W%	0.659	0.344	0.584	0.517	0.474	0.405	0.494	0.263	0.457
GB TAPG	14,669	20,360	23,278	45,587	50,834	52,413	56,644	67,737	43,611
GB W%	0.711	0.599	0.327	0.719	0.411	0.445	0.581	0.594	0.548
KC TAPG					56,304	50,000	75,831	76,430	64,641
KC W%					0.439	0.435	0.637	0.437	0.487
MIA TAPG					62,002	59,463	68,698	70,674	65,209
MIA W%					0.730	0.628	0.594	0.494	0.611
MIN TAPG				40,660	46,858	54,375	57,978	63,872	52,996
MIN W%				0.431	0.700	0.509	0.594	0.525	0.554
NE TAPG					55,493	51,682	51,688	66,767	56,408
NE W%					0.453	0.515	0.425	0.700	0.523
NO TAPG				75,125	59,901	57,963	56,748	65,612	61,107
NO W%				0.293	0.296	0.443	0.444	0.519	0.416
NYG TAPG	29,741	36,322	39,996	62,320	62,387	70,009	72,747	78,620	57,923
NYG W%	0.668	0.545	0.651	0.519	0.350	0.531	0.519	0.550	0.541
NYJ TAPG					52,395	56,905	63,182	77,818	62,575
NYJ W%					0.364	0.512	0.406	0.500	0.446
PHI TAPG	20,100	22,424	26,966	58,267	61,012	61,426	63,990	67,579	50,369
PHI W%	0.251	0.555	0.442	0.429	0.394	0.499	0.500	0.647	0.473
PIT TAPG	11,850	23,578	27,638	32,898	48,381	52,797	54,980	61,605	41,118
PIT W%	0.283	0.376	0.463	0.358	0.688	0.514	0.581	0.647	0.497
SD TAPG					43,631	49,421	57,570	62,229	53,213
SD W%					0.409	0.482	0.462	0.531	0.471
SF TAPG			41,774	38,674	47,391	56,438	62,755	67,409	52,407
SF W%			0.539	0.439	0.434	0.673	0.706	0.425	0.536
WAS TAPG	24,191	33,398	25,027	44,140	53,002	52,322	59,704	84,655	49,247
WAS W%	0.731	0.619	0.403	0.356	0.639	0.650	0.494	0.438	0.523

TABLE 7.2: NFL Franchise ADF and PP Tests (Unadjusted)

Team		**ATL**	**BUF**	**CHI**	**CIN**	**DAL**	**DEN**	**DET**
T *(seasons)*		*44*	*40*	*76*	*40*	*50*	*40*	*76*
ADF (p)	Constant	-1.654 (1)	-1.417 (4)	-2.208 (1)	-1.710 (1)	-2.658 (1)*	-2.486 (1)	-2.428 (1)
ADF (p)	Trend	-2.146 (1)	-3.928 (1)**	-4.234 (1)***	-2.805 (1)	-3.061 (1)	-2.347 (1)	-2.612 (1)
P-P (l)	Constant	-2.195 (3)	-3.352 (3)**	-1.977 (3)	-1.842 (3)	-2.452 (3)	-2.328 (3)	-2.371 (3)
P-P (l)	Trend	-2.641 (1)	-3.421 (3)*	-4.266 (3)***	-2.618 (3)	-2.832 (3)	-2.202 (3)	-2.627 (3)
Team		**GB**	**KC**	**MIA**	**MIN**	**NE**	**NO**	**NYG**
T *(seasons)*		*74*	*40*	*40*	*49*	*40*	*43*	*76*
ADF (p)	Constant	-0.826 (1)	-1.207 (2)	-2.022 (1)	-2.186 (1)	-1.681 (1)	-2.946 (1)*	-1.786 (1)
ADF (p)	Trend	-1.953 (1)	-2.242 (2)	-2.665 (1)	-3.949 (1)**	-2.331 (1)	-2.833 (1)	-3.446 (1)*
P-P (l)	Constant	-1.078 (3)	-1.956 (3)	-2.581 (3)	-1.763 (3)	-3.024 (3)**	-3.368 (3)**	-1.787 (3)
P-P (l)	Trend	-2.797 (3)	-2.583 (3)	-2.998 (3)	-3.344 (3)*	-3.259 (3)*	-3.223 (3)*	-3.902 (3)**
Team		**NYJ**	**PHI**	**PIT**	**SD**	**SF**	**WAS**	
T *(seasons)*		*40*	*73*	*76*	*40*	*60*	*73*	
ADF (p)	Constant	-1.232 (1)	-1.526 (1)	-1.098 (2)	-1.211 (1)	-1.817 (1)	-0.408 (1)	
ADF (p)	Trend	-4.096 (1)**	-2.034 (1)	-3.284 (1)*	-4.193 (1)**	-2.975 (1)	-1.965 (1)	
P-P (l)	Constant	-1.585 (3)	-1.758 (3)	-1.174 (3)	-1.239 (3)	-2.164 (3)	-0.583 (3)	
P-P (l)	Trend	-4.066 (3)**	-2.444 (3)	-3.591 (3)**	-3.229 (3)*	-3.714 (3)**	-2.040 (3)	

Data unadjusted for strikes. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 7.3: NFL Franchise Two-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
ATL	8	1985, 1997	-5.068***, 5.811***	-6.952***	λ = (0.45, 0.73)
BUF	3	1985, 1996	-6.698***, -2.521**	-8.037***	λ = (0.40, 0.68)
CHI	0	1959, 1984	-3.307***, 0.989	-5.848**	λ = (0.34, 0.67)
CIN	6	1986, 1996	6.138***, -3.415***	-7.025***	λ = (0.43, 0.68)
DAL	2	1972, 2003	-4.889***, -0.293	-5.617*	λ = (0.26, 0.88)
DEN	7	1985, 1994	-8.911***, 3.216***	-9.954***	λ = (0.40, 0.63)
DET	5	1956, 1973	1.227, 3.799***	-4.949	λ = (0.30, 0.53)
GB	0	1953, 1969	1.491, -4.260***	-4.641	λ = (0.24, 0.46)
KC	8	1980, 1996	-8.584***, 9.357***	-11.175***	λ = (0.28, 0.68)
MIA	7	1989, 2005	4.550***, -5.062***	-6.673***	λ = (0.50, 0.90)
MIN	8	1971, 1980	-0.859, 5.494***	-5.653**	λ = (0.22, 0.41)
NE	8	1980, 1992	-2.814***, 4.821***	-4.590	λ = (0.28, 0.58)
NO	7	1981, 1993	4.267***, -4.167***	-5.382*	λ = (0.35, 0.63)
NYG	6	1945, 1957	-5.635***, 6.680***	-6.912***	λ = (0.16, 0.32)
NYJ	7	1982, 1986	4.329***, 2.610**	-5.266	λ = (0.33, 0.43)
PHI	2	1949, 1960	-5.019***, 5.045***	-7.076***	λ = (0.18, 0.33)
PIT	0	1946, 1970	-2.396**, 4.069***	-5.351*	λ = (0.17, 0.49)
SD	2	1993, 2002	2.189**, 4.585***	-6.421***	λ = (0.60, 0.83)
SF	6	1964, 1980	-5.463***, -2.72***	-6.642***	λ = (0.38, 0.78)
WAS	8	1969, 1995	2.518**, 5.354***	-5.945**	λ = (0.45, 0.81)

Data unadjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 7.4: NFL Franchise One-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
CHI	0	1945	-1.104	-5.413***	λ = 0.16
DAL	2	1984	-3.013***	-3.478	λ = 0.50
DET	5	1949	3.417***	-4.486**	λ = 0.21
GB	8	1972	-0.689	-3.674	λ = 0.50
MIN	8	1995	-1.716*	-5.572***	λ = 0.71
NE	0	1991	-1.465	-3.662	λ = 0.55
NO	7	1988	3.455***	-4.328*	λ = 0.51
NYJ	4	1981	4.274***	-4.866**	λ = 0.30
PIT	0	1969	-0.245	-4.576**	λ = 0.47
WAS	8	1977	-0.984	-4.507*	λ = 0.56

NOTE: $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2.
See J. Lee and Strazicich (2003) Table 2 for critical values. Data adjusted for strikes.
***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 7.5: NFL Franchise ADF and PP Tests (Adjusted)

Team		**ATL**	**BUF**	**CHI**	**CIN**	**DAL**	**DEN**	**DET**
T (*seasons*)		*44*	*40*	*76*	*40*	*50*	*40*	*76*
ADF (p)	Constant	-1.709 (1)	-1.426 (4)	-2.196 (1)	-1.653 (1)	-2.615 (1)*	-2.575 (1)	-2.384 (1)
ADF (p)	Trend	-2.231 (1)	-4.389 (1)***	-4.053 (1)**	-2.759 (1)	-3.070 (1)	-2.444 (1)	-2.464 (1)
P-P (l)	Constant	-2.067 (3)	-3.234 (3)**	-1.965 (3)	-1.715 (3)	-2.437 (3)	-2.294 (3)	-2.326 (3)
P-P (l)	Trend	-2.537 (3)	-3.247 (3)*	-4.079 (3)**	-2.495 (3)	-2.794 (3)	-1.986 (3)	-2.460 (3)

Team		**GB**	**KC**	**MIA**	**MIN**	**NE**	**NO**	**NYG**
T (*seasons*)		*74*	*40*	*40*	*49*	*40*	*43*	*76*
ADF (p)	Constant	-0.824 (1)	-1.249 (1)	-2.028 (1)	-2.257 (1)	-1.686 (1)	-3.015 (1)**	-1.760 (1)
ADF (p)	Trend	-1.905 (1)	-2.519 (1)	-2.672 (1)	-4.027 (1)**	-2.493 (1)	-2.897 (1)	-3.369 (1)*
P-P (l)	Constant	-1.079 (3)	-1.784 (3)	-2.592 (3)	-1.742 (3)	-2.964 (3)**	-3.311 (3)**	-1.735 (3)
P-P (l)	Trend	-2.730 (3)	-2.206 (3)	-3.009 (3)	-2.916 (3)	-3.158 (3)	-3.163 (3)	-3.654 (3)**

Team		**NYJ**	**PHI**	**PIT**	**SD**	**SF**	**WAS**
T (*seasons*)		*40*	*73*	*76*	*40*	*60*	*73*
ADF (p)	Constant	-1.148 (1)	-1.521 (1)	-1.098 (2)	-1.244 (1)	-1.814 (1)	-0.433 (1)
ADF (p)	Trend	-4.066 (1)**	-2.008 (1)	-3.268 (1)*	-4.309 (1)**	-2.962 (1)	-2.010 (1)
P-P (l)	Constant	-1.321 (3)	-1.755 (3)	-1.175 (1)	-1.190 (3)	-2.161 (3)	-0.580 (3)
P-P (l)	Trend	-3.718 (3)**	-2.403 (3)	-3.553 (3)**	-3.122 (3)	-3.701 (3)**	-2.035 (3)

***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 7.6: NFL Franchise Two-Break LM Test (Adjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	**Test Statistic**	**Critical Value Break Points**
ATL	8	1985, 1997	-4.394***, 5.251***	-6.371**	λ = (0.45, 0.73)
BUF	2	1985, 1990	-5.174***, -2.510**	-8.131***	λ = (0.40, 0.53)
CHI	1	1945, 1987	-3.301***, 1.088	-5.841**	λ = (0.16, 0.71)
CIN	6	1986, 1996	4.892***, -1.538	-5.852**	λ = (0.43, 0.68)
DAL	2	1972, 2003	-4.911***, -0.277	-5.541*	λ = (0.26, 0.88)
DEN	5	1984, 1989	-5.966***, 1.606	-9.450***	λ = (0.38, 0.50)
DET	8	1959, 1973	1.619, 4.317***	-5.306	λ = (0.34, 0.53)
GB	0	1956, 1969	1.604, -4.007***	-4.581	λ = (0.28, 0.46)
KC	8	1980, 1995	-6.674***, 6.732***	-8.229***	λ = (0.28, 0.65)
MIA	7	1989, 2005	4.523***, -5.178***	-6.625***	λ = (0.50, 0.90)
MIN	8	1973, 1980	-1.612, 4.877***	-5.593*	λ = (0.27, 0.41)
NE	8	1985, 1966	-3.878***, 4.503***	-4.971	λ = (0.40, 0.68)
NO	7	1984, 1993	4.644***, -3.970***	-5.297	λ = (0.42, 0.63)
NYG	6	1945, 1957	-5.682***, 6.625***	-6.850***	λ = (0.16, 0.32)
NYJ	5	1983, 1995	2.732***, 5.467***	-5.374*	λ = (0.35, 0.65)
PHI	2	1949, 1960	-5.203***, 5.249***	-7.279***	λ = (0.18, 0.33)
PIT	0	1944, 1948	-3.415***, 1.245	-6.7296***	λ = (0.14, 0.20)
SD	2	1993, 2002	2.340**, 4.740***	-6.437***	λ = (0.60, 0.83)
SF	6	1964, 1980	-5.403***, -2.646***	-6.577***	λ = (0.25, 0.52)
WAS	8	1969, 1995	2.513**, 5.379***	-5.936**	λ = (0.45, 0.81)

Data adjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 7.7: NFL Franchise One-Break LM Test (Adjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
ATL	3	1988	2.276**	-5.435***	λ = 0.52
CHI	0	1958	-1.011	-5.252***	λ = 0.33
CIN	6	2003	3.036***	-4.110	λ = 0.85
DAL	0	1971	-3.462***	-3.156	λ = 0.24
DET	5	1949	3.522***	-4.472**	λ = 0.21
GB	8	1969	-0.632	-3.799	λ = 0.50
MIN	8	1976	-1.201	-5.644***	λ = 0.33
NE	8	2004	0.833	-3.921	λ = 0.88
NO	7	1988	3.346***	-4.211*	λ = 0.51
NYJ	7	1981	3.253***	-4.446*	λ = 0.30
WAS	8	1978	-1.093	-4.553**	λ = 0.58

NOTE: $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2.
See J. Lee and Strazicich (2003) Table 2 for critical values. Data adjusted for strikes.
***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 7.8: NFL Franchise Model Break Point Sequential Test Results (Heterogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*Breaks*
ATL	64.92***	37.70***		64.92***	64.92***	4.55		1
BUF	2.79	3.36		3.36	4.68	3.35		0
CHI	53.75***	34.43***	26.70***	53.75***	53.75***	10.94*	1.61	1
CIN	62.09***	75.58***		75.58***	105.23***	24.86***		2
DEN	27.67***	16.18***		27.67***	27.67***	8.09		1
DET	51.80***	51.94***	54.19***	54.19***	90.33***	12.16*	27.80***	1
KC	32.54***	60.17***		60.17***	83.78***	8.38		1
MIA	31.44***	45.08***		45.08***	62.76***	46.88***		2
MIN	15.15***	7.79**		15.15***	15.15**	34.83***		2
NYG	72.58***	53.46***	34.83***	72.58***	72.58***	6.93	4.98	1
PHI	312.34***	120.09***	78.17***	312.34***	312.34***	24.80***	0.08	2
PIT	37.66***	30.40***	24.17***	37.66***	40.30***	16.39***	10.82	2
SD	7.15	7.11		7.15	9.90	13.84**		0
SF	40.89***	20.19***	13.23***	40.89***	40.89***	3.11	6.74	1
WAS	42.50***	133.95***	111.76***	133.95***	186.31***	77.66***	21.19***	2

"***", "**", "*" indicate statistically significance at the 99%, 95% and 90% critical level, respectively.

TABLE 7.9: NFL Franchise Model Break Dates (Heterogeneous)

Team	T_1	T_2	*Team*	T_1	T_2
ATL	**1989** [88, 90]		***MIN***	**1981** [80, 82]	**1996** [95, 97]
CHI	**1948** [47, 49]		***NYG***	**1956** [55, 58]	
CIN	**1979** [78, 80]	**1991** [90, 92]	***PHI***	**1960** [59, 61]	**1981** [80, 84]
DEN	**1982** [81, 84]		***PIT***	**1955** [53, 57]	**1986** [85, 92]
DET	**1951** [47, 52]		***SF***	**1961** [60, 63]	
KC	**1988** [87, 90]		***WAS***	**1962** [61, 63]	**1995** [94, 96]
MIA	**1983** [82, 85]	**1995** [94, 96]			

*Brackets denote 90% confidence interval for break date

TABLE 7.10: NFL Franchise Model Breakpoint Regression Results (Heterogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3
ATL	-1245	50371	1091	8730		
t-value	*(-5.82)****	*(7.04)****	*(4.57)****	*(0.87)*		
CHI	1320	11225	381	28420		
t-value	*(6.25)****	*(3.42)****	*(12.81)****	*(11.99)****		
CIN	-1919	57851	924	31893	1130	17031.65
t-value	*(-6.82)****	*(17.05)****	*(4.12)****	*(6.11)****	*(9.62)****	*(3.93)****
DEN	2195	40331	271	58493		
t-value	*(7.43)****	*(9.77)****	*(3.65)****	*(11.21)****		
DET	598	15023	275	41217		
t-value	*(1.56)*	*(2.18)***	*(3.68)****	*(6.76)****		
KC	-664	59363	329	63494		
t-value	*(-2.61)***	*(8.57)****	*(1.46)*	*(6.35)****		
MIA	-1385	37111	316	25701	-608	63164
t-value	*(-4.70)****	*(6.63)****	*(1.18)*	*(3.84)****	*(-2.73)****	*(8.35)****
MIN	236	29240	-32	44213.39	-93	55311
t-value	*(1.97)***	*(11.91)****	*(-0.21)*	*(8.82)****	*(-0.47)*	*(6.69)****
NYG	92	31672	414	47848		
t-value	*(0.47)*	*(6.26)****	*(7.03)****	*(10.10)****		
PHI	550	19724	276	54328	337	45599
t-value	*(4.30)****	*(7.04)****	*(1.59)*	*(9.23)****	*(3.38)****	*(6.63)****
PIT	1004	8273	1080	-2955	603	13470
t-value	*(7.91)****	*(3.23)****	*(12.06)****	*(-0.90)*	*(5.22)****	*(1.68)**
SF	2460	20208	721	20253		
t-value	*(6.13)****	*(5.62)****	*(13.78)****	*(5.21)****		
WAS	17	29837	193	46869	1950	-45982.83
t-value	*(0.13)*	*(8.77)****	*(2.22)***	*(11.96)****	*(7.30)****	*(-2.62)***

"***", "**", "*" Indicate significance at the 99%, 95% and 90% critical level, respectively/
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively.

