THREE ESSAYS ON ECONOMIC BEHAVIOR OF BUSINESS IN THE U.S. SPORTS INDUSTRY

by

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ABSTRACT

This dissertation explores economic behavior of producers in the U.S. sports industry. The fundamental research questions are: (1) Can business efficiently operate under competitive and noncompetitive environment? (2) Whether or not the difference in competitive abilities leads to industry consolidation? This dissertation uses three cases to investigate the research questions at different angles. The first essay studies the managerial efficiencies in the Major League Baseball using Stochastic Frontier regressions. It discovers that cost efficiency is not related to wins. Although, cost inefficiency is associated with teams that spend more on players, especially pitchers, who is found to be less important to team wins. What more related to victories are the amount of money put in the payrolls and how efficient teams use players to produce wins. However, the technical inefficiency has grown bigger in the recent years. The second essay explores the bidding behavior of National Basketball Association teams for free-agent players, using a comparison of marginal revenue and marginal cost of wins as the judgment. Contradicts other studies that compare salaries with marginal revenue product of players, this study finds that the "winner's curse" does not exist and that teams do not over spend on players. The reason wages are higher than the marginal revenue product can be because of the bargaining power the player union exercised over the shares of teams' fixed income to raise players' salaries. The final essay studies the advertising behavior of the ski industry using the Choice-Base Conjoint analysis. It discovers that smaller ski resorts are less competitive as they face budget constraint. They do not try to compete with bigger operators and could be the reason why the number of ski resorts in the U.S., especially the small ones, has been shrinking recently.

For every drop of sweat my parents have shed

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CHAPTER 1

INTRODUCTION

Economics is a social science. Economics theories involve the study of behaviors. The two main agents are consumers and producers. While many economic studies focus on the consumer side, the studies in producer side are less common due to the lack of data. Many theories remain theories without sufficient proofs, while many of the proven producer theories are studied in laboratory setups. Fortunately, the sports industry provides a real world environment that researchers can use as the experiment not only in consumer studies, but also in the producer studies. Although the U.S. professional sports industry does not play a crucial role in the Gross Domestic Product (GDP), it is rich with data suitable for producer behaviors researches. Above all, it is of interest of society: Students play sports in school; there are sport channels on television; people speak of sports in daily life.

The main problems of studies involving business sector are the lack of data. Businesses are very sensitive to information. In the competitive environment, data are valuable, and hence, kept confidential from competitors. Unfortunately, this means that the availability of data to researchers is also limited. Unlike other businesses, major league sport teams publish a wide variety of data to public. These data include the production resources such as players' salaries, and the output of production such as winning percentage. Many financial data are publicly available, which is not common to other types of businesses. At the same time, the different types of market powers seen throughout the sports industry provide opportunity to examine economic theories in different scenarios. As a result, this dissertation uses the U.S. sports industry as the real world experimental laboratory to study the business' economic behaviors.

Talking about the producer theories, one cannot deny that the main assumption is that businesses are rational. They all try to either maximize profits or minimize costs of production. These two practices which can be achieved at various levels depend on the ability of the businesses to exercise their powers. This ability is determined by the competition in the industry. The more competition, the less power.

The structure of this dissertation is as follows. The first two chapters focus on the environment where the industry is more competitive. The first chapter, "Efficiency Examinations in the Major League Baseball: Stochastic Frontier Analyses," studies the relative efficiency in the Major League Baseball (MLB) teams' management. This study uses the stochastic frontier regression to discover the production efficiencies, namely technical efficiency, the ability of teams to maximize wins given combinations of talents, and allocative efficiency, the ability of teams to minimize cost given the levels of wins and acquiring costs of talents. The finding shows that there exists some level of technical inefficiency in the National League, and allocative inefficiency in the American League that can be improved by a better resource allocation. Although, the result of the study indicates that only technical efficiency and team's payroll are related to wins.