TABLE 7.11: NFL Franchise Model Balance and W% Coefficients (Heterogeneous)

Team	***TL***	***PU***	***CSU***	***W%***	$\bar{R}^2$ (R^2)
ATL	8275	-16767	7202	9505	0.693
t-value	*(2.64)***	*(-0.64)*	*(1.38)*	*(1.74)**	*(0.743)*
CHI	2019	-3	-967	10241	0.922
t-value	*(1.56)*	*(-0.00)*	*(-0.53)*	*(4.75)****	*(0.930)*
CIN	1100	9938	-3166	7810	0.718
t-value	*(0.81)*	*(0.83)*	*(-1.45)*	*(3.14)****	*(0.893)*
DEN	4079	-34153	2598	10534	0.897
t-value	*(2.26)***	*(-2.56)***	*(0.98)*	*(2.93)****	*(0.915)*
DET	3662	-25454	-5232	14327	0.823
t-value	*(1.23)*	*(-1.31)*	*(-1.27)*	*(2.84)****	*(0.839)*
KC	-2451	23286	-10075	10381	0.833
t-value	*(-0.88)*	*(0.91)*	*(-2.12)***	*(1.76)**	*(0.863)*
MIA	9652	80172	-252	20182	0.847
t-value	*(4.76)****	*(5.49)****	*(-0.07)*	*(5.68)****	*(0.882)*
MIN	4287	23728	3564	7622	0.928
t-value	*(3.19)****	*(2.49)***	*(1.61)*	*(3.54)****	*(0.942)*
NYG	-590	-11310	-6102	8498	0.897
t-value	*(-0.26)*	*(-0.73)*	*(-1.94)**	*(2.35)***	*(0.907)*
PHI	-2074	-13182	-6577	8210	0.955
t-value	*(-1.10)*	*(-1.28)*	*(-3.00)****	*(3.30)****	*(0.960)*
PIT	636	4037	-2135	6942	0.952
t-value	*(0.40)*	*(0.44)*	*(-1.11)*	*(2.88)****	*(0.958)*
SF	2220	8711	-349	9600	0.858
t-value	*(1.18)*	*(0.57)*	*(-0.11)*	*(3.20)****	*(0.875)*
WAS	-3957	453	-4891	4791	0.960
t-value	*(-2.20)***	*(0.04)*	*(-2.18)***	*(1.60)*	*(0.965)*

*** Significant at the 99% critical level
** Significant at the 95% critical level
** Significant at the 90% critical level

TABLE 7.12: NFL Franchise Level Economic Implications

	Game Uncertainty					Playoff Uncertainty			Consecutive Season Uncertainty		
Team	***ATL***	***DEN***	***MIA***	***MIN***	***WAS***	***DEN***	***MIA***	***MIN***	***KC***	***PHI***	***WAS***
2009 TAPG	68,174	75,116	67,543	63,775	84,794	75,116	67,543	63,775	67,514	69,144	84,794
2009 Variable	0.871	0.871	0.871	0.871	0.871	0.131	0.131	0.131	0.695	0.695	0.695
Coef. Est.[a]	8,275	4,079	9,652	4,287	*-3,957*[d]	-34,153	*80,172*	*23,728*	*10,381*	-6,577	-4,891
Elasticity	0.106	0.047	0.124	0.059	0.041	0.060	0.155	0.049	0.107	0.066	0.040
ΔVariable[b]	0.242	0.242	0.242	0.242	0.242	0.063	0.063	0.063	0.229	0.229	0.229
Inc. Factor	27.8%	27.8%	27.8%	27.8%	27.8%	48.1%	48.1%	48.1%	32.9%	32.9%	32.9%
ΔTAPG	2,009	981	2,328	1,046	*-966*	2,168	*-5,036*	*-1,503*	*-2,377*	1,501	1,116
% ΔTAPG	2.95%	1.31%	3.45%	1.64%	*-1.14%*	2.89%	*-7.46%*	*-2.36%*	*-3.52%*	2.17%	1.32%
Rev. Per Attend[c]	$96.45	$102.63	$91.61	$96.73	$110.36	$102.63	$91.61	$96.73	$111.44	$96.88	$110.36
Δ Game Rev.	$193,768	$100,680	$213,268	$101,180	*-$106,608*	$222,502	*-$461,348*	*-$145,385*	-$264,893	$145,417	$123,162

a. Coefficients taken from model with heterogeneous errors across regimes and follow the approach of Lee and Fort (2008, pp. 291).
b. All measure changes imply an *improvement* in balance.
c. Revenue per attendee data come from Team Marketing Report Fan Cost Index (2009).
d. *Italic* font indicates disagreement with Rottenberg's Uncertainty of Outcome Hypothesis.

FIGURE 7.1: Fitted NFL TAPG for ATL, CHI, CIN and DEN (Heterogeneous)

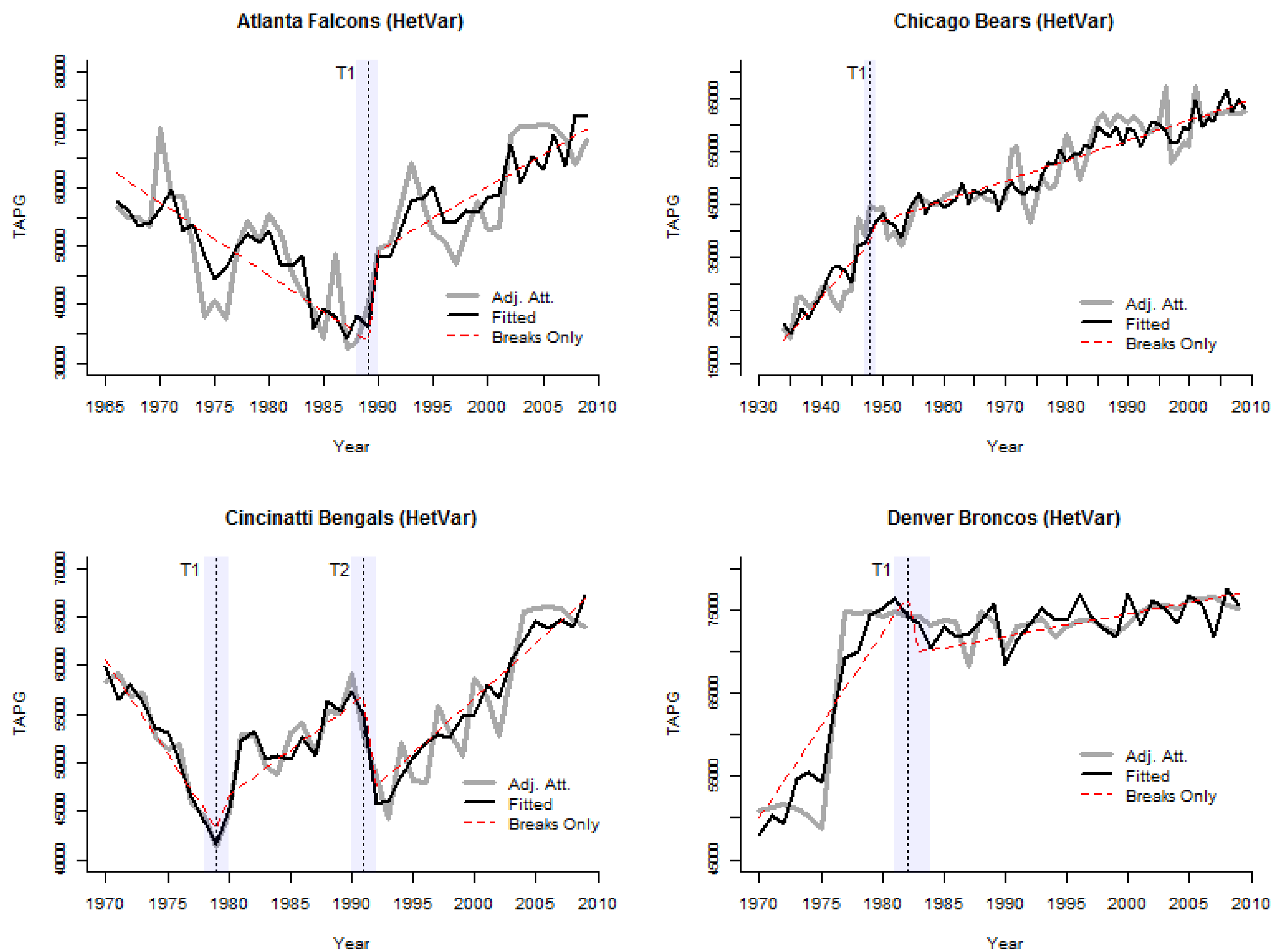


FIGURE 7.2: Fitted NFL TAPG for DET, KC, MIA and MIN (Heterogeneous)

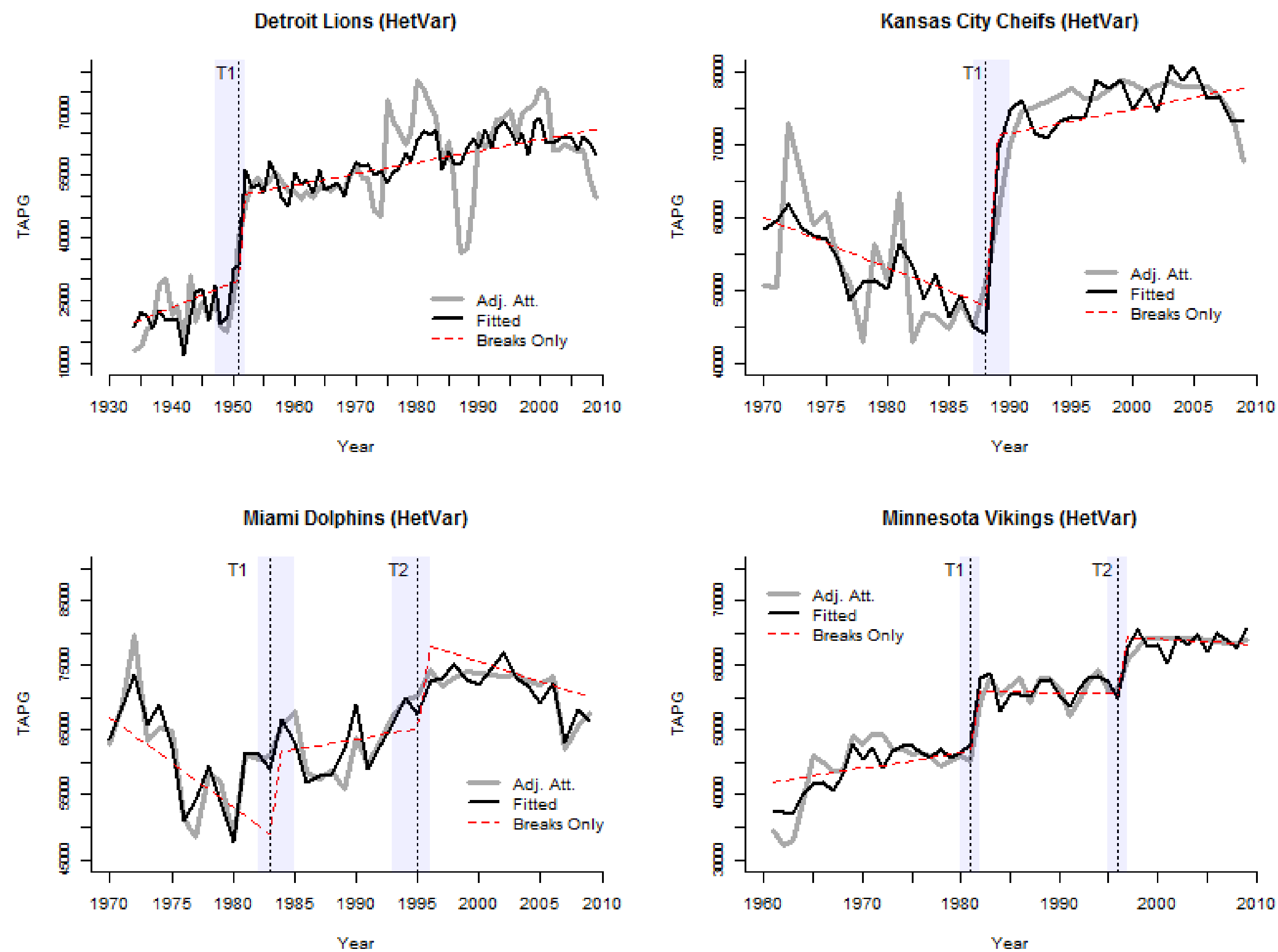


FIGURE 7.3: Fitted NFL TAPG for NYG, PHI, PIT and SF (Heterogeneous)

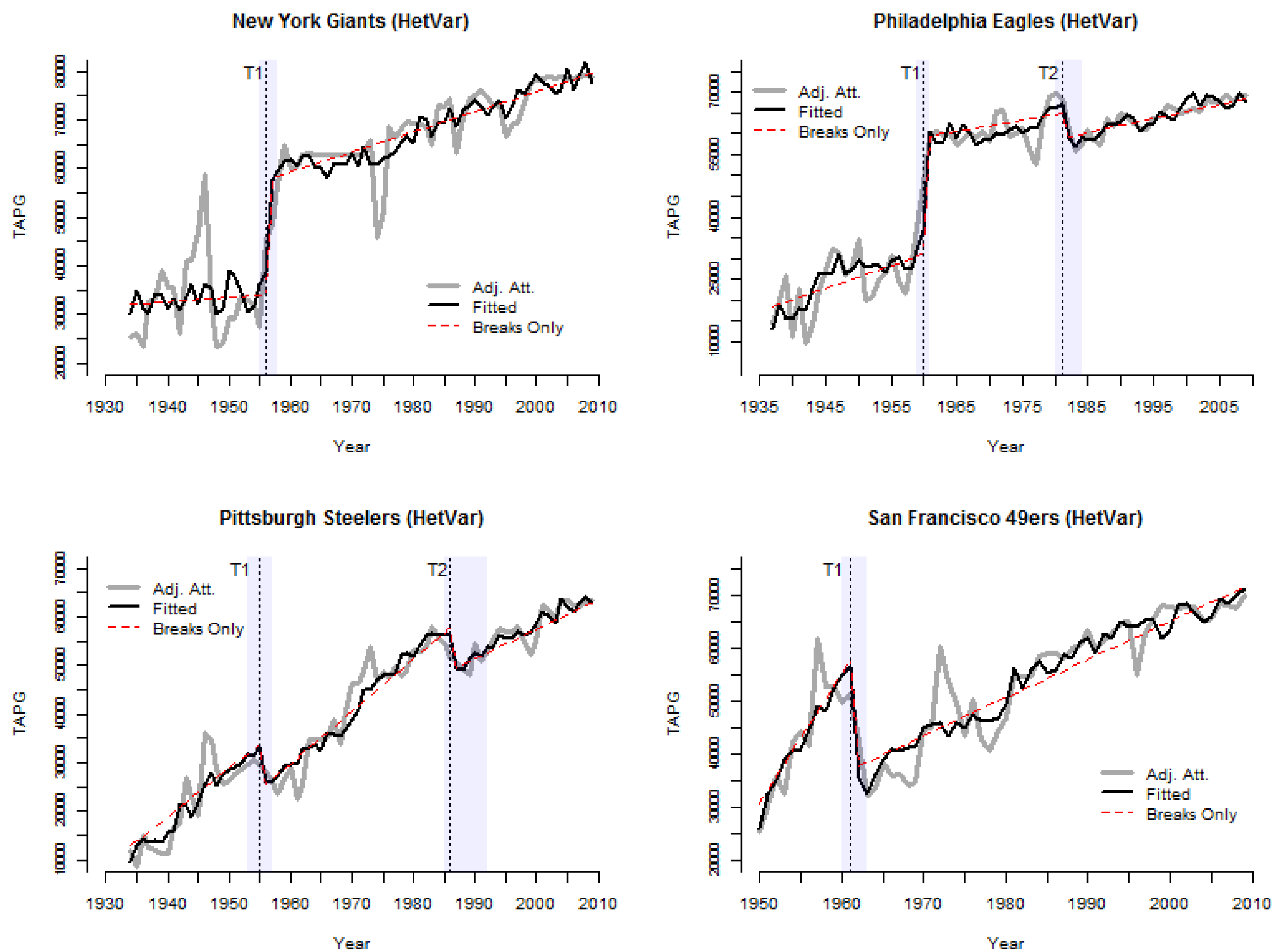
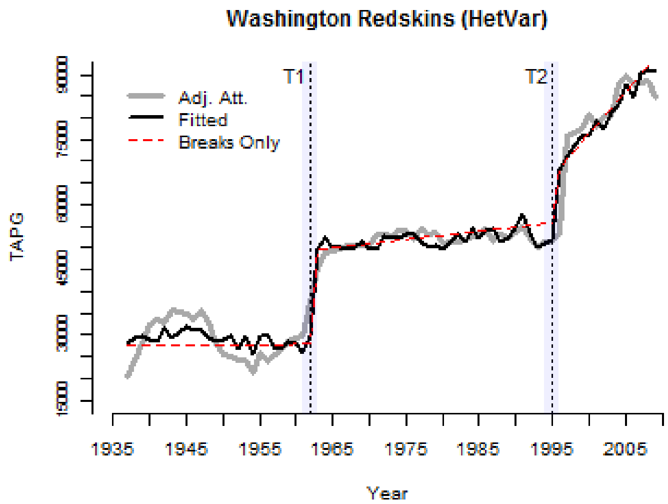


FIGURE 7.4: Fitted NFL TAPG for WAS (Heterogeneous)



CHAPTER 8

National Hockey League Franchises

8.1 Introduction/Justification

The final league under evaluation here is the NHL. The NHL has experienced significant rivalry with another league in its history, as exhibited in the league aggregate analysis. While the AFL and NFL coexisted rather well, the NHL and its counterpart the WHA were in serious competition during the short period of the WHA's existence. Understanding the influence this may have had on individual franchises is a natural next step in evaluating rival threats and league response regarding attracting fans. The significant expansion and team moves in the NHL make it an interesting case to evaluate at a micro level; however, only a few teams are analyzed here due to constraints on time series length. Because the "Original Six" teams for the NHL have remained in their initial locations for such a long period, they allow evaluation of the impacts of significant expansion, as the league doubled in size in 1967 and experienced a number of franchise additions later in the twentieth century. The following sections lay out considerations for the data—NHL data is less reliable than that of other leagues, and therefore requires further explanation—the results of the analysis, and more practical implications of the findings for the league.

8.2 Data and Methods

With the exceptions mentioned below, the NHL franchise data is identical to the league-level data in Chapter 4. The reader is referred to earlier sections for a general description of this data. The dependent variable in the regression models, TAPG, is calculated as described in the Chapters 5, 6 and 7. Again, I estimate an ancillary model as before, but with an additional lagged win percent variable (NHL Model B). Models with both heterogeneous and homogeneous variance are estimated; however, I continue with a full discussion of only the heterogeneous error variance models. Results from the alternative model fits are provided in Appendix D.

Additional sources were necessary for the collection of individual franchise attendance data in the NHL. While Sports Business Data (2010) and Andrew's Dallas Stars Page (almost all data from the 1991-92 through 1998-99 seasons) contained a large amount of the necessary attendance information, the seasons between 1967 and 1988 for a number of teams were curiously missing. However, I was able to collect attendance reports from individual game box scores for each team for these years from The Hockey Summary Project (2011). The majority of the data at the team level have been gleaned from this latter source, with the rest filling in missing data points in specific years (1961-62, 1986-87 to 1989-90 and 1991-92 to 1992-93).

Despite the additional data sources, some seasons still had a few game-level attendance reports consecutively missing. For those single missing years for each team, I used the average TAPG for the year before and year just following the missing data point. In those years that more than 15 game attendance reports are available, I take the average attendance of these games as TAPG for that team in the given season. However, for those years in which there are fewer than 15 games with attendance reported for a given team—most of which require consecutive imputations—I take a different approach. First, a linear trend is calculated between the points just before and just following the consecutive data points. Then, the imputation for each year is averaged with the available game level data for the current season. The process for year *t* with only some data available—and consecutive missing data—proceeds as follows:

$$TAPG_t = 0.6 * (TAPG_{t^*}) + 0.4 * (TAPG_N + \frac{TAPG_M - TAPG_N}{C})$$

Where *C* is the number of consecutive data points being imputed, $TAPG_{t^*}$ denotes the average per game attendance calculated from the limited number of box scores in the given season, and $TAPG_N$ and $TAPG_M$ denote the average per game attendance for the given team in the first year prior and first year following the consecutive missing (or limited) data, respectively. A list of those franchises with the specific years imputed in the data can be found in Appendix J for all leagues.

Adjusted data for NHL franchises is imputed just as with the league-level data from Chapter 4, with both adjusted and unadjusted series including an imputation for the locked out 2004-05 season. The only difference between the adjusted and unadjusted series is the weighted average for the 1994-95 season, during which there was a labor stoppage (an average of seasons just before, during, and after the labor dispute). I treat ties as one half of a win, and use win percent as the team quality covariate for NHL as with each of the other sports included in this evaluation. The uncertainty of outcome variables in the team level regressions are, of course, identical to those used at the league level. The NHL contained eleven (11) individual franchises with attendance series of sufficient length (40 years) for the breakpoint analysis. Descriptive statistics regarding TAPG and win percent for each of the franchises in each league can be found in Table 8.1 (NHL).

7.3 Unit Root Results

Finally, seven of eleven NHL teams were found to be stationary or stationary with breaks (Tables 8.2 through 8.7). Only the Philadelphia Flyers attendance series was found to be universally stationary without breaks (ADF and PP tests), while the LM tests reject the presence of a unit root for the Boston Bruins, Chicago Blackhawks, Detroit Red Wings, Los Angeles Kings, New York Rangers and St. Louis Blues with a single break. I proceed with evaluating these teams using the BP procedure.

7.4 Uncertainty of Outcome Results

As with each of the other sports, there are some mixed results regarding the impact of balance in the NHL. Only two of the teams under consideration were found to have statistically significant effects of any of the outcome uncertainty measures (Table 8.11). These include the Chicago Blackhawks and St. Louis Blues. While the coefficient for GU for the Blackhawks supports the predictions of Rottenberg, other estimates are largely in disagreement with the Uncertainty of Outcome Hypothesis. Playoff uncertainty was found to be statistically significant for both Chicago and St. Louis in the opposite direction from what UOH would predict. The same result is found for CSU in St. Louis. The effects on team revenues still tend to be relatively small, though not completely ignorable for St. Louis (Table 8.12). For both teams, changes in these balance measures may result in as much as $40,000 in revenues per game.

8.5 Breakpoint Regression Results

Breaks at the franchise level in the NHL lend support for those found at the league aggregate. Perhaps not surprisingly given the finding in the aggregate NHL analysis, some individual teams saw negative effects during the reign of the WHA. Other breaks tend to occur near sustained periods of success for certain franchises, as found for franchises in other leagues in the previous chapters. Plot for the time series of attendance for each team (with breaks exhibited) can be found in Figures 8.1 and 8.2.

8.5.1 Boston Bruins

The WHA seems to have had significant impacts on the Boston Bruins, as the first attendance break coincides with a large downward shift after the 1975-76 season. Boston was hit particularly hard, as longtime star Bobby Orr left the team after this season for the Chicago Blackhawks. While the positive attendance trend recovered following this large shift, it became muted in the 1996-97 season and has continued to be a somewhat mild slope though the 2009-10 season.

8.5.2 Chicago Blackhawks

Chicago's NHL team has had a turbulent attendance history since the beginning of the series analyzed here. While attendance generally trended upward through the 1950s, the 1963-64 season brought on a large upward shift in attendance, followed by a downward trend. This was the middle of a successful run for the Blackhawks, as they made the Stanley Cup Finals three times from 1961 to 1965. There is a second large shift up for the team in 1981-82, ultimately recovering attendance to the levels found in the early 1960s. The best explanation for this shift may be the team's unexpected wins in two playoff series after inching into the postseason. In general, Chicago seemed to see a large increase in attendance across all local pro sports teams during this time. This will be discussed further in Section 6.6.2.

8.5.3 Detroit Red Wings

While the Detroit Red Wings had been experiencing a trend upward in attendance, they realized a large jump following the 1982-83 season. The team had moved to Joe Louis Arena in 1979, but it seems that the requisite attendance increase was delayed somewhat. The year of the estimated break also marked Little Caesar's owner Mike Illitch purchase of the team. The Wings subsequently drafted the future Detroit hero Steve Yzerman. While the team had some success in the late 1980s, they did not win the Stanley Cup Trophy until the 1990s.

8.5.4 Los Angeles Kings

Not surprisingly, the 1988 acquisition of Wayne Gretzky seemed to have a large effect on Kings attendance, as the BP procedure indicates a large upward break in Kings attendance. While the number of fans at each game trended downward following this initial hype, the team experienced a second upward jump coinciding with the move to the Staples Center in 1999.

8.5.5 New York Rangers

From the beginning of the New York Rangers attendance series through the first breakpoint in 1975-76, the team had experienced a very steep upward trend. However, the WHA likely played a role in the downward trend following this season. The negative trend continued into the early 1990s, where there was an upward shift in 1991-92 when the team experienced fluctuating success culminating in a Stanly Cup in 1993-94.

8.5.6 Philadelphia Flyers

The Philadelphia Flyers seem to have been the team least affected by the formation of the WHA, as the team experienced consistent sellouts after back-to-back Stanley Cup trophies in 1973-74 and 1974-75. Before this time, the team's attendance was increasing sharply before leveling off. In the midst of this flattened trend in attendance, the team did experience an upward shift following the 1995-96 season coinciding with a Stanley Cup appearance led by Eric Lindros and expansion of seating capacity in the new Wells Fargo Center.

8.5.7 St. Louis Blues

The St. Louis Blues and its owners are known to have had significant financial troubles during the time of the first downward attendance shift in 1976. This drop in fan attendance may have been enhanced by the operation of the WHA. Fortunately for Blues fans, the team was sold to Ralston Purina in 1977 and the team experienced increasing attendance, followed by a second shift—this time positive—after the 1989-90 season.

The 1990-91 team led by Brett Hull was particularly successful, but was unfortunately knocked out of the playoffs before reaching the Stanley Cup Finals.

8.6 Summary and Conclusions

Unlike the NFL, NHL fans tend to prefer less balance as indicated both at the league aggregate level and at the team level to some extent. Only fans of the Chicago Blackhawks show a response to balance in the direction predicted by Rottenberg, and even this is only for the game-level balance measure (TL). In terms of playoff uncertainty, fans of Chicago, Boston and St. Louis tend to prefer a wider difference in the playoff race. The reason for this is unclear using the simplistic analysis employed here. Again, the impacts are relatively small economically for each of these teams. Structural change in the for those franchises considered here is generally related to league the existence of a rival league (and its downfall) and significant sustained team success not explained by win percent alone. Again, the ability to evaluate demand for attendance in the NHL (as with the other leagues) is left for further econometric consideration.

TABLE 8.1: NHL Franchise TAPG and W% by Decade

Team	1950's	1960's	1970's	1980's	1990's	2000's	Overall
BOS TAPG	11,432	12,451	13,833	13,001	15,179	15,797	13,691
BOS W%	0.488	0.412	0.689	0.583	0.545	0.524	0.546
BUF TAPG			15,457	14,639	15,790	17,274	15,790
BUF W%			0.569	0.553	0.520	0.540	0.545
CHI TAPG	9,596	15,292	13,913	16,021	18,342	15,814	15,010
CHI W%	0.366	0.575	0.558	0.491	0.532	0.471	0.482
DET TAPG	11,703	12,602	12,993	16,755	19,821	19,856	15,757
DET W%	0.595	0.511	0.410	0.414	0.625	0.650	0.528
LAK TAPG		8,394	10,947	11,997	14,661	17,127	13,314
LAK W%		0.373	0.484	0.454	0.484	0.480	0.468
MON TAPG	13,741	15,101	16,919	16,941	18,578	20,864	17,137
MON W%	0.609	0.623	0.724	0.606	0.528	0.507	0.580
NYR TAPG	11,790	14,395	17,405	17,063	17,755	18,137	16,239
NYR W%	0.443	0.466	0.564	0.503	0.525	0.486	0.497
PHI TAPG		11,431	16,350	17,084	18,105	19,491	17,316
PHI W%		0.425	0.627	0.592	0.559	0.537	0.569
PIT TAPG		6,832	10,603	12,129	15,906	15,588	13,087
PIT W%		0.403	0.469	0.412	0.586	0.477	0.469
STL TAPG		13,185	15,637	13,894	17,859	17,364	15,979
STL W%		0.539	0.445	0.500	0.568	0.494	0.504
TOR TAPG	13,013	14,923	16,440	16,121	16,215	19,345	16,113
TOR W%	0.499	0.556	0.506	0.391	0.499	0.510	0.510

TABLE 8.2: NHL Franchise ADF and PP Tests (Unadjusted)

Team		**BOS**	**BUF**	**CHI**	**DET**	**LAK**	**MON**
T (*seasons*)		*58*	*40*	*58*	*58*	*53*	*58*
ADF (*p*)	Constant	-1.653 (2)	-2.100 (1)	-2.886 (1)*	-1.192 (1)	-1.432 (1)	-0.599 (1)
ADF (*p*)	Trend	-3.417 (1)*	-2.576 (1)	-3.178 (1)*	-2.677 (1)	-3.955 (2)**	-2.648 (1)
P-P (*l*)	Constant	-1.303 (3)	-4.231 (3)***	-1.807 (3)	-0.997 (3)	-1.578 (3)	-1.432 (3)
P-P (*l*)	Trend	-3.081 (3)	-4.469 (3)***	-2.439 (3)	-2.457 (3)	-2.965 (3)	-3.022 (3)

Team		**NYR**	**PHI**	**PIT**	**STL**	**TOR**
T (*seasons*)		*58*	*43*	*43*	*43*	*58*
ADF (*p*)	Constant	-2.336 (1)	-3.541 (1)**	-2.261 (1)	-2.716 (1)*	-1.013 (1)
ADF (*p*)	Trend	-1.828 (1)	-4.532 (1)***	-3.098 (1)	-3.042 (1)*	-2.062 (1)
P-P (*l*)	Constant	-2.071 (3)	-4.895 (3)***	-1.626 (3)	-3.257 (3)**	-1.472 (3)
P-P (*l*)	Trend	-1.752 (3)	-5.067 (3)***	-2.497 (3)	-3.254 (3)*	-2.124 (3)

***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 8.3: NHL Franchise Two-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
BOS	1	1966/67, 1975/76	1.270, -3.684***	-4.944	λ = (0.26, 0.41)
BUF	0	1981/82, 2005/06	-1.927*, 0.631	-2.611	λ = (0.30, 0.90)
CHI	7	1984/85, 1987/88	-2.143**, -1.284	-4.200	λ = (0.57, 0.62)
DET	1	1982/83, 1985/86	4.208***, 1.981**	-4.564	λ = (0.53, 0.59)
LAK	5	1982/83, 2000/01	-1.920*, -1.411	-4.820	λ = (0.44, 0.79)
MON	1	1974/75, 1979/80	-1.063, -0.731	-2.963	λ = (0.40, 0.48)
NYR	8	1967/68, 1987/88	1.917*, -0.818	-3.011	λ = (0.28, 0.62)
PHI	4	1977/78, 1999/00	1.290, -1.906*	-2.261	λ = (0.26, 0.77)
PIT	7	1977/78, 2002/03	1.247, -3.874***	-3.832	λ = (0.26, 0.84)
STL	7	1979/80, 2003/04	1.841*, -2.197**	-4.197	λ = (0.30, 0.86)
TOR	6	1995/96, 1999/00	-1.154, -3.743***	-2.621	λ = (0.76, 0.83)

Data adjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 8.4: NHL Franchise One-Break LM Test (Unadjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
BOS	1	1974/75	-3.497***	-4.955**	λ = 0.40
BUF	0	1982/83	-3.789***	-4.304*	λ = 0.33
CHI	7	1984/85	-2.720***	-5.182***	λ = 0.57
DET	1	1982/83	2.799***	-4.539**	λ = 0.53
LAK	8	1983/84	-4.222***	-5.512***	λ = 0.40
MON	1	1974/75	-1.846*	-3.285	λ = 0.40
NYR	8	1983/84	-6.347***	-6.183***	λ = 0.55
PHI	4	1980/81	-3.771***	-3.713	λ = 0.33
PIT	1	1995/96	-2.392**	-3.747	λ = 0.67
STL	7	2003/04	-2.048**	-5.292***	λ = 0.86
TOR	6	1983/84	-2.067**	-3.400	λ = 0.55

NOTE: $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2.
See J. Lee and Strazicich (2003) Table 2 for critical values. Data adjusted for strikes.
***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 8.5: NHL Franchise ADF and PP Tests (Adjusted)

Team		**BOS**	**BUF**	**CHI**	**DET**	**LAK**	**MON**
T (*seasons*)		*58*	*40*	*58*	*58*	*43*	*58*
ADF (*p*)	Constant	-1.616 (2)	-2.110 (1)	-2.947 (1)**	-1.193 (1)	-1.421 (1)	-0.568 (1)
ADF (*p*)	Trend	-3.521 (1)**	-2.591 (1)	-3.239 (1)*	-2.679 (1)	-4.018 (2)**	-2.537 (1)
P-P (*l*)	Constant	-1.258 (3)	-4.190 (3)***	-1.796 (3)	-0.997 (3)	-1.572 (3)	-1.436 (3)
P-P (*l*)	Trend	-2.988 (3)	-4.411 (3)***	-2.428 (3)	-2.458 (3)	-2.951 (3)	-3.031 (3)

Team		**NYR**	**PHI**	**PIT**	**STL**	**TOR**
T (*seasons*)		*58*	*43*	*43*	*43*	*58*
ADF (*p*)	Constant	-2.336 (1)	-3.547 (1)**	-2.261 (1)	-2.694 (1)	-1.013 (1)
ADF (*p*)	Trend	-1.828 (1)	-4.536 (1)***	-3.090 (1)	-3.021 (1)	-2.062 (1)
P-P (*l*)	Constant	-2.072 (3)	-4.898 (3)***	-1.626 (3)	-3.261 (3)**	-1.472 (3)
P-P (*l*)	Trend	-1.751 (3)	-5.071 (3)***	-2.488 (3)	-3.258 (3)*	-2.124 (3)

***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 8.6: NHL Franchise Two-Break LM Test (Adjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	Test Statistic	Critical Value Break Points
BOS	1	1965/66, 1975/76	0.377, -3.684***	-5.042	λ = (0.24, 0.41)
BUF	0	1981/82, 2005/06	-1.933*, 0.649	-2.573	λ = (0.30, 0.90)
CHI	7	1984/85, 1987/88	-2.774***, -1.519	-4.583	λ = (0.57, 0.62)
DET	1	1982/83, 1985/86	4.209***, 1.982**	-4.568	λ = (0.53, 0.59)
LAK	5	1985/86, 2000/01	-2.107**, -1.607	-4.989	λ = (0.44, 0.79)
MON	0	1974/75, 1994/95	-1.004, 0.732	-2.684	λ = (0.40, 0.74)
NYR	8	1967/68, 1987/88	1.955*, -0.823	-3.003	λ = (0.28, 0.62)
PHI	4	1977/78, 1999/00	1.289, -1.915*	-2.265	λ = (0.26, 0.77)
PIT	7	1977/78, 2002/03	1.222, -3.840***	-3.805	λ = (0.26, 0.84)
STL	7	1979/80, 2003/04	1.662*, -2.250**	-4.138	λ = (0.30, 0.86)
TOR	6	1995/96, 1999/00	-1.148, -3.745***	-2.620	λ = (0.76, 0.83)

Data adjusted for strikes. $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2. See J. Lee and Strazicich (2003) Table 2 for critical values. ***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 8.7: NHL Franchise One-Break LM Test (Adjusted)

Team	$\hat{k}$	$\hat{T}_b$	$\hat{t}_{\gamma j}$	**Test Statistic**	**Critical Value Break Points**
BOS	1	1974/75	-3.514***	-5.044**	λ = 0.40
BUF	0	1982/83	-3.722***	-4.228*	λ = 0.33
CHI	7	1958/59	-2.934***	-5.556***	λ = 0.12
DET	1	1982/83	2.800***	-4.543**	λ = 0.53
LAK	8	1983/84	-4.275***	-5.592***	λ = 0.40
MON	1	1976/77	-1.895*	-3.087	λ = 0.43
NYR	8	1983/84	-6.339***	-6.178***	λ = 0.55
PHI	4	1980/81	-3.772***	-3.717	λ = 0.33
PIT	1	1995/96	-2.396**	-3.752	λ = 0.67
STL	7	2003/04	-2.128**	-5.342***	λ = 0.86
TOR	6	1983/84	-2.607**	-3.400	λ = 0.55

NOTE: $\hat{k}$ is the optimal number of lagged first-difference terms included in the unit root test to correct for serial correlation. $\hat{T}_b$ denotes the estimated break points. $\hat{t}_{\gamma j}$ is the value of DT_{jt} for j = 1,2.
See J. Lee and Strazicich (2003) Table 2 for critical values. Data adjusted for strikes.
***, **, * = significant at 99%, 95%, and 90% critical levels, respectively.

TABLE 8.8: NHL Franchise Model Break Point Sequential Test Results (Heterogeneous)

Team	*SupF$_t$(1)*	*SupF$_t$(2)*	*SupF$_t$(3)*	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*Breaks*
BOS	55.90***	44.71***	28.19***	54.90***	59.03***	14.45**	5.12	2
CHI	13.42**	20.38***	21.25***	21.25***	35.42***	15.97***	13.18*	2
DET	127.20***	78.98***	60.44***	127.20***	127.20***	9.38	10.32	1
LAK	13.04**	19.82***		19.82***	27.59***	36.95***		2
NYR	92.07***	78.48***	70.27***	92.07***	117.14***	55.55***	4.27	2
PHI	16.36***	54.70***		54.70***	76.15***	217.21***		2
STL	36.71***	32.03***		36.71***	44.59***	26.74***		2

"***" Significant at the 99% critical level
"**" Significant at the 95% critical level
"*" Significant at the 90% critical level

TABLE 8.9: NHL Franchise Model Break Dates (Heterogeneous)

Team	T_1	T_2
BOS	**1975-76** [74-75, 76-77]	**1996-97** [92-93, 98-99]
CHI	**1963-64** [62-63, 64-65]	**1981-82** [80-81, 82-83]
DET	**1982-83** [81-82, 83-84]	
LAK	**1987-88** [86-87, 88-89]	**1998-99** [97-98, 01-02]
NYR	**1975-76** [74-75, 76-77]	**1991-92** [90-91, 93-94]
PHI	**1976-77** [75-76, 77-78]	**1995-96** [94-95, 96-97]
STL	**1976-77** [75-76, 77-78]	**1989-90** [87-88, 90-91]

*Brackets denote 90% confidence interval for break date

TABLE 8.10: NHL Franchise Model Breakpoint Regression Results (Heterogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3
BOS	156	8357	229	2755	99	8369
t-value	*(5.80)****	*(11.54)****	*(6.43)****	*(1.65)*	*(1.65)*	*(2.53)***
CHI	235	2582	-238	10955	-3	8487
t-value	*(1.86)**	*(2.06)***	*(-3.57)****	*(5.04)****	*(-0.10)*	*(3.71)****
DET	120	7953	2	15752		
t-value	*(5.88)****	*(8.14)****	*(0.08)*	*(13.45)****		
LAK	126	6967	-297	20754	119	10656
t-value	*(3.36)****	*(7.79)****	*(-3.43)****	*(7.43)****	*(1.27)*	*(2.70)****
NYR	305	8848	-111	18944	17	15530
t-value	*(17.49)****	*(16.62)****	*(-3.36)****	*(15.31)****	*(0.72)*	*(11.37)****
PHI	796	10406	31	16556	4	19537
t-value	*(9.64)****	*(21.18)****	*(1.14)*	*(15.66)****	*(0.10)*	*(11.70)****
STL	16	6385	427	-4931	106	4315
t-value	*(0.07)*	*(3.46)****	*(3.10)****	*(-1.59)*	*(1.74)**	*(1.36)*

"***", "**", "*" Indicate significance at the 99%, 95% and 90% critical level, respectively/
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE 8.11: NHL Franchise Model Balance and W% Coefficients (Heterogeneous)

Team	*TL*	*PU*	*CSU*	*W%*	$\bar{R}^2$ (R^2)
BOS	137	9888	-595	3953	0.830
t-value	*(0.29)*	*(2.04)***	*(-1.22)*	*(3.74)****	*(0.857)*
CHI	2230	16762	-1483	14328	0.839
t-value	*(2.93)****	*(2.05)***	*(-1.81)**	*(6.50)****	*(0.864)*
DET	233	-2814	-360	6458	0.949
t-value	*(0.49)*	*(-0.55)*	*(-0.75)*	*(4.84)****	*(0.956)*
LAK	-912	4281	128	4638	0.918
t-value	*(-1.67)**	*(0.65)*	*(0.19)*	*(2.63)***	*(0.935)*
NYR	154	1220	-398	3563	0.954
t-value	*(0.51)*	*(0.39)*	*(-1.29)*	*(3.93)****	*(0.961)*
PHI	-158	-1109	626	-546	0.949
t-value	*(-0.52)*	*(-0.27)*	*(1.55)*	*(-0.52)*	*(0.960)*
STL	526	34837	3520	11457	0.746
t-value	*(0.57)*	*(3.05)****	*(3.11)****	*(4.23)****	*(0.800)*

*** Significant at the 99% critical level
** Significant at the 95% critical level
** Significant at the 90% critical level

TABLE 8.12: NHL Franchise Level Economic Implications

	Game Uncertainty	Playoff Uncertainty		Consecutive Season Uncertainty
Team	***CHI***	***CHI***	***STL***	***STL***
2009 TAPG	21,130	21,130	18,760	18,760
2009 Variable	0.698	0.061	0.061	0.378
Coef. Est.[a]	2,230	16,762	34,837	3,520
Elasticity	0.074	0.048	0.113	0.071
ΔVariable[b]	0.222	0.012	0.012	0.184
Inc. Factor	31.8%	19.7%	19.7%	48.7%
ΔTAPG	497.2	*-199.8*[d]	*-417.6*	*-648.7*
% ΔTAPG	2.35%	*-0.95%*	*-2.23%*	*-3.46%*
Rev. Per Attend[c]	$79.80	$79.80	$58.65	$58.65
Δ Game Rev.	$39,677	*-$15,944*	*-$24,492*	*-$38,046*

a. Coefficient taken from model with heterogeneous errors across regimes and follow the approach of Lee and Fort (2008, pp. 291).
b. All measure changes imply an *improvement* in balance.
c. Revenue per attendee data come from Team Marketing Report Fan Cost Index (2009).
d. *Italic* font indicates disagreement with Rottenberg's Uncertainty of Outcome Hypothesis.