The second chapter, "The Winner's Curse in the Market for Free-Agent NBA Players," explores the absolute cost efficiency in the bidding process for players of the National Basketball Association (NBA) teams. As the competition for talent becomes crucial for the competition for wins that can influence team revenue, there is a possibility that teams will fall victims to the "winner's curse" where they pay players too much in comparison to the benefit that they can reap from the players. The result contradicts the theory and previous literature. This study does not find that NBA teams are victims of the winner's curse. Instead teams pay players less than their revenue contributions. The seem-to-be-overpaid salaries needs not being a result of the winner's curse. It may be because of the bargaining power exercised by the player union that countervails the bargaining power of the league over the share of fixed revenue, which is a part of revenue that is independent of teams' performance.

The focus then shifts to the less competitive environment of the U.S. ski resort industry. The final chapter, "Advertising Behavior in the U.S. Ski Industry: An Applied Conjoint Analysis Method," incorporates the Choice-Based Conjoint Analysis (CBC) of consumer choice-selection studies into the study of business' competitive strategies selection. The study focuses on advertising behavior of ski resorts with different financial constraints. The results indicate that ski resorts of different sizes have different competitive behaviors, in which the bigger resorts are more aggressive in competition.

CHAPTER 2

EFFICIENCY EXAMINATIONS IN THE MAJOR LEAGUE BASEBALL: STOCHASTIC FRONTIER ANALYSES

2.1 Introduction

Despite being an entertaining sport, the Major League Baseball (MLB) generates millions of dollar each year to teams' owners. The business of baseball involves conversion of fans' love to revenue. In the production process, baseball teams produce games from inputs: players and staffs. Winning is the key to economic success of every team–it increases fans' spending on tickets, merchandises, media broadcasting rights, and so forth (H. F. Lewis, Sexton, & Lock, 2007). At the team level, hence, victory is the output produced from combinations of inputs, including players' talents, managerial skills, training budget, stadium facilities, and so forth.

Many studies attempt to discover the relationship between victory and inputs used under different setups and objectives, and figure out how wins relate to revenue (Burger & Walters, 2003; Hakes & Sauer, 2006; Jewell & Molina, 2004; M. B. Schmidt & Berri, 2002; Szymanski, 2003; Zech, 1981). In contrast, many focus on efficiency perspective of team management (Einolf, 2004; H. F. Lewis, Lock, & Sexton, 2009; H. F. Lewis et al., 2007; Porter & Scully, 1982). Most conclusions are similar–there is inefficiency in the MLB; teams in bigger markets tend to overspend on players.

This study aims to evaluate managerial efficiencies of MLB teams using the stochastic frontier analysis. A similar study that uses the same technique is that of Porter and Scully (1982) in which the authors use the 1961-1980 MLB seasons data to evaluate managerial efficiency of the MLB managers. They conclude that there is no significant difference in efficiency among teams' managers.[1] However, the market structure of the MLB has dramatically changed after the present of free agent contracts in 1977. Salaries of players have been increasing tremendously in the past few decades as a result. This leads to a question whether baseball managers are still efficiently exercising their budgets. As evidence from recent studies apply another efficiency assessment technique, the Data Envelopment Analysis (DEA), has shown that bigger teams spend much more on players than smaller teams but need not be more successful. There is a possibility that some teams, especially teams in bigger markets, are less efficient than others.

While this paper is in line with other efficiency-related studies, it fills the gap with another methodology that has not been pursued since there has been an adjustment in the league's market structure. Also, most stochastic frontier studies only focus on technical efficiency. This study includes allocative efficiency to improve understanding of managerial efficiencies. The outline of this paper is as follows. The next section discusses the theoretical background of the methodology and data used in this study. The following section presents results. The last section concludes.

2.2 Methodology

2.2.1 Theoretical Background

There are two aspects of efficiency measurement: technical efficiency and allocative efficiency. The former is the measurement in productive efficiency. The main idea is that the more efficient firm can produce more output than the less efficient firm, given the same level of input(s). In microeconomic theory, an efficient firm is a firm that uses the combination of inputs to produce the maximum output level given a particular technology. As a result, the production function represents the highest possible level of output (production possibility frontier) a firm can hope for. This highest possible output production is also applied to other firms in the same industry and technology. In other words, the production function of the most relatively efficient firm is the industry production function (Aigner & Chu, 1968).