FIGURE 8.1: Fitted NHL TAPG for BOS, CHI, DET and NYR (Heterogeneous)

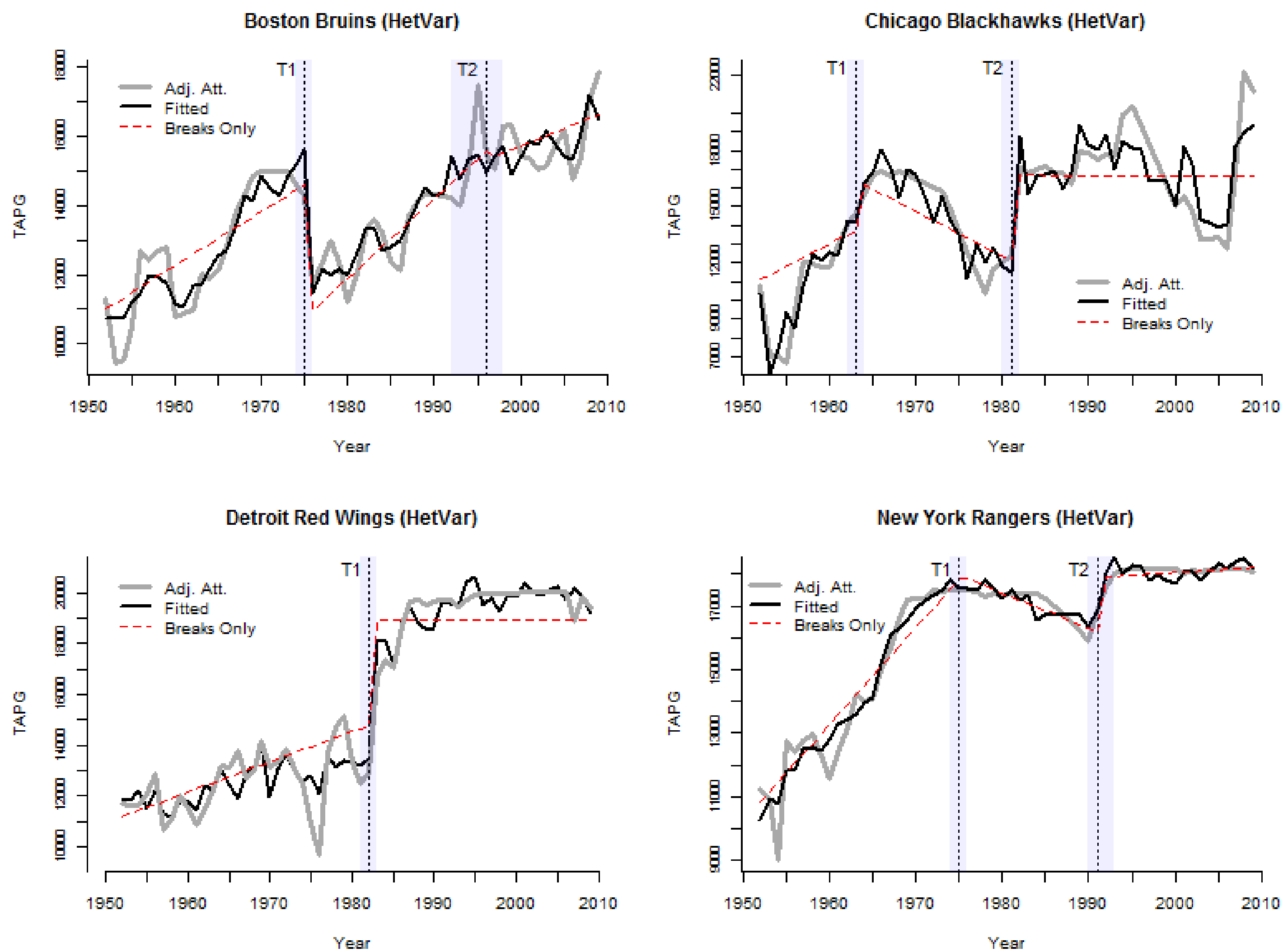
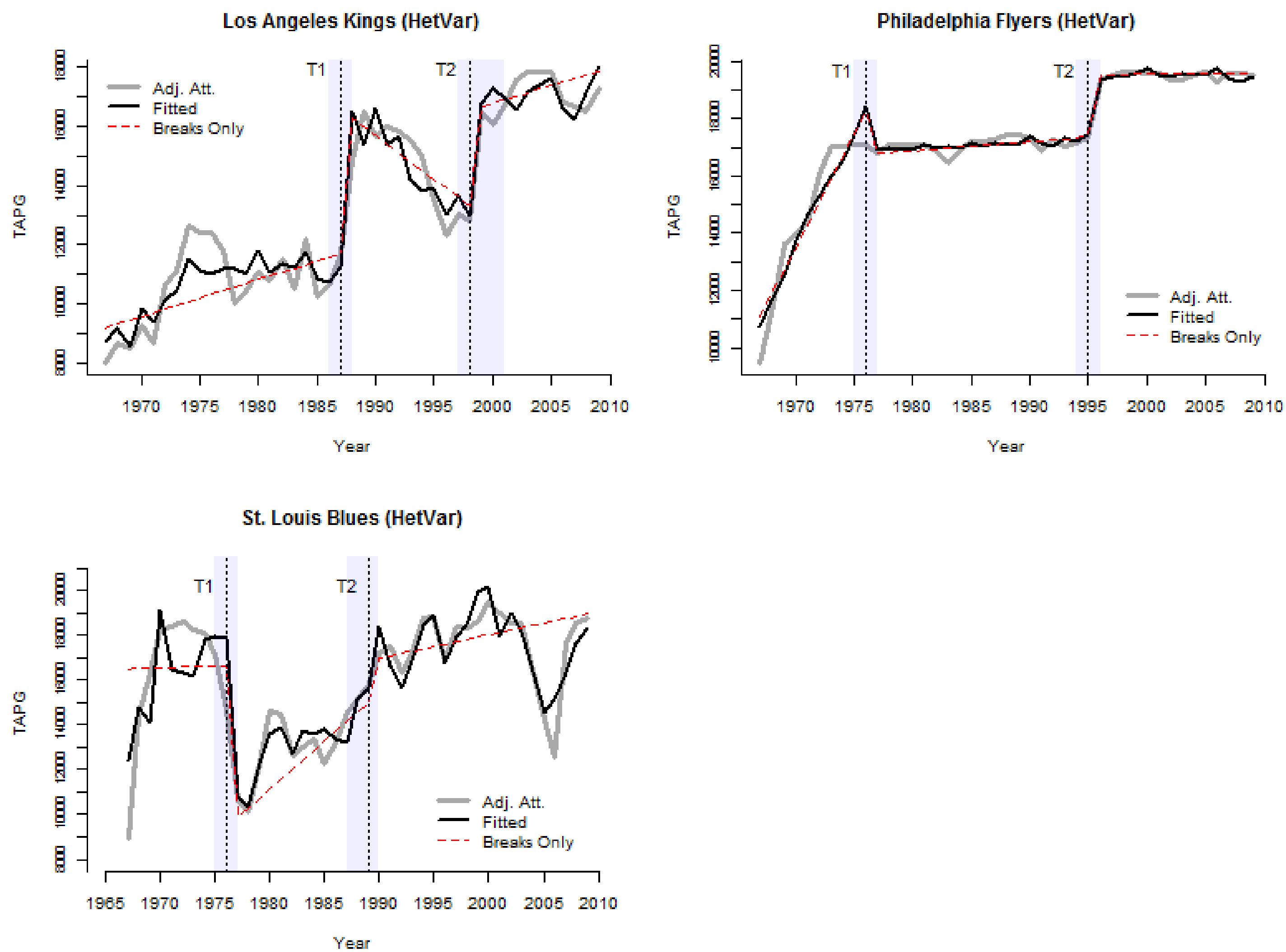


FIGURE 8.2: Fitted NHL TAPG for LAK, PHI and STL (Heterogeneous)



CHAPTER 9

Summary and Conclusions

9.1 Summary and Implications

The research contained in this dissertation fills gaps in the literature on long-term North American professional sports attendance tracking and uncertainty of outcome. I extend the literature on attendance breakpoints to the NBA, NFL and NHL at the league level in Chapter 4. Chapters 5 through 8 are dedicated to evaluating the heterogeneous effects of uncertainty at the franchise level for these three leagues and MLB at the seasonal level. This former portion is the most important contribution of this work; however, this latter application provide interesting differences across markets important for team managers and league managers implementing league policies with interest in maximizing interest in the league as a whole. Past research has found changes in attendance at a more micro level with respect to balance, usually when individual games have playoff implications. However, the analysis presented here finds that the implications of these changes tend to be minimal at the aggregate level. However, it is important to note the limitations of the methodology here. Because of a lack of micro-level analysis, fan interests cannot be fully discerned as they may be in a fully specified demand model. This makes the conclusions with respect to balance limited in their reach with respect to managerial implications. Nevertheless, the macro-level implications provide both historical context for future analyses, as well as exhibition of time series properties important to this future empirical work.

Table 9.1 provides a summary of the results from each chapter within this dissertation regarding Rottenbeg's UOH. Fans of the NBA respond most to Playoff and Game Uncertainty and NHL fans seem to be interested in Playoff Uncertainty, while NFL fans—at least at the league level—tend to have little preference for any of the uncertainty measures included here. The NHL case exemplifies the importance of correct econometric breakpoint method specifications in the shorter series analyzed in the sports context. The team level analysis tells a bit of a different story, and shows the importance of evaluating fans across markets. In these analyses, we see a limited view of fans in different markets reacting differently to the changes in uncertainty of outcome. Why this would be the case is relegated to further investigation. Most likely, employing surveys of fans in different markets regarding their preferences for different team and league characteristics would provide valuable information regarding the preferences of fans for more or less competitive balance (uncertainty of outcome).

Of course, the collection of empirical research here does not necessarily mean fans do not care about balance at its extremes. It may be that market sizes of teams in each of these leagues are relatively close as to not affect fan behavior in any significant economic way. If this is so, it may have important implications with respect to analysis of optimal league size, given the viable markets for professional teams. League expansion and relocation choice has often been affected by the market rights of its individual owners. Therefore, if many teams are further expanded into smaller markets—with no third team, for example, in New York—it seems feasible that the extremes of unbalance created here could affect fan interest more than found here. In order to assess this possibility, one would likely have to investigate past leagues with significantly more competitive balance issues than is currently found in North American leagues.

Perhaps more important are the implications for past league policy implied here. First, as in Lee and Fort (2008), there tends to be very little sudden impact of league policy decisions. Owners often espouse the idea that implementing rules such as free agency and the draft are used in order to preserve competitive balance and ultimately help the league to thrive through more fan interest. However, there is little evidence of significant structural change in attendance near these policy changes in any league. Rottenberg (1956) and Fort and Quirk (1995) inform us that this is to be expected, as moves such as the amateur draft and free agency tend to redistribute profits to owners from players, rather than change balance in any way (see Chapter 1 for details). If balance is not changed, then the UOH would predict that fan interest in the league would also remain unchanged, ceteris paribus.

On the other hand, the models presented here show only mixed evidence for Rottenberg's UOH and its subsequent extension to dynasties, which were not initially mentioned by Rottenberg. As mentioned earlier, econometric specifications could have some impact on these estimations. In the analysis presented here, a number of individual franchises were found to have coefficients that indicated interest in imbalance in certain situations. Fort and Lee (2006, 2007) inform us that there are also no structural breaks near these policy changes, lending further evidence to Rottenberg's claims regarding the invariance principle in North American sports leagues. Of course, addressing European leagues (such as the EPL) are left for further evaluation.

9.2 Evidence for Substitution

While the direct causal effects of increases in attendance for one franchise on a decrease in attendance for another local franchise cannot be extracted from this sort of analysis, large shifts in opposite directions may provide preliminary evidence of substitution between sports teams within the same market. Therefore, I briefly discuss this possibility here for those markets with multiple sports franchises under analysis. These include Atlanta, Boston, Chicago, Cincinnati, Cleveland, Detroit, Los Angeles, New York, Philadelphia, Pittsburgh, St. Louis and the San Francisco/Oakland markets. Only the Boston, Chicago, New York and Pittsburgh markets have concurrent attendance shifts for franchises across leagues, and I limit discussion to these four in this section.

9.2.1 Boston Metropolitan Area

As with previous work on years in which there is a labor stoppage, the Red Sox saw a *temporary* downward shift concurrent with the player strike of 1995. However, both the Celtics and Bruins experienced changes in attendance near this time in the opposite direction of the Red Sox. In 1994, the Celtics experienced a small upward shift of about 2,000 fans per game, while the Bruins saw a downward shift in 1996 following a short spike concurrent with the MLB player strike. Given that Red Sox attendance had decreased for a short duration by about 3,000 fans, it seems that the changes in attendance to the other two sports could have accounted for the small dip during this time. The additional space for both the Bruins and Celtics in their new arena, however, seems to be a more plausible reason for these changes than direct fan substitution between sports.

9.2.2 Chicago Metropolitan Area

In Chicago, something seems to have happened to attendance at sporting events in the early 1980s. While there is little evidence of between-sport fan substitution in the city from this analysis alone, fans began attending both Cubs and Blackhawks games at a much higher rate beginning in 1983 and 1981, respectively. Interestingly, the city's population had declined by nearly 18% from 1970 to 1990, while the metro area population remained relatively stagnant (increasing less than 3.7% throughout the same period). With the upward shift in White Sox attendance in the mid-1970s, it seems reasonable to conclude that interest in sport shifted substantially during this period and/or disposable sports income increased for residents of the Chicago area. Even more perplexing is that this era marked a low point in the success of Chicago professional athletics teams. Only in the mid-1980s did the Bulls and Bears begin to have relevant levels of success again. Further work is suggested analyzing this shift in overall sports consumption in Chicago and its relationship to disposable income changes in the city.

9.2.3 New York Metropolitan Area

While the Knicks and Giants experienced what seem to be attendance shifts independent from any other local franchise, the Mets and Rangers experienced two concurrent or very close attendance shifts. The first occurs in 1975, in which the Mets saw a downward shift followed by an upward trend, while the Rangers see their attendance trend change in a negative direction. These shifts seem to be relatively unrelated, though it could indicate a slow shift of Rangers fans preferring a successful 1980s Amazing Mets team. The next pair of estimated breaks happens in 1993 for the Mets (a downward shift) and 1991 for the Rangers (and upward shift). This later shift likely has more to do with the move to Madison Square Garden for the Rangers. Whether or not this increase in fans came from those previously enamored with the success of 1980s Mets teams remains to be fully analyzed, as with the shifts near this time in Boston.

9.2.4 Pittsburgh Metropolitan Area

Finally, the analysis presented here suggests that the Steelers and Pirates experienced concurrent shifts in the opposite direction near the 1986 and 1987 seasons when Barry Bonds and Jim Leyland arrived. However, contrary to popular belief about the struggling Pirates, the shift is in the direction of *more fans attending Pirates games and fewer heading to Steelers games*. Since this time, both teams have seen an upward trend in attendance, though for the Pirates this seems mostly due to the opening of a new stadium and subsequent honeymoon attendance spike. Despite this, it is still generally assumed that Pittsburgh sports fans abandoned the Pirates for their NFL counterpart in recent years. While there was no break estimated for either team in the 2000 or 2001 season, the spike in Pirates attendance and the new stadium may have affected overall Steelers attendance, which experienced a very short downward spike during the same time. As a whole, there seems to be only some evidence of substitution between MLB and NFL for sports fans in Pittsburgh, and price changes over this time may prove insightful with respect to changes in fan behavior during this time.

As a whole, there is mixed evidence for fan substitution between sports, suggesting that substitution may vary depending on the market in which multiple teams are located. More work is suggested with more granular data to evaluate shorter-term day-to-day fan substitution in a number of markets.

9.3 Limitations and Suggested Future Research

As mentioned throughout this work, there are limitations with understanding the full effects of coefficients on balance measures in breakpoint regressions. Because there is not currently an implementation of tobit analysis in the breakpoint context, some coefficients—especially for those teams with consistent sellouts—will be biased toward zero. This issue may be resolved in a shorter term study with heterogeneous effects of balance measures in a censored panel model context. This is the next step in the progression of the chapters presented here, and is already under way. However, it is important to note that there are always sellouts for some tickets. If we view front row seats and bleacher seats as a form of product differentiation by the team (with supply physically limited), then accounting for sellout of each separate product would be necessary. As of yet, there are very few studies that fully account for the variation in ticket prices and viewing products around an entire stadium. This would be a fruitful line of research in understanding the determinants of fan attendance and understanding the influence of sellouts at multiple levels of aggregation with respect to seating location.

While the methods in Chapter 3 are sufficient for a first look at varying attendance across markets within a given league, understanding the economic factors that affect this demand is also an important addition. Because of data availability, this is more appropriate in shorter term demand studies. For example, teams in the lower half of the standings may have fans who attend games to see the opponent. An in depth analysis of home fan interest in visiting team quality would be a natural progression from the research in this paper. Meehan et al. (2007) have taken the research in this direction with the National League in MLB.

Variability in fans could also arise with respect to the substitutability of professional sports leagues may differ depending on the market. Winfree (2009b) has taken the fan substitution research in this direction, and the breakpoint analysis presented here provides some limited additional information about the total sports demand in specific markets such as Boston and Pittsburgh. Finally, a further understanding this phenomenon would inform team mangers of their direct competitors for entertainment dollars and antitrust issues involved in multiple team ownership within a single market. Evaluating a shorter term series of attendance, while controlling for other economic factors, is a suggested next step. In this analysis, the researcher could evaluate the impact of other teams in a given market using a difference-in-differences approach when a new team arrives in town from another league.

Of course, substitution of sport fans may not be limited to spectator sport, but also sport participation or other entertainment options available within a city. Because people generally have a fixed allocation for entertainment purposes, this could have important implications for team relocation decisions for both the public sector looking to provide subsidies as well as leagues and their franchises deciding to venture into new markets. Understanding the full scope of the sport industry and the interaction between sport participation and spectator sport is a topic I would like to progress toward with the analysis here informing structural shifts in the market. In fact there are important public health considerations in this context of sport consumption, in which Sports Economics research can play an important role.

Lastly, much of the literature regarding attendance and the Uncertainty of Outcome Hypothesis discusses uncertainty in a one-dimensional light as directly causing attendance changes. However—as Rottenberg originally states in his seminal work and as El-Hodiri and Quirk (1971) model—while uncertainty offers excitement, it seems reasonable to believe that a preference for the home team reaching the playoffs would dominate preferences for suspense and balance for many fans. This interactive effect seems to be underemphasized in the literature and explicitly separating the two will be important if we want to understand the influence of uncertainty itself and the excitement it creates. I recommend evaluation of direct and indirect effects of balance and team quality in order to more fully understand the interaction of these factors.

All in all, the work here lays a foundation for informed time series analysis on professional sports attendance data. Without accounting for breaks, coefficient standard errors could be biased in both aggregate and cross-sectional panel considerations. From the understanding of the time series properties of North American professional sports league attendance presented here, researchers will be well-equipped to correctly analyze impacts of different factors influencing attendance.

TABLE 9.1: Summary of Uncertainty of Outcome Results

	Support UOH			No Influence			Inverse UOH		
Leagues	**GU**	**PU**	**CSU**	**GU**	**PU**	**CSU**	**GU**	**PU**	**CSU**
MLB*		**X**		**X**		**X**			
NBA	**X**		**X**					**X**	
NFL				**X**	**X**	**X**			
NHL				**X**				**X**	**X**
Franchises	**GU**	**PU**	**CSU**	**GU**	**PU**	**CSU**	**GU**	**PU**	**CSU**
MLB	**1**	**4**	**1**	**13**	**12**	**14**	**2**	**0**	**1**
NBA	**1**	**1**	**2**	**7**	**7**	**6**	**1**	**1**	**1**
NFL	**4**	**1**	**4**	**8**	**10**	**9**	**1**	**2**	**0**
NHL	**1**	**0**	**0**	**6**	**4**	**6**	**0**	**3**	**1**

*MLB league aggregate taken from Lee and Fort (2008).

APPENDIX A

MAJOR LEAGUE BASEBALL FRANCHISE ALTERNATIVE MODELS

TABLE A.1: MLB Franchise Model 1B Break Point Test Results (Heterogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
BAL	185.89[a]	201.47[a]				201.47[a]	280.49[a]	67.86[a]				2
BOS	58.12[a]	124.03[a]	110.78[a]	94.90[a]	68.07[a]	124.03[a]	168.63[a]	113.65[a]	28.97[a]	28.97[a]		3
CHC	142.02[a]	110.63[a]	104.14[a]	103.95[a]	64.64[a]	142.02[a]	184.70[a]	31.36[a]	32.33[a]	4.36		3
CHW	17.63[a]	17.89[a]	23.97[a]	27.52[a]	22.61[a]	27.52[a]	49.63[a]	40.69[a]	40.69[a]	13.23[c]	2.86	3
CIN	150.56[a]	98.71[a]	82.08[a]	81.93[a]	76.91[a]	150.56[a]	168.88[a]	31.06[a]	30.35[a]	30.43[a]	6.88	2
CLE	47.18[a]	38.55[a]	39.78[a]	36.99[a]	35.01[a]	47.18[a]	76.87[a]	16.93[a]	15.38[b]	11.26	9.77	3
DET	21.19[a]	21.89[a]	36.31[a]	26.58[a]	23.66[a]	36.31[a]	54.34[a]	16.09[b]	26.49[a]	14.15[c]		3
HOU	22.37[a]	14.80[a]				22.37[a]	22.37[a]	6.42				1
LAD	40.75[a]	41.61[a]				41.61[a]	57.94[a]	7.09				1
MIL	15.72[a]	18.97[a]				18.97[a]	26.42[a]	4.60				1
NYM	74.52[a]	102.41[a]				102.41[a]	142.57[a]	46.71[a]				2
OAK	44.64[a]	45.67[a]				45.67[a]	63.59[a]	13.31[b]				1
PHI	83.49[a]	71.02[a]	62.48[a]	55.20[a]	50.96[a]	83.49[a]	111.89[a]	48.02[a]	48.02[a]	31.65[a]	10.24	3
PIT	15.13[b]	38.45[a]	47.48[a]	41.00[a]	28.79[a]	47.48[a]	72.85[a]	84.92[a]	66.40[a]	10.35		4
SFG	103.30[a]	54.90[a]				103.30[a]	103.30[a]	6.13				1
STL	129.98[a]	124.04[a]	117.59[a]	90.54[a]	69.31[a]	129.98[a]	175.98[a]	42.74[a]	14.47[b]	7.00		3

a. Significant at the 99% critical level; b. Significant at the 95% critical level; c. Significant at the 90% critical level

TABLE A.2: MLB Franchise Model 1B Estimated Break Dates (Heterogeneous)

Team	T_1	T_2	T_3	T_4	*Team*	T_1	T_2	T_3	T_4
BAL	**1974**	**1991**			***LAD***	**1974**			
	[73, 75]	[90, 92]				[73, 75]			
BOS	**1918**	**1945**	**1986**		***MIL***	**1995**			
	[17, 20]	[44, 49]	[84, 89]			[90, 96]			
CHC	**1932**	**1955**	**1983**		***NYM***	**1977**	**1994**		
	[30, 33]	[54, 58]	[82, 89]			[76, 78]	[92, 95]		
CHW	**1945**	**1965**	**1993**		***OAK***	**1994**			
	[42, 46]	[63, 66]	[91, 95]			[93, 97]			
CIN	**1945**	**1969**			***PHI***	**1930**	**1945**	**1970**	
	[43, 46]	[68, 70]				[23, 31]	[44, 46]	[69, 71]	
CLE	**1946**	**1964**	**1992**		***PIT***	**1927**	**1946**	**1961**	**1987**
	[43, 47]	[63, 66]	[90, 93]			[26, 28]	[44, 47]	[58, 62]	[84, 89]
DET	**1918**	**1945**	**1967**	**1989**	***SFG***	**1970**			
	[15, 19]	[44, 46]	[66, 70]	[85, 90]		[69, 71]			
HOU	**1978**				***STL***	**1945**	**1964**	**1981**	
	[77, 80]					[44, 46]	[62, 65]	[80, 83]	

*Brackets denote 90% confidence interval for break date

TABLE A.3: MLB Franchise Model 1B (Heterogeneous) Breakpoint Regression Results

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5
BAL	-288	1804	1237	-28840	-117	35178	-1396	91264		
t-value	*(-3.03)*[a]	*(0.76)*	*(11.32)*[a]	*(-5.82)*[a]	*(-0.50)*	*(3.11)*[a]	*(-5.05)*[a]	*(6.16)*[a]		
BOS	-273	3039	109	-2008.78	-310	26286	447	-16389	653	-39416
t-value	*(-2.50)*[b]	*(1.69)*[c]	*(2.35)*[b]	*(-1.21)*	*(-4.41)*[a]	*(5.56)*[a]	*(9.84)*[a]	*(-3.97)*[a]	*(6.66)*[a]	*(-3.98)*[a]
CHC	403	-14086	487	-24063	301	-20001	611	-40652		
t-value	*(7.09)*[a]	*(-5.19)*[a]	*(5.96)*[a]	*(-5.12)*[a]	*(5.24)*[a]	*(-4.78)*[a]	*(7.84)*[a]	*(-5.42)*[a]		
CHW	49	-8267	-130	6360.87	325	-22701				
t-value	*(1.05)*	*(-2.73)*[a]	*(-1.71)*[c]	*(1.24)*	*(5.56)*[a]	*(-3.88)*[a]				
CIN	38	-7064	4	-1453	142	1132.60				
t-value	*(1.09)*	*(-3.13)*[a]	*(0.04)*	*(-0.31)*	*(3.59)*[a]	*(0.24)*				
CLE	91	-9668	-1040	58480	264	-21410	-849	104045		
t-value	*(2.07)*[b]	*(-3.02)*[a]	*(-6.36)*[a]	*(5.71)*[a]	*(3.17)*[a]	*(-2.94)*[a]	*(-4.58)*[a]	*(5.27)*[a]		
DET	382	-17136	176	-14823	-439	23042	218	-15110	976	-90325
t-value	*(5.47)*[a]	*(-6.64)*[a]	*(1.23)*	*(-2.51)*[b]	*(-4.81)*[a]	*(4.21)*[a]	*(2.39)*[b]	*(-1.98)*[c]	*(8.52)*[a]	*(-7.84)*[a]
HOU	1110	-4738	638	-11818						
t-value	*(1.74)*[c]	*(-0.82)*	*(9.81)*[a]	*(-1.65)*						
LAD	-268	10918	1093	-4895	343	8970				
t-value	*(-1.91)*[c]	*(2.28)*[b]	*(5.28)*[a]	*(-0.66)*	*(3.96)*[a]	*(1.70)*[c]				
MIL	339	-13656	1418	-47260						
t-value	*(3.11)*[a]	*(-2.54)*[b]	*(6.15)*[a]	*(-5.40)*[a]						
NYM	-554	274	52	-997	1521	-59809				
t-value	*(-4.76)*[a]	*(0.08)*	*(0.10)*	*(-0.06)*	*(7.59)*[a]	*(-6.84)*[a]				
OAK	713	-13932	-1361	41140	-170	10484				
t-value	*(5.63)*[a]	*(-3.07)*[a]	*(-4.67)*[a]	*(4.27)*[a]	*(-0.38)*	*(0.55)*				
PHI	144	-12260	469	-25518	-57	-830	213	-7983		
t-value	*(1.45)*	*(-3.43)*[a]	*(2.19)*[b]	*(-2.91)*[a]	*(-0.56)*	*(-0.13)*	*(4.05)*[a]	*(-1.50)*		
PIT	238	-13545	311	-20816	-183	10885	180	-15082	191	-11002
t-value	*(3.15)*[a]	*(-5.05)*[a]	*(3.09)*[a]	*(-4.68)*[a]	*(-1.25)*	*(1.41)*	*(2.75)*[a]	*(-2.73)*[a]	*(1.82)*[c]	*(-1.03)*
SFG	-564	2185	441	-10248	-8	21689				
t-value	*(-4.62)*[a]	*(0.42)*	*(4.32)*[a]	*(-2.03)*[b]	*(-0.02)*	*(1.15)*				
STL	-70	-4857	-40	3558	-100	1485	462	-20641		
t-value	*(-1.83)*[c]	*(-2.74)*[a]	*(-0.43)*	*(0.62)*	*(-0.92)*	*(1.76)*[c]	*(8.62)*[a]	*(-4.01)*[a]		

a. Significant at the 99% critical level. b. Significant at the 95% critical level. c. Significant at the 90% critical level. α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively.

TABLE A.4: MLB Franchise Model 1B (Heterogeneous) Regression Coefficients

Team	***TL***	***CSU***	***PU***	***W%***	***L1(W%)***	$\bar{R}^2$ (R^2)	***Team***	***TL***	***CSU***	***PU***	***W%***	***L1(W%)***	$\bar{R}^2$ (R^2)
BAL	1479	1081	18763	15633	9987	0.966	***LAD***	2962	-1601	-75499	41645	22412	0.863
t-value	*(0.71)*	*(0.67)*	*(1.21)*	*(2.52)*[a]	*(1.78)*[c]	*(0.972)*	*t-value*	*(1.63)*	*(-1.16)*	*(-3.99)*[a]	*(4.79)*[a]	*(2.79)*[a]	*(0.884)*
BOS	-2957	-3451	97	22623	8877	0.953	***MIL***	-2599	2649	32693	16875	42576	0.826
t-value	*(-1.66)*	*(-3.00)*[a]	*(0.01)*	*(5.76)*[a]	*(2.46)*[b]	*(0.958)*	*t-value*	*(-1.08)*	*(0.90)*	*(-1.09)*	*(1.49)*	*(4.12)*[a]	*(0.862)*
CHC	1142	-93	-28348	24486	12886	0.952	***NYM***	-382	2293	-21382	45052	45679	0.933
t-value	*(0.83)*	*(-0.11)*	*(-3.25)*[a]	*(6.50)*[a]	*(3.40)*[a]	*(0.958)*	*t-value*	*(-0.22)*	*(1.70)*[c]	*(-1.15)*	*(7.12)*[a]	*(7.34)*[a]	*(0.948)*
CHW	1198	-1773	4111	25139	12123	0.854	***OAK***	-1892	-3878	34973	38158	26774	0.882
t-value	*(0.50)*	*(-1.14)*	*(0.39)*	*(5.04)*[a]	*(2.46)*[b]	*(0.871)*	*t-value*	*(-0.71)*	*(-1.71)*[c]	*(1.44)*	*(5.42)*[a]	*(3.89)*[a]	*(0.905)*
CIN	-3357	308	-18876	22548	7587	0.925	***PHI***	-158	-803	-34403	31660	8858	0.909
t-value	*(-2.17)*[b]	*(0.35)*	*(-1.94)*[c]	*(5.38)*[a]	*(1.82)*[c]	*(0.932)*	*t-value*	*(-0.08)*	*(-0.67)*	*(-2.56)*[b]	*(5.46)*[a]	*(1.64)*	*(0.920)*
CLE	1141	1838	-6723	22518	8172	0.894	***PIT***	2270	852	-11139	23645	12736	0.885
t-value	*(0.44)*	*(1.02)*	*(-0.57)*	*(3.89)*[a]	*(1.40)*	*(0.906)*	*t-value*	*(1.62)*	*(1.02)*	*(-1.24)*	*(6.00)*[a]	*(3.18)*[a]	*(0.901)*
DET	5367	-1182	-739	31615	108745	0.904	***SFG***	1623	181	-38599	48086	26936	0.881
t-value	*(2.74)*[a]	*(-0.90)*	*(-0.08)*	*(8.33)*[a]	*(2.73)*[a]	*(0.916)*	*t-value*	*(0.68)*	*(0.10)*	*(-1.68)*	*(4.51)*[a]	*(2.82)*[a]	*(0.899)*
HOU	642	5758	-49973	32847	22142	0.779	***STL***	1583	1394	-4812	21021	499	0.971
t-value	*(0.23)*	*(2.77)*[a]	*(-1.83)*[c]	*(2.46)*[b]	*(1.66)*	*(0.817)*	*t-value*	*(1.17)*	*(1.74)*[c]	*(-0.59)*	*(5.47)*[a]	*(0.13)*	*(0.974)*

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE A.5: MLB Franchise Model 1 Break Point Test Results (Homogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
BAL	214.05[a]	179.72[a]	330.31[a]	248.04[a]	243.31[a]	330.31[a]	534.24[a]	80.80[a]	41.36[a]	12.60	6.55	3
BOS	61.22[a]	131.84[a]	96.00[a]	105.81[a]	75.32[a]	131.84[a]	188.02[a]	117.74[a]	29.84[a]	29.84[a]		4
CHC	156.74[a]	138.53[a]	106.57[a]	114.65[a]	86.77[a]	156.74[a]	203.72[a]	27.39[a]	31.20[a]	9.41		3
CHW	17.26[a]	15.83[a]	21.54[a]	26.52[a]	23.81[a]	26.52[a]	52.29[a]	43.92[a]	43.92[a]	13.38[c]		2
CIN	157.01[a]	102.66[a]	84.40[a]	82.63[a]	70.28[a]	157.01[a]	157.01[a]	32.19[a]	31.04[a]	31.06[a]	5.36	2
CLE	56.08[a]	44.08[a]	47.56[a]	44.56[a]	39.10[a]	56.08[a]	85.86[a]	15.78[b]	35.29[a]	12.22	7.81	3
DET	21.76[a]	20.58[a]	30.89[a]	27.69[a]	24.29[a]	30.89[a]	53.33[a]	14.52[b]	28.64[a]	16.26[b]		4
HOU	21.67[a]	12.80[a]	16.26[a]	19.96[a]	16.37[a]	21.67[a]	35.94[a]	9.25	6.61	6.66	34.66[a]	1
LAD	38.44[a]	34.90[a]	34.87[a]	37.55[a]	47.09[a]	47.09[a]	103.40[a]	20.36[a]	7.68	11.47	3.69	2
MIL	12.08[b]	17.15[a]	18.92[a]	22.71[a]	13.35[a]	22.71[a]	40.35[a]	17.85[a]	25.09[a]	1.72	1.33	2
NYM	34.32[a]	54.72[a]	50.03[a]	60.10[a]	46.45[a]	60.10[a]	106.79[a]	40.54[a]	9.60	4.76		2
OAK	35.31[a]	21.95[a]	26.89[a]	25.12[a]	78.69[a]	78.69[a]	172.78[a]	16.80[b]	16.80[b]	20.28[a]	15.75[b]	2
PHI	86.27[a]	72.57[a]	57.35[a]	50.96[a]	45.75[a]	86.27[a]	100.45[a]	51.10[a]	51.10[a]	34.97[a]	10.78	3
PIT	15.95[a]	38.05[a]	30.98[a]	32.45[a]	24.67[a]	38.05[a]	57.67[a]	62.30[a]	51.30[a]	45.76[a]		4
SDN	8.96	10.98[b]	10.16[b]	11.28[a]	9.01[a]	11.28	20.44[a]	13.33[b]	12.95[c]	29.40[a]	0.34	0
SFG	68.12[a]	72.52[a]	74.19[a]	63.98[a]	50.12[a]	74.19[a]	113.68[a]	37.60[a]	10.68	3.38	1.47	2
STL	160.13[a]	151.07[a]	137.00[a]	108.22[a]	83.68[a]	160.13[a]	205.03[a]	47.16[a]	17.05[b]	6.02		3

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE A.6: MLB Franchise Model 1 Estimated Break Dates (Homogeneous)

Team	T_1	T_2	T_3	T_4	*Team*	T_1	T_2	T_3	T_4
BAL	**1974** [73, 75]	**1991** [90, 92]	**2001** [00, 02]		***LAD***	**1973** [72, 75]	**1986** [85, 88]		
BOS	**1918** [17, 20]	**1945** [44, 46]	**1966** [65, 67]	**1993** [92, 95]	***MIL***	**1983** [82, 85]	**1993** [90, 94]		
CHC	**1932** [30, 33]	**1955** [54, 58]	**1983** [82, 90]		***NYM***	**1984** [83. 86]	**1993** [91, 94]		
CHW	**1945** [42, 46]	**1975** [73, 76]			***OAK***	**1988** [86, 89]	**2000** [99, 04]		
CIN	**1945** [43, 46]	**1969** [68, 70]			***PHI***	**1930** [24, 31]	**1945** [44, 46]	**1970** [69, 71]	
CLE	**1946** [44, 47]	**1964** [63, 66]	**1992** [90, 93]		***PIT***	**1927** [25, 28]	**1946** [43, 47]	**1961** [56, 63]	**1987** [84, 89]
DET	**1929** [27, 40]	**1945** [43, 46]	**1967** [66, 69]	**1989** [84, 90]	***SFG***	**1977** [76, 78]	**1999** [98, 00]		
HOU	**1970** [69, 72]				***STL***	**1945** [44, 46]	**1964** [62, 65]	**1981** [80, 83]	