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[1] The Stochastic Frontier Regression is used in efficiency examinations in other major league sports, such as English Soccer (Dawson, Dobson, & Gerrard, 2000a, 2000b) and the National Basketball Association (Lee & Berri, 2008) as well.

Allocative efficiency, on the other hand, considers the ability of the firm to minimize the cost of production at a given output level. A more efficient firm can produce the same level of output as the less efficient team at a lower cost. If input prices and input demand function are obtainable, by performing and analogous derivation in the dual cost function problem to the production function, one can achieve cost-efficiency frontier (Kumbhakar & Lovell, 2000).[2]

The stochastic frontier models were introduced by Aigner, Lovell, and Schmidt (1977) and Meeusen and van Den Broeck (1977). The analysis was developed to fit the context of production function. The econometricians had been using the Ordinary Least Square (OLS) to estimate production function prior to the introduction of the stochastic frontier analysis. However, the OLS contradicts the tenet of production function that is supposed to be the production possibility frontier or the highest possible output at a given input level. The OLS estimates the average production, not the most efficient production.

The stochastic frontier applies different assumptions by assuming that there is an inefficient factor in the error term. As a result, the "composed error" can be separated into two main components: idiosyncratic error and inefficient factor. The idiosyncratic error, which has the same definition as residual in the OLS, is a combined random factor contributing to lower production which is beyond the firms' control. The inefficiency factor is a factor that lead to lower production; this factor is controllable by firms but is not efficiently controlled. Coelli, Rao, and Battese (1998) and Kumbhakar and Lovell (2000) provide great details of the stochastic frontier analysis. Greene (2011) also describes mathematical derivations of the analysis in details.

A stochastic frontier function $f(x_i, \beta)$ can be written as

$$y_i = \beta_0 + \beta_x \mathbb{X}_i + v_i \mp u_i \tag{2.1}$$

where y_i is the performance of the firm (output level, which assumes to be strictly positive, for production function or cost for cost function), $\mathbb{X}_i$ is a vector of inputs (and output for cost function), and v_i is the two-sided noise or the idiosyncratic component of the error. The term u_i is the nonnegative technical inefficiency component of the error term for the frontier production which indicates that inefficient firms produce less output than

[2] A detailed discussion of technical efficiency and allocative efficiency can be found in Appendix A.

the efficient firm, or nonpositive for the frontier cost function which implies that the inefficient firms use higher cost of production than the efficient firm. The estimation from the stochastic frontier approach, hence, represents the upper bound of production of the production possibility frontier.

Although, the stochastic frontier analysis is very useful, there is another commonly used technique for efficiency estimation, the linear programing Data Envelopment Analysis (DEA) method. The two approaches produce frontier of production with different assumptions and techniques. They are not superior to one another but have different advantages and disadvantages.

Measurement error, other noise, and outliers may influence the shape and position of the frontier in the DEA method. This problem is less an issue in the stochastic frontier model because the stochastic frontier separates the random error clearly from the inefficient factor. The exclusion of an important input or output can result in biased results under the DEA. In this regard, the stochastic frontier allows the tests of hypotheses regarding the significance of the inputs, the existence of inefficiency, and the structure of the production technology.

The stochastic frontier method, however, is only well-developed for single-output technologies. The production technology must be specified by a particular functional form which might affect the estimation. In general, the stochastic frontier approach is more appropriate in the study where the data might contain heavily measurement error that is a major drawback of the DEA. Although, it might not be suitable for a study in which multiple-output production is important, prices are difficult to define, behavioral assumption such as cost minimization or profit maximization are difficult to justify (Coelli et al., 1998).

In the context of MLB, one can consider the winning percentage from a given combination of offensive and defensive skills as the production function of the industry. Although the data in the baseball industry are accurate, the DEA method might not be necessary since it is an only single-output production. An assumption for this study requires cost minimization to test the hypotheses of inefficiency, as a result, the stochastic frontier analysis seems to be a more appropriate method for estimations.