*Brackets denote 90% confidence interval for break date

TABLE A.7: MLB Franchise Model 1 (Homogeneous) Breakpoint Regression Results

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5
BAL	-288	1804	1237	-28840	-117	35178	-1396	91264		
t-value	*(-3.03)*[a]	*(0.76)*	*(11.32)*[a]	*(-5.82)*[a]	*(-0.50)*	*(3.11)*[a]	*(-5.05)*[a]	*(6.16)*[a]		
BOS	-273	3039	109	-2009	-310	26286	447	-16389	653	-39416
t-value	*(-2.50)*[b]	*(1.69)*[c]	*(2.35)*[b]	*(-1.21)*	*(-4.41)*[a]	*(5.56)*[a]	*(9.84)*[a]	*(-3.97)*[a]	*(6.66)*[a]	*(-3.98)*[a]
CHC	403	-14086	487	-24063	301	-20001	611	-40652		
t-value	*(7.09)*[a]	*(-5.19)*[a]	*(5.96)*[a]	*(-5.12)*[a]	*(5.24)*[a]	*(-4.78)*[a]	*(7.84)*[a]	*(-5.42)*[a]		
CHW	49	-8267	-130	6361	325	-22701				
t-value	*(1.05)*	*(-2.73)*[a]	*(-1.71)*[c]	*(1.24)*	*(5.56)*[a]	*(-3.88)*[a]				
CIN	38	-7064	4	-1453	142	1133				
t-value	*(1.09)*	*(-3.13)*[a]	*(0.04)*	*(-0.31)*	*(3.59)*[a]	*(0.24)*				
CLE	91	-9668	-1040	58480	264	-21410	-849	104045		
t-value	*(2.07)*[b]	*(-3.02)*[a]	*(-6.36)*[a]	*(5.71)*[a]	*(3.17)*[a]	*(-2.94)*[a]	*(-4.58)*[a]	*(5.27)*[a]		
DET	382	-17136	176	-14823	-439	23042	218	-15110	976	-90325
t-value	*(5.47)*[a]	*(-6.64)*[a]	*(1.23)*	*(-2.51)*[b]	*(-4.81)*[a]	*(4.21)*[a]	*(2.39)*[b]	*(-1.98)*[c]	*(8.52)*[a]	*(-7.84)*[a]
HOU	1110	-4738	638	-11818						
t-value	*(1.74)*[c]	*(-0.82)*	*(9.81)*[a]	*(-1.65)*						
LAD	-268	10918	1093	-4895	343	8970				
t-value	*(-1.91)*[c]	*(2.28)*[b]	*(5.28)*[a]	*(-0.66)*	*(3.96)*[a]	*(1.70)*[c]				
MIL	1138	-1390	167	7335	1346	-27724				
t-value	*(4.18)*[a]	*(-0.23)*	*(0.44)*	*(0.81)*	*(6.55)*[a]	*(-3.30)*[a]				
NYM	-554	274	52	-997	1521	-59809				
t-value	*(-4.76)*[a]	*(0.08)*	*(0.10)*	*(-0.06)*	*(7.59)*[a]	*(-6.84)*[a]				
OAK	713	-13932	-1361	41140	-170	10484				
t-value	*(5.63)*[a]	*(-3.07)*[a]	*(-4.67)*[a]	*(4.27)*[a]	*(-0.38)*	*(0.55)*				
PHI	144	-12260	469	-25518	-57	-830	213	-7983		
t-value	*(1.45)*	*(-3.43)*[a]	*(2.19)*[b]	*(-2.91)*[a]	*(-0.56)*	*(-0.13)*	*(4.05)*[a]	*(-1.50)*		
PIT	238	-13545	311	-20816	-183	10885	180	-15082	191	-11002
t-value	*(3.15)*[a]	*(-5.05)*[a]	*(3.09)*[a]	*(-4.68)*[a]	*(-1.25)*	*(1.41)*	*(2.75)*[a]	*(-2.73)*[a]	*(1.82)*[c]	*(-1.03)*
SFG	-564	2185	441	-10248	-8	21689				
t-value	*(-4.62)*[a]	*(0.42)*	*(4.32)*[a]	*(-2.03)*[b]	*(-0.02)*	*(1.15)*				
STL	-70	-4857	-40	3558	-100	1485	462	-20641		
t-value	*(-1.83)*[c]	*(-2.74)*[a]	*(-0.43)*	*(0.62)*	*(-0.92)*	*(1.76)*[c]	*(8.62)*[a]	*(-4.01)*[a]		

a. Significant at the 99% critical level. b. Significant at the 95% critical level. c. Significant at the 90% critical level. α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE A.8: MLB Franchise Model 1 (Homogeneous) Regression Coefficients

Team	***TL***	***CSU***	***PU***	***W%***	$\bar{R}^2$ (R^2)	***Team***	***TL***	***CSU***	***PU***	***W%***	$\bar{R}^2$ (R^2)
BAL	2674	-531	7837	24243	0.978	***LAD***	2388	416	-67546	34837	0.886
t-value	*(1.56)*	*(-0.39)*	*(0.61)*	*(4.94)*[a]	*(0.982)*	*t-value*	*(1.39)*	*(0.31)*	*(-3.92)*[a]	*(4.25)*[a]	*(0.906)*
BOS	-2959	-1949	-1592	13481	0.974	***MIL***	-2038	-3176	6475	24473	0.794
t-value	*(-2.22)*[b]	*(-2.22)*[b]	*(-0.27)*	*(4.59)*[a]	*(0.977)*	*t-value*	*(-0.73)*	*(-1.19)*	*(0.20)*	*(2.04)*[b]	*(0.841)*
CHC	1008	321	-30218	29134	0.941	***NYM***	2779	1369	-24272	58223	0.871
t-value	*(0.68)*	*(0.36)*	*(-3.26)*[a]	*(7.52)*[a]	*(0.947)*	*t-value*	*(1.08)*	*(0.77)*	*(-0.96)*	*(7.11)*[a]	*(0.895)*
CHW	3699	-1422	3095	29418	0.831	***OAK***	652	-2554	-10990	40565	0.856
t-value	*(1.54)*	*(-0.91)*	*(0.27)*	*(6.13)*[a]	*(0.845)*	*t-value*	*(0.20)*	*(-0.97)*	*(-0.43)*	*(5.07)*[a]	*(0.888)*
CIN	-3465	376	-19632	25238	0.923	***PHI***	-151	-925	-36253	36026	0.908
t-value	*(-2.21)*[b]	*(0.42)*	*(-1.99)*[b]	*(6.36)*[a]	*(0.930)*	*t-value*	*(-0.07)*	*(-0.77)*	*(-2.68)*[a]	*(6.94)*[a]	*(0.917)*
CLE	1069	2622	-8773	24129	0.893	***PIT***	1717	1102	-17650	28571	0.872
t-value	*(0.41)*	*(1.52)*	*(-0.75)*	*(4.23)*[a]	*(0.904)*	*t-value*	*(1.16)*	*(1.26)*	*(-1.91)*[c]	*(7.43)*[a]	*(0.888)*
DET	5386	-1034	-701	35046	0.894	***SFG***	-2292	-464	-32040	37221	0.921
t-value	*(2.62)*[b]	*(-0.78)*	*(-0.08)*	*(9.21)*[a]	*(0.907)*	*t-value*	*(-1.15)*	*(-0.30)*	*(-1.62)*	*(4.29)*[a]	*(0.935)*
HOU	-447	6826	-62461	33088	0.781	***STL***	1622	1405	-4703	21090	0.971
t-value	*(-0.15)*	*(3.62)*[a]	*(-2.23)*[a]	*(2.45)*[a]	*(0.814)*	*t-value*	*(1.24)*	*(1.77)*[c]	*(-0.58)*	*(5.57)*[a]	*(0.974)*

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

APPENDIX B

NATIONAL BASKETBALL ASSOCIATION FRANCHISE ALTERNATIVE MODELS

TABLE B.1: NBA Franchise **Model B** Break Point Sequential Test Results (Heterogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*Breaks*
ATL	12.46**	16.45***		16.45***	22.91***	11.37*		**1**
BOS	64.48***	50.61***	50.80***	64.48***	84.69***	10.87*	11.53*	**2**
CLE	30.19***	25.96***		30.19***	36.15***	11.31**		**1**
DET	44.79***	53.67***		53.67***	74.72***	7.36		**1**
NYK	143.17***	133.33***	123.09***	143.17***	205.19***	13.93**	1.27	**2**
PHI	65.38***	53.01***		65.38***	72.41***	9.54*		**1**
PHO	143.63***	83.26***		143.63***	143.63***	2.40		**1**
POR	96.56***	70.16***		96.56***	97.69***	122.51***		**2**
SEA	97.39***	95.98***		97.39***	133.63***	12.92**		**2**

"***" Significant at the 99% critical level
"**" Significant at the 95% critical level
"*" Significant at the 90% critical level

TABLE B.2: NBA Franchise **Model B** Break Dates (Heterogeneous)

Team	T_1	T_2
ATL	**1985-86** [82-83, 86-87]	
BOS	**1960-61** [58-59, 61-62]	**1973-74** [71-72, 74-75]
CLE	**1984-85** [83-84, 85-86]	
DET	**1982-83** [80-81, 83-84]	
NYK	**1976-77** [75-76, 77-78]	**1995-96** [92-93, 08-09]
PHI	**1995-96** [94-95, 96-97]	
PHO	**1989-90** [88-89, 90-91]	
POR	**1979-80** [78-79, 80-81]	**1994-95** [93-94, 95-96]
SEA	**9181-82** [80-81, 82-83]	**1992-93** [91-92, 93-94]

*Brackets denote 90% confidence interval for break date

TABLE B.3: NBA Franchise **Model B** Breakpoint Regression Results (Heterogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3
ATL	276	669	181	5252		
t-value	*(3.93)****	*(0.38)*	*(4.01)****	*(2.13)***		
BOS	85	2633	344	-1388	163	6370
t-value	*(0.98)*	*(3.25)****	*(5.00)****	*(-0.85)*	*(9.60)****	*(5.34)****
CLE	56	4237	156	8140		
t-value	*(0.53)*	*(2.31)***	*(3.74)****	*(3.57)****		
DET	301	-3965	51	9835		
t-value	*(5.46)****	*(-2.03)***	*(1.14)*	*(3.43)****		
NYK	567	-5754	328	-5168	248	-1371
t-value	*(18.84)****	*(-3.64)****	*(5.53)****	*(-2.67)***	*(2.58)***	*(-0.24)*
PHI	400	-1457	-302	24843		
t-value	*(17.52)****	*(-1.18)*	*(-3.69)****	*(7.32)****		
PHO	312	3686	-111	18583		
t-value	*(10.53)****	*(3.51)****	*(-3.02)****	*(10.58)****		
POR	536	2847	-41	7578	-108	17282
t-value	*(3.45)****	*(2.04)***	*(-0.71)*	*(4.38)****	*(-1.79)**	*(6.22)****
SEA	566	-4593	281	-8566	719	-24258
t-value	*(7.53)****	*(-3.42)****	*(3.10)****	*(-3.28)****	*(7.57)****	*(-5.09)****

*** Significant at the 99% critical level

** Significant at the 95% critical level

* Significant at the 90% critical level

α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE B.4: NBA Franchise **Model B** Balance and W% Coefficients (Heterogeneous)

Team	***TL***	***PU***	***CSU***	***W%***	***L1(W%)***	$\bar{R}^2$ (R^2)
ATL	-1453	10130	-1659	2748	5039	0.901
t-value	*(-0.61)*	*(1.21)*	*(-1.18)*	*(1.27)*	*(1.98)**	*(0.920)*
BOS	1458	5074	669	3773	-1886	0.963
t-value	*(1.32)*	*(1.05)*	*(1.13)*	*(3.44)****	*(-1.67)**	*(0.969)*
CLE	-1643	-18551	-5106	11742	4703	0.934
t-value	*(-0.62)*	*(-2.03)***	*(-2.95)****	*(4.85)****	*(2.07)***	*(0.948)*
DET	-4976	-1798	822	6946	7044	0.948
t-value	*(-1.70)**	*(-0.19)*	*(0.52)*	*(2.94)****	*(2.78)****	*(0.956)*
NYK	680	12358	-946	8370	6490	0.942
t-value	*(0.47)*	*(1.84)**	*(-1.21)*	*(4.32)****	*(3.64)****	*(0.952)*
PHI	6377	2152	-3737	4532	7430	0.944
t-value	*(3.43)****	*(0.31)*	*(-3.68)****	*(2.87)****	*(4.76)****	*(0.953)*
PHO	-1739	3918	-2179	3496	3710	0.970
t-value	*(-1.22)*	*(0.83)*	*(-2.39)***	*(2.68)***	*(3.37)****	*(0.976)*
POR	-1997	8658	39	8169	1026	0.953
t-value	*(-1.13)*	*(1.40)*	*(0.03)*	*(4.97)****	*(0.58)*	*(0.965)*
SEA	91	-12423	3825	15403	9367	0.937
t-value	*(0.06)*	*(-2.16)***	*(3.53)****	*(7.93)****	*(5.26)****	*(0.953)*

"***", "**", "*" indicate statistical significance at the 99%, 95% and 90% critical level, respectively.

TABLE B.5: NBA Franchise Break Point Sequential Test Results (Homogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
ATL	15.13[b]	16.45[a]	19.20[a]	28.89[a]	28.72[a]	28.89[a]	52.59[a]	34.51[a]	132.32[a]	132.32[a]	19.60[b]	**5**
BOS	58.66[a]	40.17[a]	51.61[a]	54.27[a]	44.52[a]	58.66[a]	89.02[a]	24.08[a]	19.26[a]	21.10[a]	4.46	**4**
CLE	30.87[a]	28.30[a]	21.22[a]	23.22[a]	25.89[a]	30.87[a]	47.42[a]	15.15[b]	15.99[b]	142.04[a]	15.15[c]	**2**
DET	55.30[a]	47.83[a]	72.94[a]	63.03[a]	62.38[a]	72.94[a]	114.24[a]	19.52[a]	47.91[a]	15.71[b]	10.97	**2**
NYK	92.07[a]	119.66[a]	94.59[a]	94.50[a]	100.44[a]	119.66[a]	183.94[a]	44.91[a]	9.81	29.11[a]	8.47	**3**
PHI	62.77[a]	41.17[a]	29.75[a]	27.83[a]	30.68[a]	62.77[a]	62.77[a]	9.03	3.42	63.16[a]	7.64	**1**
PHO	103.96[a]	93.00[a]	78.87[a]	78.72[a]	82.36[a]	103.96[a]	150.83[a]	37.82[a]	37.82[a]	44.30[a]	44.30[a]	**4**
POR	72.47[a]	80.98[a]	184.78[a]	141.85[a]	143.92[a]	184.78[a]	269.03[a]	195.59[a]	229.70[a]	392.61[a]	338.75[a]	**4**
SEA	106.49[a]	108.95[a]	95.70[a]	73.30[a]	76.41[a]	108.95[a]	139.94[a]	19.40[a]	11.36	8.98	8.98	**2**

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE B.6: NBA Franchise Break Dates (Homogeneous)

Team	T_1	T_2	T_3	T_4	T_5
ATL	**1981-82**	**1985-86**	**1990-91**	**1996-97**	**2001-02**
	[80-81, 82-83]	[84-85, 86-87]	[89-90, 92-93]	[95-96, 97-98]	[00-01, 02-03]
BOS	**1958-59**	**1973-74**	**1994-95**	**2000-01**	
	[55-56, 59-60]	[71-72, 74-75]	[93-94, 95-96]	[99-00, 01-02]	
CLE	**1976-77**	**1995-96**			
	[75-76 ,77-78]	[94-95, 96-97]			
DET	**1977-78**	**1987-88**			
	[76-77, 78-79]	[86-87, 88-89]			
NYK	**1968-69**	**1974-75**	**1983-84**		
	[67-68, 69-70]	[73-74, 75-76]	[82-83, 84-85]		
PHI	**2003-04**				
	[02-03, 04-05]				
PHO	**1975-76**	**1991-92**	**2000-01**	**2005-06**	
	[74-75, 76-77]	[90-91, 92-93]	[99-00, 02-03]	[03-04, 08-09]	
POR	**1979-80**	**1987-88**	**1994-95**	**2002-03**	
	[78-79, 80-81]	[70-71, 88-89]	[93-94, 95-96]	[00-01, 03-04]	
SEA	**1980-81**	**1986-87**			
	[79-80, 81-82]	[85-86, 88-89]			

*Brackets denote 90% confidence interval for break date

TABLE B.7: NBA Franchise Breakpoint Regression Results (Homogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5	α_6	β_6
ATL	446	3048	453	-682	-26	12832	161	6714	-975	45158	286	3553
t-value	*(7.24)*[a]	*(2.89* [a]	*(1.78)*	*(-0.17)*	*(-0.10)*	*(2.19)*[b]	*(0.84)*	*(1.36)*	*(-3.62)*[a]	*(5.03)*[a]	*(1.86)*[c]	*(0.62)*
BOS	159	1007	347	-3112	199	3307	-498	39399	219	1445		
t-value	*(1.99)*[b]	*(1.65)*	*(8.31)*[a]	*(-2.89)*[a]	*(6.89)*[a]	*(2.49)*[b]	*(-3.02)*[a]	*(4.82)*[a]	*(2.40)*[b]	*(0.28)*		
CLE	735	4253	791	-1013	120	13033						
t-value	*(2.24)*[b]	*(2.63)*[b]	*(10.46)*[a]	*(-0.62)*	*(1.22)*	*(3.83)*[a]						
DET	100	450	1659	-32845	-10	16385						
t-value	*(1.41)*	*(0.26)*	*(7.75)*[a]	*(-6.40)*[a]	*(-0.18)*	*(5.74)*[a]						
NYK	468	-2839	313	4408	-761	31133	251	337				
t-value	*(12.08)*[a]	*(-2.38)*[b]	*(1.40)*	*(0.83)*	*(-5.92)*[a]	*(7.54)*[a]	*(10.32)*[a]	*(0.21)*				
PHI	411	-270	-132	17899								
t-value	*(21.15)*[a]	*(-0.22)*	*(-0.47)*	*(1.42)*								
PHO	111	3608	199	5499	7	15198	-47	15557	-42	15875		
t-value	*(0.91)*	*(4.53)*[a]	*(4.38)*[a]	*(4.46)*[a]	*(0.09)*	*(5.50)*[a]	*(-0.21)*	*(1.93)* [c]	*(-0.14)*	*(1.29)*		
POR	675	4830	-44	11681	58	9637	-185	23923	686	-9064		
t-value	*(8.81)*[a]	*(5.79)*[a]	*(-0.50)*	*(8.33)*[a]	*(0.57)*	*(3.84)*[a]	*(-2.02)*[b]	*(8.24)*[a]	*(5.53)*[a]	*(-2.13)*[b]		
SEA	903	-1215	-1419	28544	302	-2412						
t-value	*(10.91)*[a]	*(-0.97)*	*(-5.00)*[a]	*(5.45)*[a]	*(6.46)*[a]	*(-1.04)*						

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE B.8: NBA Franchise Balance and W% Coefficients (Homogeneous)

Team	***TL***	***PU***	***CSU***	***W%***	$\bar{R}^2$ (R^2)
ATL	-5570	-4630	36	3688	0.963
t-value	*(-3.66)****	*(-0.86)*	*(0.04)*	*(2.47)***	*(0.977)*
BOS	1199	386	-121	5675	0.981
t-value	*(1.41)*	*(0.10)*	*(-0.29)*	*(6.60)****	*(0.985)*
CLE	-2724	-9804	-8236	11017	0.948
t-value	*(-0.96)*	*(-1.12)*	*(-5.12)****	*(4.99)****	*(0.960)*
DET	342	5859	-2071	8439	0.959
t-value	*(0.12)*	*(0.66)*	*(-1.50)*	*(4.10)****	*(0.966)*
NYK	1579	4023	483	10300	0.971
t-value	*(1.46)*	*(0.83)*	*(0.84)*	*(8.75)****	*(0.977)*
PHI	4095	10863	-4759	9764	0.937
t-value	*(2.06)*[b]	*(1.42)*	*(-4.20)****	*(8.28)****	*(0.946)*
PHO	-419	9100	-625	5339	0.979
t-value	*(-0.28)*	*(1.98)***	*(-0.81)*	*(5.10)****	*(0.986)*
POR	-1247	3630	-1294	4094	0.983
t-value	*(-1.08)*	*(0.85)*	*(-1.70)*	*(3.64)****	*(0.989)*
SEA	-717	-4012	2869	12049	0.915
t-value	*(-0.36)*	*(-0.54)*	*(2.43)***	*(6.94)****	*(0.934)*

"***", "**", "*" indicate statistical significance at the 99%, 95% and 90% critical level, respectively.

APPENDIX C

NATIONAL FOOTBALL LEAGUE FRANCHISE ALTERNATIVE MODELS

TABLE C.1: NFL Franchise **Model B** Break Point Sequential Test Results (Heterogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*Breaks*
ATL	49.84***	35.37***		49.84***	49.84***	2.99		**1**
BUF	2.86	6.12		6.12	8.52	5.26		**0**
CHI	51.70***	33.61***	26.25***	51.70***	51.70***	7.30	2.57	**1**
CIN	40.57***	34.41***		40.57***	47.91***	13.12**		**2**
DEN	8.93	12.98***		12.98**	18.07***	11.76**		**1**
DET	46.64***	35.59***	45.44***	46.64***	75.75***	13.14**	95.25***	**2**
KC	27.47***	43.83***		43.83***	61.02***	4.17		**1**
MIA	38.04***	44.08***		44.08***	61.38***	33.13***		**2**
MIN	21.98***	29.40***		29.40***	40.93***	33.84***		**2**
NYG	72.10***	58.35***	39.40***	72.10***	77.04***	7.07	3.58	**1**
PHI	289.47***	159.05***	112.36***	289.47***	289.47***	22.04***	6.48	**2**
PIT	28.63***	36.17***	22.54***	36.17***	47.75***	22.28***	12.35*	**3**
SD	7.97	7.02		7.97	9.77	5.67		**0**
SF	39.08***	20.88***	14.84***	39.08***	39.08***	3.13	10.66	**1**
WAS	47.77***	106.41***	101.79***	106.41***	169.69***	69.80***	11.78*	**2**

"***", "**", "*" Indicate significance at the 99%, 95% and 90% critical level, respectively.