It shall be remarked that the stochastic frontier analyses need extra attention when it comes to the interpretations of results. The efficiency scores are only "relative efficiency"–it is efficiency among the sample group which is different from the "absolute efficiency." The efficient firm under the conclusion of the stochastic frontier analysis (and the DEA) needs not be absolutely efficient–the firm might use a better technique than other firms in the sample but that technology may not be the best. This also means that the efficiency scores are estimated in comparison with other firms within the group of samples and shall not be compared across sample groups. For example, a higher efficiency score observed in a team in the National League does not say that the team is more efficient than a team with a lower efficiency score from the American League. Finally, the model does not take in consideration the external environmental differences and may give misleading indication of relative managerial competence (Coelli et al., 1998).

Despite the usefulness of the stochastic frontier model, there exist difficulties. First, the technical inefficiency of a firm, although can be estimated, is not consistent due to the fact that the variance of distribution of inefficiency is conditional on the whole error term. Second, the specific assumptions about distribution of the inefficiency and the noise must be specified. Third, the inefficiency is assumed to be uncorrelated with the regressors which may or may not be true. These problems can be overcome if the panel data are presented (P. Schmidt & Sickles, 1984).

Given the nature of the dataset that are obtained from the whole sample group of the MLB team, the fixed effect regression seems to be a more appropriate tool for the analyses of both technical and allocative efficiency. The Fixed Effect (FE) model is taken in the form of

$$y_{it} = \beta_0 + \beta_x \mathbb{X}_{it} + v_{it} \mp u_i \tag{2.2}$$

where y_{it} is the performance (production or cost) of team i in season t, $\mathbb{X}_{it}$ is the vector of time-variant factors (inputs or input prices and output level), v_{it} is the statistical noise and u_i is the time-invariant inefficiency parameter that takes different sign depends on function (minus for production function and plus for cost function). This model can be simplified as

$$y_{it} = \alpha_i + \beta_x \mathbb{X}_{it} + v_{it} \tag{2.3}$$

where $\alpha_i = \beta_0 \mp u_i$. In other words, it is the team-specific effect that captures inefficiency of the team.

For efficiency analyses, the fixed effect model has been criticized due to the time-invariant assumption. Also, the model cannot separate the inefficiency parameter from the time-invariant heterogeneity factor of each team. The intercept β_{0i} is considered as the inefficiency factor which may not be true. The stochastic frontier analyses on the panel data have been developed to separate the individual effect from the inefficiency factor such that

$$y_{it} = \alpha_i + \beta_x \mathbb{X}_{it} + v_{it} \pm u_{it} \tag{2.4}$$

where α_i is team-specific intercept in this case and u_{it} is the time-variant inefficiency.[3] As for the stochastic production frontier analysis, the identical temporal variation assumption shall not be used since the outcome of the game is zero-sum.[4] Stochastic frontier models that permit the team-specific temporal variation in efficiency are recommended by Lee and Berri (2008) for sports team analysis. So, the following stochastic production frontier analysis in this study is based on the time-varying, fixed effect models developed by Cornwell, Schmidt, and Sickles (1990) (from now on this model will be referred as FECSS model), which is the most suitable with the nature of the industry.

The estimation of FECSS is based on the following equation:

$$y_{it} = \beta_0 + \beta_x \mathbb{X}_{it} + v_{it} - u_{it} \tag{2.5}$$

where y_{it} is output level of firm i at time t, $\mathbb{X}_{it}$ is the input vector of firm i at time t, v_{it} is the statistical noise and u_i is the technical inefficiency parameter of firm i at time t. One can rewrite this equation as

$$y_{it} = \alpha_i + \beta_{Xi} \mathbb{X}_{it} + v_{it} \tag{2.6}$$

where $\alpha_i = \beta_0 - u_i$. If there is inefficiency among firms, the intercepts will be different. Cornwell et al. (1990) relax the assumption of time-invariant by assuming that inefficiency can vary over time. They assume a quadratic form of flexible inefficiency parameter as

$$\alpha_{it} = \theta_{i1} + \theta_{i2} t + \theta_{i3} t^2 \tag{2.7}$$

[3] Some stochastic frontier models still assume time-invariant property in the inefficiency term.

[4] As one team performs better and get closer to the frontier, other teams will unavoidably perform worse and push away from the frontier. If one team is successful in one season but not in other seasons, it does not make sense to assume that the efficiency is the same over time.

where t denotes time period. Hence, the firm-specific level of technical inefficiency of firm i at time t can be estimated from

$$\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it} \tag{2.8}$$

where $\hat{\alpha}_t = \max_j(\hat{\alpha}_{jt})$. This helps preserve the benefit of panel data while allowing for cross-sectional variation in productivity growth rates and time-varying inefficiency.

As for the allocative efficiency analysis, there is no problem of the identical temporal variation, hence, the time-varying "true fixed effect" (TFE) model introduced by Greene (2005) is used in the analysis. The fixed effect (FE) model can be considered as "time-invariant" stochastic frontier where u is assumed to be constant over time. The true fixed effect (TFE) model assumes that u is varying overtime. The cost frontier model to be estimated is

$$c_{it} = \beta_0 + \beta_x \mathbb{X}_{it} + \beta_y y_{it} + v_{it} + u_{it}. \tag{2.9}$$

2.2.2 Data

The team data used in this study are obtained online. The richness of the MLB data makes it possible to compare and contrast the available data across various sources for accuracy. The 2010 to 2015 MLB seasons are considered in this study since they are recent and the league is stable over the time span. The outputs produced by teams, winning percentages, are available on the MLB official website (`www.mlb.com`).

There are two types of inputs corresponding the two analyses. The inputs for examining technical efficiency are offensive and defensive statistics. In a game of baseball, the team at bats is considered the offending team while the pitching team is the defending team. Batters, hence, are in charge of team offense. Pitchers are responsible for team defense. In this study, players are divided into batters and pitchers. Both contribute to team wins differently via different types of performance. These performances are converted to team wins. Players' Wins Above Replacement (WAR) is used as players' performance that is included in the models as input of production. The data can be obtained from `www.baseball-reference.com/teams`.

WAR is a single number that presents the number of wins the player added to the team in comparison to a replacement player (from a AAA league) would add. Although pitchers and batters have different roles, their performance both contribute to team's wins. Hence they both have WAR reported on the website. However, the calculations for the two positions are different, some denotes pitchers' WAR as DRAWAR[5] to distinguish it from batters' WAR[6], although the definitions are the same. For production factors, the cumulative WAR and DRAWAR of previous season are used in the model.

Players' WAR (and DRAWAR) are collected individually each year from the 2010 to 2015 season. From team rosters, players' previous season performance is added up to get the "cumulative WAR." These are the total win players on the roster expected to jointly produce to the team based on their latest performance.

As for allocative efficiency evaluation, inputs used are the factor prices. In the perspective of a baseball team, money spent on offensive and defensive ability directly serves as the cost of production. There are, of course, other omitted operational costs associated with running a team, such as managers' payroll, stadium maintenance, and so forth. However, there is evidence that managers' salaries do not influence teams' performance (Silvers & Susmel, 2014), only players' salaries are considered as input prices in this study. The cost of win production only scopes on team payrolls. Input price for offensive ability (P_{WAR}) is team's total batter salary divided by team's cumulative WAR. The price of defensive ability (P_{DRAWAR}) is total team's pitcher salary divided by team's DRAWAR. The salary information is from `www.baseball-reference.com/teams`.

Figure 2.1 illustrates scatter plots of the variables used in this study. The Pearson's test for correlation indicates that team wins has a significantly positive relationship with team's cumulative WAR (both WAR and DRAWAR) at 84.5%. Players' salary is 25.63% significantly positively correlated with players' performance. The list of summaries of statistics is in Table 2.1. Teams in the two leagues, National League (NL) and American League (AL) have similar budget and cost (as for input factors) but it seems that teams in the AL have, on average, relatively better players (higher WAR and DRAWAR).