TABLE C.2: NFL Franchise **Model B** Break Dates (Heterogeneous)

Team	T_1	T_2	T_3	*Team*	T_1	T_2	T_3
ATL	**1989** [88, 90]			***MIN***	**1981** [80, 82]	**1996** [95, 97]	
CHI	**1948** [47, 50]			***NYG***	**1956** [55, 58]		
CIN	**1979** [78, 80]	**1991** [89, 92]		***PHI***	**1958** [57, 59]	**1981** [80, 86]	
DEN	**1982** [81, 84]			***PIT***	**1948** [47, 54]	**1969** [68, 70]	**1986** [81, 88]
DET	**1950** [48, 52]	**1985** [82, 87]		***SF***	**1961** [60, 63]		
KC	**1988** [87, 90]			***WAS***	**1962** [61, 63]	**1995** [94, 96]	
MIA	**1983** [82, 84]	**1995** [94, 96]					

*Brackets denote 90% confidence interval for break date

TABLE C.3: NFL Franchise **Model B** Breakpoint Regression Results (Heterogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4
ATL	-1245	47746	1025	8002				
t-value	*(-5.43)*[a]	*(6.20)*[a]	*(4.17)*[a]	*(0.79)*				
CHI	1348	9449	385	27134				
t-value	*(6.36)*[a]	*(2.60)*[b]	*(12.88)*[a]	*(10.35)*[a]				
CIN	-1988	57462	900	31429	1098	17764		
t-value	*(-7.30)*[a]	*(17.08)*[a]	*(4.05)*[a]	*(6.09)*[a]	*(9.27)*[a]	*(4.12)*[a]		
DEN	2008	38260	276	54612				
t-value	*(6.23)*[a]	*(8.80)*[a]	*(3.76)*[a]	*(9.27)*[a]				
DET	735	10232	755	23201	659	14554		
t-value	*(1.78)*[c]	*(1.38)*	*(4.75)*[a]	*(3.26)*[a]	*(2.99)*[a]	*(0.90)*		
KC	-624	56467	389	58921				
t-value	*(-2.46)*[b]	*(7.80)*[a]	*(1.71)*	*(5.59)*[a]				
MIA	-1479	37315	422	23183	-430	57292		
t-value	*(-5.24)*[a]	*(7.04)*[a]	*(1.63)*	*(3.60)*[a]	*(-1.89)*[c]	*(7.47)*[a]		
MIN	114	30080	-83	45217	-9	51087		
t-value	*(0.98)*	*(13.10)*[a]	*(-0.62)*	*(9.96)*[a]	*(-0.05)*	*(6.61)*[a]		
NYG	113	30098	413	46612				
t-value	*(0.56)*	*(5.02)*[a]	*(6.98)*[a]	*(8.67)*[a]				
PHI	245	20116	612	38720	371	40557		
t-value	*(1.68)*	*(6.88)*[a]	*(3.97)*[a]	*(7.55)*[a]	*(3.74)*[a]	*(5.85)*[a]		
PIT	1584	3853	523	12574	404	26510	605	11705
t-value	*(7.61)*[a]	*(1.35)*	*(4.05)*[a]	*(3.26)*[a]	*(2.27)*[b]	*(3.21)*[a]	*(5.58)*[a]	*(1.58)*
SF	2492	18553	713	19297				
t-value	*(6.30)*[a]	*(5.03)*[a]	*(13.77)*[a]	*(4.98)*[a]				
WAS	66	27867	180	45667	1938	-46730		
t-value	*(0.50)*	*(7.33)*[a]	*(2.07)*[b]	*(11.39)*[a]	*(7.29)*[a]	*(-2.68)*[b]		

“a”, “b”, “c” Indicate significance at the 99%, 95% and 90% critical level, respectively/
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE C.4: NFL Franchise **Model B** Balance and W% Coefficients (Heterogeneous)

Team	*TL*	*PU*	*CSU*	*W%*	*L1(W%)*	$\bar{R}^2$ (R^2)
ATL	7494	-15450	8327	9455	7454	0.697
t-value	*(2.31)*[b]	*(-0.58)*	*(1.53)*	*(1.69)*	*(1.29)*	*(0.755)*
CHI	2026	697	-810	9674	2397	0.923
t-value	*(1.57)*	*(0.08)*	*(-0.44)*	*(4.38)*[a]	*(1.14)*	*(0.931)*
CIN	941	4458	-3528	7755	3387	0.864
t-value	*(0.70)*	*(0.36)*	*(-1.62)*	*(3.16)*[a]	*(1.32)*	*(0.899)*
DEN	4799	-33064	2388	11212	4262	0.900
t-value	*(2.58)*[b]	*(-2.50)*[b]	*(0.91)*	*(3.13)*[a]	*(1.36)*	*(0.920)*
DET	853	-32680	-5136	14406	9638	0.848
t-value	*(0.27)*	*(-1.79)*[c]	*(-1.34)*	*(2.95)*[a]	*(1.95)*[c]	*(0.868)*
KC	-1891	14505	-9238	8288	7397	0.836
t-value	*(-0.68)*	*(0.55)*	*(-1.94)*[c]	*(1.37)*	*(1.26)*	*(0.869)*
MIA	9026	63819	-1910	18935	6793	0.863
t-value	*(4.65)*[a]	*(4.04)*[a]	*(-0.59)*	*(5.55)*[a]	*(2.13)*[b]	*(0.898)*
MIN	3768	18140	3652	4491	6339	0.937
t-value	*(3.04)*[a]	*(2.07)*[b]	*(1.80)*[c]	*(2.07)*[b]	*(2.86)*[a]	*(0.950)*
NYG	-381	-9898	-5786	8261	1790	0.896
t-value	*(-0.16)*	*(-0.63)*	*(-1.79)*[c]	*(2.25)*[b]	*(0.50)*	*(0.907)*
PHI	-826	-16685	-2912	-2736	12314	0.955
t-value	*(-0.43)*	*(-1.62)*	*(-1.31)*	*(-0.97)*	*(4.36)*[a]	*(0.961)*
PIT	2283	11241	-2276	1277	4299	0.959
t-value	*(1.53)*	*(1.25)*	*(-1.23)*	*(0.48)*	*(1.70)*	*(0.966)*
SF	2087	7860	-879	7708	5033	0.862
t-value	*(1.12)*	*(0.52)*	*(-0.28)*	*(2.42)*[b]	*(1.61)*	*(0.881)*
WAS	-3835	3351	-5362	3386	4033	0.960
t-value	*(-2.14)*[b]	*(0.32)*	*(-2.37)*[a]	*(1.07)*	*(1.28)*	*(0.966)*

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE C.5: NFL Franchise Break Point Sequential Test Results (Homogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
ATL	66.32[a]	46.79[a]	38.95[a]	33.95[a]	41.14[a]	66.32[a]	75.34[a]	12.98[c]	14.03[c]	14.03[c]	5.61	**1**
BUF	10.09	7.19	10.99	12.36	7.99	12.36[c]	20.28[a]	11.82	35.40[a]	5.69	5.69	**0**
CHI	85.84[a]	54.22[a]	45.09[a]	38.52[a]	35.21[a]	85.84[a]	85.84[a]	9.52	8.70	13.01	13.01	**1**
CIN	37.74[a]	53.46[a]	43.34[a]	37.45[a]	32.44[a]	53.46[a]	67.09[a]	21.50[a]	46.78[a]	46.78[a]	46.78[a]	**2**
DEN	94.93[a]	60.06[a]	61.24[a]	49.83[a]	43.13[a]	94.93[a]	94.93[a]	8.38	6.41	3838.7[a]	3838.7[a]	**1**
DET	50.07[a]	40.29[a]	55.72[a]	58.61[a]	58.25[a]	58.61[a]	106.68[a]	11.74[c]	49.44[a]	49.44[a]	27.96[a]	**1**
KC	40.14[a]	41.31[a]	32.52[a]	38.26[a]	37.83[a]	41.31[a]	69.28[a]	46.73[a]	63.25[a]	33.77[a]	183.29[a]	**3**
MIA	24.71[a]	34.97[a]	28.63[a]	28.77[a]	25.24[a]	34.97[a]	47.20[a]	37.34[a]	6.16	23.27[a]	3.08	**3**
MIN	15.31[b]	28.67[a]	41.35[a]	51.99[a]	57.82[a]	57.82[a]	105.90[a]	36.90[a]	41.68[a]	41.68[a]	27.00[a]	**5**
NYG	73.54[a]	84.17[a]	52.23[a]	56.80[a]	47.98[a]	84.17[a]	105.63[a]	28.76[a]	6.72	12.85	11.85	**2**
PHI	285.39[a]	193.49[a]	141.98[a]	115.13[a]	98.68[a]	285.39[a]	285.39[a]	18.26[a]	18.26[b]	4.98	4.98	**2**
PIT	25.92[a]	40.11[a]	39.64[a]	39.85[a]	34.59[a]	40.11[a]	65.37[a]	17.29[a]	22.80[a]	28.56[a]	4.33	**2**
SD	23.47[a]	16.64[a]	20.08[a]	19.47[a]	16.96[a]	23.47[a]	31.93[a]	7.41	13.74[c]	7.34	4.34	**1**
SF	51.10[a]	50.41[a]	53.78[a]	55.16[a]	47.17[a]	55.16[a]	90.48[a]	20.32[a]	8.34	9.53	15.04[c]	**2**
WAS	51.67[a]	152.51[a]	204.61[a]	278.70[a]	250.63[a]	278.70[a]	459.02[a]	133.37[a]	33.21[a]	20.80[a]	20.80[a]	**4**

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE C.6: NFL Franchise Break Dates (Homogeneous)

Team	T_1	T_2	T_3	T_4	T_5
ATL	**1989** [88, 90]				
CHI	**1945** [42, 46]				
CIN	**1979** [78, 80]	**1991** [90, 92]			
DEN	**1975** [74, 76]				
DET	**1951** [47, 52]				
KC	**1981** [80, 82]	**1992** [91, 93]	**2005** [03, 06]		
MIA	**1983** [82, 84]	**1989** [88, 90]	**1995** [94, 96]		
MIN	**1964** [63, 65]	**1981** [80, 82]	**1986** [85, 89]	**1996** [95, 98]	**2000** [99, 01]
NYG	**1946** [45, 47]	**1956** [55, 57]			
PHI	**1960** [59, 61]	**1981** [80, 84]			
PIT	**1954** [53, 55]	**1969** [68, 70]			
SD	**1973** [72, 74]				
SF	**1956** [55, 57]	**1969** [68, 70]			
WAS	**1949** [48, 50]	**1962** [61, 63]	**1979** [78, 85]	**1996** [95, 97]	

*Brackets denote 90% confidence interval for break date

TABLE C.7: NFL Franchise Breakpoint Regression Results (Homogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4	α_5	β_5	α_6	β_6
ATL	-1245	50371	1091	8730								
t-value	*(-5.82)*[a]	*(7.04)*[a]	*(4.57)*[a]	*(0.87)*								
CHI	676	15070	384	29191								
t-value	*(2.54)*[b]	*(4.68)*[a]	*(14.48)*[a]	*(13.52)*[a]								
CIN	-1919	57851	924	31893	1130	17032						
t-value	*(-6.82)*[a]	*(17.05)*[a]	*(4.12)*[a]	*(6.12)*[a]	*(9.62)*[a]	*(3.93)*[a]						
DEN	-305	46621	167	61718								
t-value	*(-0.56)*	*(14.61)*[a]	*(4.10)*[a]	*(17.30)*[a]								
DET	598	15023	275	41217								
t-value	*(1.56)*	*(2.18)*[b]	*(3.68)*[a]	*(6.76)*[a]								
KC	-412	56030	3534	-12607	-246	78090	--963	109381				
t-value	*(-0.89)*	*(8.31)*[a]	*(7.28)*[a]	*(-1.17)*	*(-0.67)*	*(5.75)*[\a]	*(-0.45)*	*(1.31)*				
MIA	-1548	42760	-1226	56659	1438	3444	-586	65925				
t-value	*(-5.34)*[a]	*(7.56)*[a]	*(-1.53)*	*(3.63)*[a]	*(1.99)*[b]	*(0.21)*	*(-2.81)*[a]	*(9.21)*[a]				
MIN	415	29508	-187	40584	1547	11300	57	45857	872	21181	-287	68974
t-value	*(0.59)*	*(12.24)*[a]	*(-2.26)*[b]	*(19.88)*[a]	*(3.07)*[a]	*(0.90)*	*(0.39)*	*(9.54)*[a]	*(1.42)*	*(0.89)*	*(-1.53)*	*(8.40)*[a]
NYG	1949	23051	1101	10642	409	49055						
t-value	*(5.66)*[a]	*(4.93)*[a]	*(2.10)*[b]	*(1.13)*	*(8.91)*[a]	*(12.82)*[a]						
PHI	550	19724	276	54328	337	45599						
t-value	*(4.30)*[a]	*(7.04)*[a]	*(1.59)*	*(9.23)*[a]	*(3.38)*[a]	*(6.63)*[a]						
PIT	1049	9576	1125	-3326	380	29819						
t-value	*(8.07)*[a]	*(3.81)*[a]	*(5.06)*[a]	*(-0.50)*	*(8.03)*[a]	*(7.36)*[a]						
SD	1452	44667	691	36154								
t-value	*(0.92)*	*(8.26)*[a]	*(11.97)*[a]	*(9.33)*[a]								
SF	2322	18684	-2280	66132	640	22822						
t-value	*(2.96)*[a]	*(5.13)*[a]	*(-7.39)*[a]	*(14.34)*[a]	*(11.92)*[a]	*(5.57)*[a]						
WAS	767	26154	947	9420	389	39777	123	48198	1336	-4432		
t-value	*(3.81)*[a]	*(9.43)*[a]	*(5.24)*[a]	*(2.43)*[b]	*(2.83)*[a]	*(9.20)*[a]	*(1.02)*	*(6.72)*[a]	*(7.43)*[a]	*(-0.38)*		

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE C.8: NFL Franchise Balance and W% Coefficients (Homogeneous)

Team	*TL*	*PU*	*CSU*	*W%*	$\bar{R}^2$ (R^2)	*Team*	*TL*	*PU*	*CSU*	*W%*	$\bar{R}^2$ (R^2)
ATL	8275	-16767	7202	9505	0.693	***MIN***	3366	8211	25	6647	0.978
t-value	*(2.64)***	*(-0.64)*	*(1.38)*	*(1.74)*	*(0.743)*	*t-value*	*(4.01)****	*(1.37)*	*(0.02)*	*(4.63)****	*(0.985)*
CHI	1636	-4752	425	9096	0.935	***NYG***	-198	-15351	-5566	6315	0.938
t-value	*(1.38)*	*(-0.57)*	*(0.26)*	*(4.66)****	*(0.941)*	*t-value*	*(-0.11)*	*(-1.25)*	*(-2.25)***	*(2.16)***	*(0.945)*
CIN	1100	9938	-3166	7810	0.860	***PHI***	-2074	-13182	-6577	8210	0.955
t-value	*(0.81)*	*(0.83)*	*(-1.45)*	*(3.14)****	*(0.893)*	*t-value*	*(-1.10)*	*(-1.28)*	*(-3.00)****	*(3.30)****	*(0.960)*
DEN	4239	-2027	-758	6191	0.944	***PIT***	1265	4641	-4189	4852	0.956
t-value	*(3.35)****	*(-0.18)*	*(-0.41)*	*(2.23)***	*(0.954)*	*t-value*	*(0.88)*	*(0.51)*	*(-2.24)***	*(1.89)**	*(0.961)*
DET	3662	-25454	-5232	14327	0.823	***SD***	-893	-22352	-3290	13895	0.847
t-value	*(1.23)*	*(-1.31)*	*(-1.27)*	*(2.84)****	*(0.839)*	*t-value*	*(-0.44)*	*(-1.39)*	*(-1.05)*	*(3.89)****	*(0.874)*
KC	19	50978	-15610	10047	0.884	***SF***	1954	26203	-937	9257	0.903
t-value	*(0.01)*	*(2.24)***	*(-3.34)****	*(1.88)**	*(0.917)*	*t-value*	*(1.13)*	*(1.93)**	*(-0.36)*	*(3.71)****	*(0.918)*
MIA	9588	72620	-2808	16792	0.869	***WAS***	-2294	-13878	-2682	5200	0.986
t-value	*(4.78)****	*(5.22)****	*(-0.86)*	*(4.49)****	*(0.906)*	*t-value*	*(-1.96)**	*(-2.13)***	*(-1.80)**	*(2.56)***	*(0.988)*

*** Significant at the 99% critical level
** Significant at the 95% critical level
** Significant at the 90% critical level

APPENDIX D

NATIONAL HOCKEY LEAGUE FRANCHISE ALTERNATIVE MODELS

TABLE D.1: NHL Franchise **Model B** Break Point Sequential Test Results (Heterogeneous)

Team	*SupF$_t$(1)*	*SupF$_t$(2)*	*SupF$_t$(3)*	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*Breaks*
BOS	61.21***	49.54***	55.73***	61.21***	92.91***	17.00***	7.39	**2**
CHI	18.16***	26.16***	20.82***	26.16***	34.70***	14.54**	15.50**	**2**
DET	139.43***	64.50***	41.79***	139.43***	139.43***	6.52	6.52	**1**
LAK	9.79*	19.99***		19.99***	27.83***	17.45***		**2**
NYR	75.19***	63.49***	49.74***	75.19***	83.82***	50.90***	5.18	**2**
PHI	7.17	35.77***		35.77***	49.81***	156.23***		**0**
STL	27.41***	19.41***		27.41***	27.41***	9.25*		**1**

"***" Significant at the 99% critical level
"**" Significant at the 95% critical level
"*" Significant at the 90% critical level

TABLE D.2: NHL Franchise **Model B** Break Dates (Heterogeneous)

Team	T_1	T_2
BOS	**1975-1976** [74-75, 76-77]	**1998-1999** [95-96, 01-02]
CHI	**1967-1968** [66-67, 68-69]	**1981-1982** [80-81, 82-83]
DET	**1982-1983** [81-82, 83-84]	
LAK	**1986-1987** [85-86, 87-88]	**1997-1998** [96-97, 01-02]
NYR	**1976-1977** [75-76, 77-78]	**1991-1992** [90-91, 94-95]
STL	**1985-86** [84-85, 89-90]	

*Brackets denote 90% confidence interval for break date

TABLE D.3: NHL Franchise **Model B** Breakpoint Regression Results (Heterogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3
BOS	148	7957	223	2238	103	7467
t-value	*(5.60)****	*(11.00)****	*(7.51)****	*(1.45)*	*(1.35)*	*(1.79)**
CHI	187	566	-350	10628	26	4482
t-value	*(2.06)***	*(0.47)*	*(-3.45)****	*(3.52)****	*(0.79)*	*(1.88)**
DET	143	6726	-28	15966		
t-value	*(6.35)****	*(6.06)****	*(-1.01)*	*(14.03)****		
LAK	94	5788	-265	17833	170	6605
t-value	*(2.44)***	*(5.45)****	*(-3.20)****	*(6.14)****	*(1.84)**	*(1.58)*
NYR	295	8545	-111	18531	21	14898
t-value	*(17.25)****	*(13.33)****	*(-3.04)****	*(12.57)****	*(0.88)*	*(9.77)****
STL	-353	8094	141	1487		
t-value	*(-4.98)****	*(4.10)****	*(2.86)****	*(0.51)*		

"***", "**", "*" Indicate significance at the 99%, 95% and 90% critical level, respectively/
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE D.4: NHL Franchise **Model B** Balance and W% Coefficients (Heterogeneous)