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[5]DRAWAR is Fielding Independent Pitching (FIP), adjusted for replacement level, converted to Run Scale and adjusted for park adjustments factor and runs environment. For more information, see `www.fangraphs.com/library/war/calculating-war-pitchers/`.

[6]WAR = (Batting Runs + Base Running Runs + Fielding Runs + Positional Adjustment + League Adjustment + Replacement Runs) / (Runs Per Win). For more information, see `www.fangraphs.com/library/war/war-position-players/`.

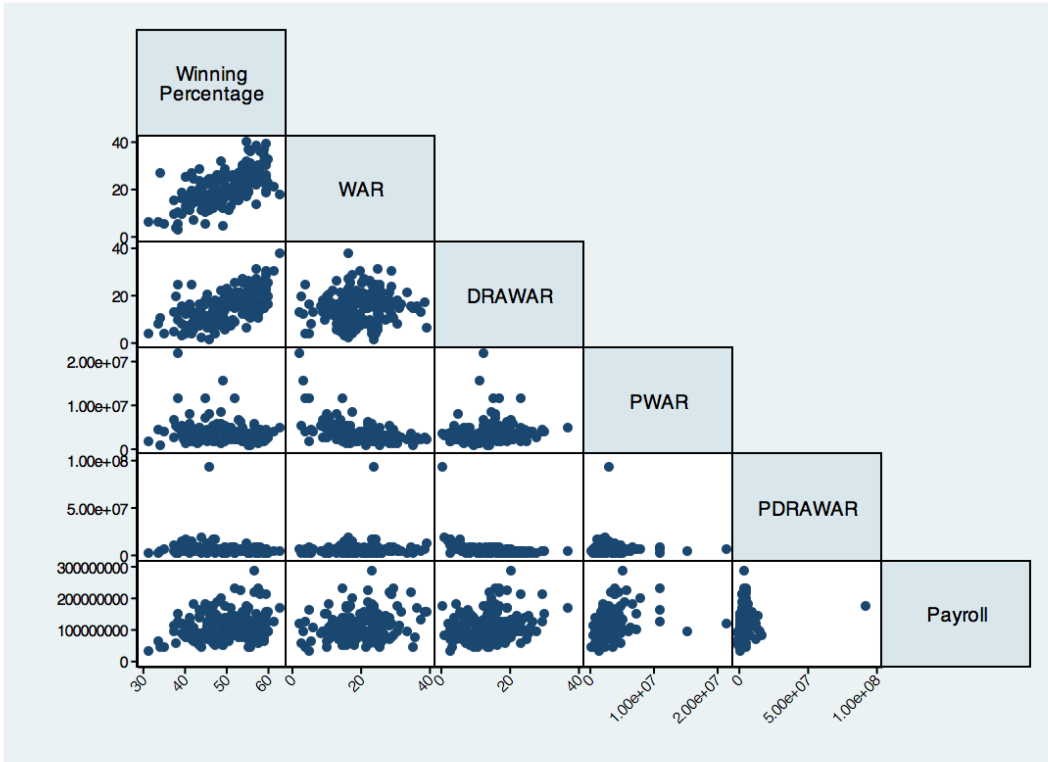

Figure 2.1: Scatter plots of variables used

2.3 Results

2.3.1 Technical Efficiency

Table 2.2 presents the results from four models: OLS, Cross-section Stochastic Frontier (SF), Fixed Effect (FE), and Panel Stochastic Frontier (FECSS) from the MLB and the two major leagues: National League (NL) and American League (AL). There are two reasons the estimations should be performed separately: First, different leagues use different technique and cost in their win production due to its different rules; second, the data used are from regular seasons in which teams barely play against teams from another league.

The production function is assumed to be a Cobb-Douglas production function in every model. The models estimated are in the following forms.

OLS: $\ln WINPCT_i = \beta_0 + \beta_1 \ln WAR_i + \beta_2 \ln DRAWAR_i + \epsilon_i$

SF: $\ln WINPCT_i = \beta_0 + \beta_1 \ln WAR_i + \beta_2 \ln DRAWAR_i + v_i - u_i$

FE: $\ln WINPCT_{it} = \alpha_i + \beta_1 \ln WAR_{it} + \beta_2 \ln DRAWAR_{it} + v_{it}$

FECSS: $\ln WINPCT_{it} = \alpha_i + \beta_1 \ln WAR_{it} + \beta_2 \ln DRAWAR_{it} + v_{it} - u_{it}$

Table 2.1: Summaries of statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
MLB					
WINPCT	180	50.00	6.77	31.50	63.00
WAR	180	20.13	7.23	2.7	39.7
PWAR	150	3,175,482.36	2,421,969.20	521,389.97	21,622,778.00
DRAWAR	180	14.46	6.50	1	37.2
PDRAWAR	150	4,362,470.32	7,193,063.21	415,567.72	92,365,000.00
Payroll	150	105,952,210.20	42,755,806.07	26,105,600.00	282,175,296.00
NL					
WINPCT	90	50.09	6.68	35.2	63.0
WAR	90	18.95	6.24	3.20	31
PWAR	75	3,001,511.13	1,717,436.75	676,433.81	11,248,627.00
DRAWAR	90	13.84	6.66	2.70	37.2
PDRAWAR	75	4,286,416.62	3,047,704.54	415,567.72	15,537,205.00
Payroll	90	103,305,326.90	40,647,339.50	37,799,300.00	282,175,296.00
AL					
WINPCT	90	49.92	6.91	31.5	60.5
WAR	90	21.32	7.97	2.70	39.70
PWAR	75	3,349,453.58	2,964,283.71	521,389.97	21,622,778 .00
DRAWAR	90	15.08	6.31	1.00	30.2
PDRAWAR	75	4,438,524.02	9,734,550.10	660,387.00	92,365,000.00
Payroll	90	108,599,093.50	44,836,171.39	26,105,600.00	228,106,128.00

where $WINPCT_{it}$ is team i's winning percentage in season t, WAR_{it} is team i's cumulative WAR in season t, $DRAWAR_{it}$ is team i's cumulative DRAWAR in season t, v_{it} represents the idiosyncratic error and u_{it} is nonnegative value represents other errors contributed to lower level of output (productive inefficiency) independently distributed of v_{it}. The season-specific dummies were included in the pooled regressions but removed due to the insignificance and inferiority according to the model selection criteria. The estimated individual effects of the panel regressions are not presented in the table to conserve space.

Every model shows a similar result. The performance statistics are all highly statistically significant with a positive sign as expected. The magnitudes are similar between the four models (the chi-square test indicates that the mean marginal effects from the four models are not statistically different). The predictabilities of the models are decent. The likelihood-ratio test from the SF model rejects the null hypothesis that the inefficient parameter is zero.[7] In other words, it cannot be rejected that there is inefficiency in every group of sample. The mean inefficiency scores are higher in the panel analyses (except

[7]See Appendix B for details on inefficiency score.