Team	***TL***	***PU***	***CSU***	***W%***	***L1(W%)***	$\bar{R}^2$ (R^2)
BOS	320	9438	-644	2377	2693	0.842
t-value	*(0.70)*	*(1.98)***	*(-1.34)*	*(1.92)**	*(2.18)***	*(0.870)*
CHI	2534	26078	-1210	11814	6347	0.865
t-value	*(3.47)****	*(3.34)****	*(-1.57)*	*(5.58)****	*(2.87)****	*(0.888)*
DET	267	-5121	-368	5633	2954	0.953
t-value	*(0.58)*	*(-1.01)*	*(-0.80)*	*(4.17)****	*(2.11)***	*(0.959)*
LAK	-420	-526	81	5164	3659	0.923
t-value	*(-0.75)*	*(-0.08)*	*(0.12)*	*(3.00)****	*(2.16)***	*(0.942)*
NYR	167	1657	-366	3406	892	0.953
t-value	*(0.55)*	*(0.51)*	*(-1.16)*	*(3.60)****	*(0.88)*	*(0.961)*
STL	1112	9454	1831	9273	8268	0.688
t-value	*(1.20)*	*(0.89)*	*(1.67)*	*(3.18)****	*(2.93)****	*(0.749)*

*** Significant at the 99% critical level
** Significant at the 95% critical level
** Significant at the 90% critical level

TABLE D.5: NHL Franchise Break Point Sequential Test Results (Homogeneous)

Team	$SupF_t(1)$	$SupF_t(2)$	$SupF_t(3)$	$SupF_t(4)$	$SupF_t(5)$	*UDmax*	*WDmax*	*SupF(2/1)*	*SupF(3/2)*	*SupF(4/3)*	*SupF(5/4)*	*Breaks*
BOS	53.99[a]	36.71[a]	27.98[a]	27.41[a]	25.84[a]	53.99[a]	53.99[a]	22.74[a]	9.06	7.38	7.38	**2**
CHI	12.52[b]	17.99[a]	24.67[a]	28.57[a]	29.67[a]	29.67[a]	54.34[a]	10.99[c]	17.36[b]	63.00[a]	39.29[a]	**3**
DET	87.78[a]	56.57[a]	65.21[a]	69.92[a]	69.99[a]	87.78[a]	128.17[a]	74.34[a]	74.34[a]	11.79	13.17	**2**
LAK	9.81	24.22[a]	30.46[a]	34.53[a]	36.81[a]	36.81[a]	67.42[a]	41.24[a]	124.09[a]	124.09[a]	124.09[a]	**0**
NYR	101.43[a]	87.35[a]	73.25[a]	62.13[a]	52.95[a]	101.43[a]	109.63[a]	57.64[a]	15.06[b]	16.22[b]	17.43[b]	**3**
PHI	33.76[a]	128.13[a]	91.90[a]	74.79[a]	81.11[a]	128.13[a]	160.81[a]	220.58[a]	5.90	76.95[a]	5.76	**3**
STL	58.09[a]	76.20[a]	87.51[a]	52.74[a]	50.42[a]	87.51[a]	127.42[a]	15.34[b]	27.26[a]	15.61[b]	17.52[b]	**2**

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level

TABLE D.6: NHL Franchise Break Dates (Homogeneous)

Team	T_1	T_2	T_3
BOS	**1975-76** [74-75, 76-77]	**1999-00** [97-98, 02-03]	
CHI	**1963-64** [59-60, 64-65]	**1976-77** [75-76, 77-78]	**1982-83** [81-82, 83-84]
DET	**1982-83** [81-82, 83-84]	**1987-88** [86-87, 88-89]	
NYR	**1975-76** [74-75, 76-77]	**1990-91** [89-90, 91-92]	**1997-98** [96-97, 98-99]
PHI	**1970-71** [69-70, 71-72]	**1974-75** [73-74, 75-76]	**1995-96** [94-95, 96-97]
STL	**1975-76** [74-75, 76-77]	**1989-90** [85-86, 90-91]	

*Brackets denote 90% confidence interval for break date

TABLE D.7: NHL Franchise Breakpoint Regression Results (Homogeneous)

Team	α_1	β_1	α_2	β_2	α_3	β_3	α_4	β_4
BOS	156	8322	236	2506	216	1962		
t-value	*(a6.05)*[a]	*(12.05)*[a]	*(8.40)*[a]	*(1.71)*	*(2.48)*[b]	*(0.41)*		
CHI	213	1973	-104	7743	685	-16394	-8	8124
t-value	*(1.80)*[c]	*(1.68)*	*(-1.09)*	*(3.20)*[a]	*(2.26)*[b]	*(-1.88)*[c]	*(-0.25)*	*(3.81)*[a]
DET	110	8711	502	-959	-27	18252		
t-value	*(5.56)*[a]	*(8.92)*[a]	*(1.82)*[c]	*(-0.10)*	*(-0.99)*	*(11.57)*[a]		
NYR	300	8897	106	18806	306	2790	-44	18852
t-value	*(16.85)*[a]	*(16.67)*[a]	*(-2.94)*[a]	*(14.02)*[a]	*(3.01)*[a]	*(0.62)*	*(-1.00)*	(7.96)[a]
PHI	1757	7783	899	10542	-1	17380	-2	19681
t-value	*(11.05)*[a]	*(15.12)*[a]	*(5.83)*[a]	*(11.04)*[a]	*(-0.06)*	*(30.12)*[a]	*(-0.12)*	*(21.39)*[a]
STL	421	5197	-730	93	4815			
t-value	*(1.81)*[c]	*(2.89)*[a]	*(1.92)*[c]	*(-0.26)*	*(1.59)*	*(1.58)*		

a. Significant at the 99% critical level
b. Significant at the 95% critical level
c. Significant at the 90% critical level
α_M *and* β_M refer to the slope and intercept coefficients for regime M, respectively

TABLE D.8: NHL Franchise Balance and W% Coefficients (Homogeneous)

Team	***TL***	***PU***	***CSU***	***W%***	$\bar{R}^2$ (R^2)
BOS	-22	8678	-493	4115	0.845
t-value	*(-0.05)*	*(1.85)**	*(-1.06)*	*(4.06)****	*(0.869)*
CHI	2111	22530	-1476	15176	0.859
t-value	*(2.87)****	*(2.87)****	*(-1.93)**	*(7.38)****	*(0.887)*
DET	-166	-2642	-318	5238	0.954
t-value	*(-0.35)*	*(-0.52)*	*(-0.69)*	*(3.87)****	*(0.962)*
NYR	-2	1950	-629	3829	0.954
t-value	*(-0.01)*	*(0.62)*	*(-1.97)***	*(4.06)****	*(0.963)*
PHI	49	-4257	-240	311	0.985
t-value	*(0.29)*	*(-1.82)**	*(-0.83)*	*(0.49)*	*(0.989)*
STL	1004	25782	3189	11852	0.765
t-value	*(1.14)*	*(2.36)***	*(2.93)****	*(4.56)****	*(0.816)*

*** Significant at the 99% critical level
** Significant at the 95% critical level
** Significant at the 90% critical level

APPENDIX E

CALCULATION OF VARIABLES

- **LAPG**: League Average Attendance Per Game is calculated by the following formula:

$$LAPG = \frac{1}{TN}\sum_{t=1}^{T} Att_t.$$

In this representation, T indicates the total number of teams and N the number of games for the given season. Because there are two teams participating in each game, this total number of games must be divided by two for the total number of home games played for the league in the given year. Att_t represents the total attendance for team *t* for the given season, and aggregate league attendance is simply the sum of all these team totals.

- **TAPG**: Team Average Attendance Per Game is calculated similarly to LAPG, but must account for possible variation in the number of home games for each team (which differs in some seasons). Therefore, TAPG is calculated from the using,

$$TAPG = \frac{1}{H}\sum_{i=1}^{H} Att_i.$$

With *i* indexing each home game for the given team in a given season and *H* representing the total number of home games for the team under consideration.

- **Win Percent**: Win percent is calculated in the usual way, dividing the total number of wins by the total number of games played for each team in each season. However, it is important to note the treatment of ties. In any league, ties are considered half a win for each team participating in the contest that ended in such a way. Therefore, Win Percent comes from,

$$WP = \frac{W + 0.5(D)}{N}$$

In this representation, *W* and *D* are the number of wins and ties (draws) by a given team in a given season. The length of the season (total number of games) is in the denominator as *N*.

- **Game Uncertainty**: *Tail Likelihood* is defined as in Lee (2004), and consists of the sum of the likelihood of the winning percentages of the top and bottom 20% of teams that occurred in the idealized normal distribution from:

$$TL = \sum_{r} f(Z_r),$$

where r indexes the rank number of top and bottom teams as a percentage of teams in the league (i.e. 20% of a 10 team league would result in using the First and Second and Ninth and Tenth ranked teams' winning percentages in the league as each 'tail'), and the function, $f(\cdot)$ is the standard normal probability density function. Z_r represents the z-score of each team's winning percentage compared to a perfectly balanced league, or

$$Z_r = \frac{(WP_r - .500)}{\sigma}.$$

And σ represents the idealized standard deviation under a perfectly balanced league from the binomial-based calculation,

$$\sigma = \frac{0.5}{\sqrt{N}}$$

With *N* representing the season length for the given season. The index, r, is not always an integer, as 20% of the total number of teams in a league may not be an integer. For example, if there are 14 teams in a given league, the top and bottom tails would be represented by ranks 1, 2, and 2.8 and 14, 13 and 12.2, respectively. Therefore, for ranks such as 2.8 and 12.2, WP_i is calculated using a weighted average of the win percent of teams ranked 2nd and 3rd, and 12th and 13th, respectively. *TL* and all other balance measures are calculated separately for the AL and NL in Major League Baseball, and use the entire league for NBA, NFL and NHL, respectively.

- **Playoff Uncertainty**: *WinDiff* is defined differently depending on the league playoff structure and season in question. For a league without wild cards in which only the winner of each division is awarded a playoff berth, PU is calculated by,

$$\frac{1}{n}\sum_{i=1}^{n} WP_{i1} - WP_{i2},$$

Where WP_1 *and* WP_2 represent the respective 1st and 2nd ranked teams in each division, i indexes each division, and n is the number of divisions in the given league. With wild cards, the above equation is adjusted to include an additional difference in win percent of the first team out and the last team in the playoffs. Additionally, if multiple wild cards are required to come from each division, then additional win percent differences are included in the calculation. For a full description of the changes in playoff structures across leagues and time, see Appendices 2 through 5.

- **<u>Consecutive Season Uncertainty</u>**: *Corr3* is calculated by correlating the current year's team win percents with the average win percent for each team in the 3 years prior to the current season. In other words, it is the correlation of two paired vectors containing the WP_{ti} and $W3_{ti}$ described by:

$$WP_{i,t} = W\% \; in \; Year \; i \; for \; Team \; t, \qquad and \; \mu(W3_{i,t}) = \frac{1}{n}\sum_{s=t-3}^{t-1} WP_{i,s}.$$

Here, t indexes the current year and $n = 3$. The subscript i indexes the team for which each calculation is made. For *each* year under analysis, *Corr3* is described by,

$$Corr_i = Cor(WP, W3)$$

$$Cor(WP, W3) = \frac{n\sum WP_{i,t}\mu(W3_{i,t}) - \sum WP_{i,t}\sum \mu(W3_{i,t})}{\sqrt{n\sum WP_{i,t}^2 - \left(\sum WP_{i,t}\right)^2}\sqrt{n\sum \mu(W3_{i,t}^2) - (\sum \mu(W3_{i,t}))^2}},$$

Where here *n* is the number of teams in year *t* for the league.

- **<u>Competitive Balance Ratio</u>**: *CBR* (2002) is taken directly from Humphreys (2002) description as a ratio of within and across season balance for a given league. Beginning with the across season standard deviation,

$$\sigma_{T,i} = \sqrt{\frac{\sum_t (WP_{i,t} - \overline{WP}_{i,T})^2}{T}},$$

where the second term in the numerator is each team's average won-loss percentage during T seasons (from 1 to T). As Humphreys describes, there will be a vector of $\sigma_{T,i}$, one for each team in the league, and the smaller the value of $\sigma_{T,i}$, the less the variation in team *i*'s winning percentage during the seasons under analysis.

Following with the within-season variation in win-loss percentage, Humphreys defines a simple standard deviation such that,

$$\sigma_{N,t} = \sqrt{\frac{\sum_t (WP_{i,t} - 0.500)^2}{N}}.$$

Here, $\sigma_{N,t}$ is a vector with one value for each season. Each of these vectors is then averaged across all teams and all seasons, respectively:

$$\bar{\sigma}_T = \frac{\sum_i \sigma_{T,i}}{N}, \qquad \bar{\sigma}_N = \frac{\sum_i \sigma_{N,t}}{T}.$$

Finally, the competitive balance ratio is constructed using these averaged values,

$$CBR = \frac{\bar{\sigma}_T}{\bar{\sigma}_N}.$$

APPENDIX F

NATIONAL BASKETBALL ASSOCIATION (NBA) PLAYOFF UNCERTAINTY CALCULATION

Season	Calculation Details
2006/07 to 2009/10:	Average Difference between Top 2 in each Division (3 Divs) for East and West Average Difference between 8 and 9 seed (Last Playoff Spot) for East and West
2004/05 to 2005/06:	Average Difference between Top 2 in each Division (3 Divs) for East and West Average Difference between 8 and 9 seed (Last Playoff Spot) for East and West
1983/84 to 2003/04:	Average Difference between Top 2 in each Division (2 Divs) for East and West Average Difference between 8 and 9 seed (Last Playoff Spot) for East and West
1976/77 to 1982/83:	Average Difference between Top 2 in each Division (2 Divs) for East and West Average Difference between 6 and 7 seed (Last Playoff Spot) for East and West
1974/75 to 1975/76:	Average Difference between Top 2 in each Division (2 Divs) for East and West Average Difference between Last 2 in contention for Playoff Spot for East and West
1970/71 to 1973/74:	Average Difference between Top 2 in each Division (2 Divs) for East and West Average Difference between 2nd and 3rd in each Division (2 Teams from each Div) for East and West
1966/67 to 1969/70:	Average Difference between 1st and 2nd place (Conference Reg. Season Champ) for East and West Average Difference between 4 and 5 seed (Last Playoff Spot) for East and West
1955/56 to 1965/66:	Average Difference between 1st and 2nd place (Conference Reg. Season Champ) for East and West Average Difference between 3 and 4 seed (Last Playoff Spot) for East and West

APPENDIX G

NATIONAL FOOTBALL LEAGUE (NFL) PLAYOFF UNCERTAINTY CALCULATION

Season	**Calculation Details**
2002 to 2009:	Average of difference between Each 8 Division Winners and Runner-Up and difference between Last WC Berth (6th) and Runner-Up (7th) for NFC and AFC
1990 to 2001:	Average of difference between Each 6 Division Winners and Runner-Up and difference between Last WC Berth (6th) and Runner-Up (7th) for NFC and AFC
1983 to 1989:	Average of difference between Each 6 Division Winners and Runner-Up and difference between Last WC Berth (5th) and Runner-Up (6th) for NFC and AFC
1982:	Average of difference between Each 6 Division Winners and Runner-Up and difference between Last WC Berth (8th) and Runner-Up (9th) for NFC and AFC
1978 to 1981:	Average of difference between Each 6 Division Winners and Runner-Up and difference between Last WC Berth (5th) and Runner-Up (6th) for NFC and AFC
1970 to 1977:	Average of difference between Each 6 Division Winners and Runner-Up and difference of WC Team (4th) and WC Runner-Up (5th) for NFC and AFC
1967 to 1969:	Average of difference between Each 4 Division Winners (Capital, Century, Coastal, Central) and Runner-Up in NFL
1953 to 1966:	Average of difference between Each 2 Division Winners (East, West) and Runner-Up in NFL
1950 to 1952	Average of difference between Each 2 Division Winners (American, National) and Runner-Up in NFL
1933 to 1949	Average of difference between Each 2 Division Winners (East, West) and Runner-Up in NFL
1922 to 1932	Difference between NFL Regular Season Champion and Runner-Up

APPENDIX H

NATIONAL HOCKEY LEAGUE (NHL) PLAYOFF UNCERTAINTY CALCULATION

Season	Calculation Details
1998/99 to 2009/10:	Average of difference between Each 6 Division Winners and Runner-Up and difference between Last Playoff Slot (8th) and Runner-Up (9th) for East and West Conferences
1993/94 to 1997/98:	Average of difference between Each 4 Division Winners and Runner-Up and difference between Last Playoff Slot (8th) and Runner-Up (9th) for East and West Conferences
1981/82 to 1992/93:	Average of difference between Each 4 Division Winners and Runner-Up and difference between Last Divisional Playoff Slot (4th in Div.) and Runner-Up (5th in Div.) in Each Division for Clarence-Campbell and Prince of Wales Conferences
1979/80 to 1980/81	Average of difference between Each 4 Division Winners and Runner-Up and difference between Last Playoff Slot (8th) and Runner-Up (9th) for Clarence-Campbell and Prince of Wales Conferences
1977/78 to 1978/79:	Average of difference between Each 4 Division Winners and Runner-Up and difference between Last Playoff Slot (6th) and Runner-Up (7th) for Clarence-Campbell and Prince of Wales Conferences
1974/75 to 1976/77:	Average of difference between Each 4 Division Winners and Runner-Up and difference between Last Divisional Playoff Slot (3rd in Div.) and Runner-Up (4th in Div.) in Each Division for Clarence-Campbell and Prince of Wales Conferences
1967/68 to 1973/74:	Average of difference between Each 4 Division Winners and Runner-Up and difference between Last Divisional Playoff Slot (4th in Div.) and Runner-Up (5th in Div.) in Each Division for East and West Conferences
1942/43 to 1966/67:	Average of difference between Regular Season Champion and Runner-Up and difference between Last Playoff Slot (4th) and Runner-Up (5th)
1938/39 to 1941/42	Average of difference between Regular Season Champion and Runner-Up and difference between Last Playoff Slot (6th) and Runner-Up (7th)
1926/27 to 1937/38	Average of difference between Each 2 Division Winners and Runner-Up and difference between Last Divisional Playoff Slot (3rd in Div.) and Runner-Up (4th in Div.) in American and Canadian Divisions

APPENDIX I

MAJOR LEAGUE BASEBALL (MLB) PLAYOFF UNCERTAINTY CALCULATION

Season	**Calculation Details**
1995 to 2009:	Average Difference between 1st and 2nd place for East, Central and West Divisions in NL & Average Difference between 4^{th} and 5^{th} seed (Last Playoff Spot) in the NL
	Average Difference between 1st and 2nd place for East, Central and West Divisions in AL & Average Difference between 4^{th} and 5^{th} seed (Last Playoff Spot) in the AL
1994 (*no playoffs*):	Average Difference between 1st and 2nd place for East, Central and West Divisions in NL & Average Difference between 4^{th} and 5^{th} seed (Last Playoff Spot) in the NL ***(at strike)***
	Average Difference between 1st and 2nd place for East, Central and West Divisions in AL & Average Difference between 4^{th} and 5^{th} seed (Last Playoff Spot) in the AL ***(at strike)***
1981 to 1993:	Average Difference between 1st and 2nd place for East and West Divisions in NL
	Average Difference between 1st and 2nd place for East and West Divisions in AL
1980:	Average Difference between 1st and 2nd place for East and West Divisions in NL for both season halves Average Difference between 1st and 2nd place for East and West Divisions in AL for both season halves
1969 to 1980:	Average Difference between 1st and 2nd place for East and West Divisions in NL
	Average Difference between 1st and 2nd place for East and West Divisions in AL
1901 to 1968:	Difference between 1st and 2nd place in NL
	Difference between 1st and 2nd place in AL

APPENDIX J

YEARS WITH MISSING OR LIMITED ATTENDANCE DATA (NBA, NFL, NHL)

NBA

Boston Celtics (BOS): 1977/78

NFL

All Teams (NFL): 1992 & 1998
Chicago Bears (CHI): 1961 & 1962
Green Bay Packers (GB): 1952
New York Giants (NYG): 1953 & 1958
Philadelphia Eagles (PHI): 1938
Pittsburgh Steelers (PIT): 1938, 1944, 1951-1953, 1957 & 1965
Washington Redskins (WAS): 1938-1939, 1951, 1957, 1960, 1962 & 1965

NHL

Boston Bruins (BOS): 1961/62
Chicago Blackhawks (CHI): 1956/57-1961/62, 1970/71-1972/73 & 1975/76-1976/77
Montreal Canadiens (MON): 1958/59-1961/62 & 1986/87-1988/89
New York Rangers (NYR): 1961/62 & 1986/87-1988/89
Toronto Maple Leafs (TOR): 1959/60-1961/62 & 1986/87-1987/88

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