Table 2.2: Regressions of $\ln(WinningPercentage)$

	MLB				National League				American League			
	OLS	SF	FE	FECSS	OLS	SF	FE	FECSS	OLS	SF	FE	FECSS
$\ln(WAR)$	0.175***	0.168***	0.177***	0.161***	0.189***	0.182***	0.181***	0.186***	0.172***	0.164***	0.172***	0.150***
	(0.014)	(0.013)	(0.016)	(0.017)	(0.018)	(0.000)	(0.019)	(0.025)	(0.020)	(0.021)	(0.026)	(0.024)
$\ln(DRAWAR)$	0.130***	0.125***	0.136***	0.117***	0.149***	0.146***	0.150***	0.115***	0.117***	0.110***	0.124***	0.121***
	(0.011)	(0.010)	(0.012)	(0.013)	(0.013)	(0.000)	(0.014)	(0.014)	(0.016)	(0.016)	(0.019)	(0.022)
Constant	3.061***	3.171***	3.041***		2.991***	3.115***	3.012***		3.086***	3.204***	3.070***	
	0.046	0.052	0.054		0.060	0.0 00	0.061		0.069	0.096	0.091	
$\ln \sigma_v^2$		-5.747				-38.014				-5.368		
$\ln \sigma_u^2$		-4.693				-4.290				-4.746		
σ_α			0.041				0.041				0.031	
σ_u				0.071				0.063				0.076
σ_v			0.078	0.058			0.062	0.046			0.092	0.068
ρ			0.214				0.304				0.110	
Observations	180	180	180	180	90	90	90	90	90	90	90	90
R^2	0.661		0.647		0.746		0.766		0.624		0.550	
Adjusted R^2	0.657		0.573		0.740		0.715		0.615		0.451	
Within R^2			0.647				0.766				0.550	
Between R^2			0.702				0.694				0.826	
Overall R^2			0.661				0.746				0.623	
Test of $\sigma_u = 0$		Reject				Reject				Reject		
Mean inefficiency		0.075		0.132		0.095		0.077		0.074		0.133

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\sigma^2 = \sigma_v^2 + \sigma_u^2; \rho = \frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}; \lambda = \frac{\sigma_u}{\sigma_v}$

for the NL). The F-test against the null hypothesis that the coefficients of the team-specific dummies are equal to each other (no individual effects) is rejected at the 5% level (F(28, 148) = 1.66 and p = 0.0295). This implies that the panel models are more appropriate for the study.

The estimated coefficients indicate that the production function has a decreasing returns to scale. Using the concept of production possibility frontier, one can draw isoquants of baseball production as in Figure 2.2 (using the estimations from the FECSS model). Each isoquant represents the technical-efficient combinations of inputs used to produce each level of wins. In comparison, Figures 2.3 and 2.4 are the plots of inputs combination each team would be using in order to produce a winning percentage of 50% had they adjusted their inputs combination proportionately to their current combination.

The fraction of variance due to the individual effect ($\rho = \frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}$) for the NL is bigger than that of the AL implies that inefficiency plays a bigger portion in production variation in the NL case, in comparison to the AL. Consider the histogram of distribution in tech-

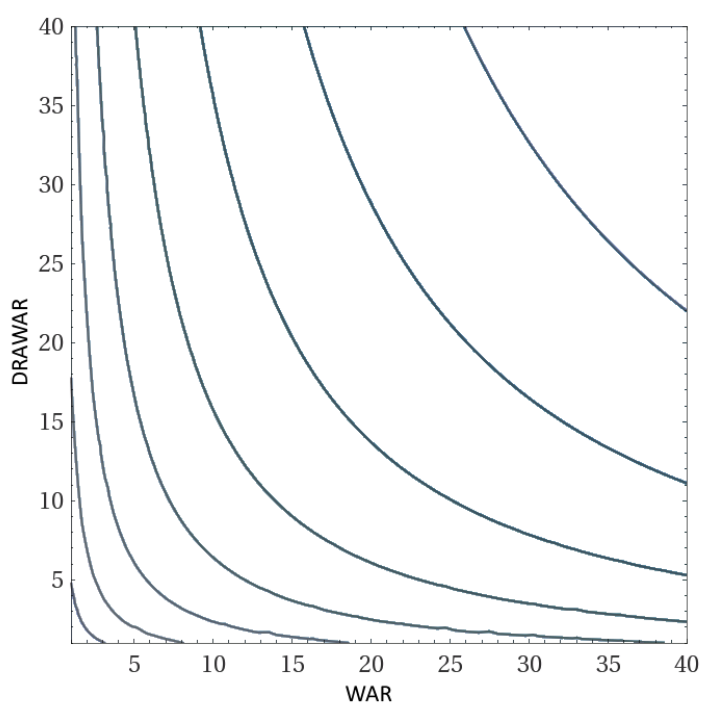

Figure 2.2: MLB's Isoquants

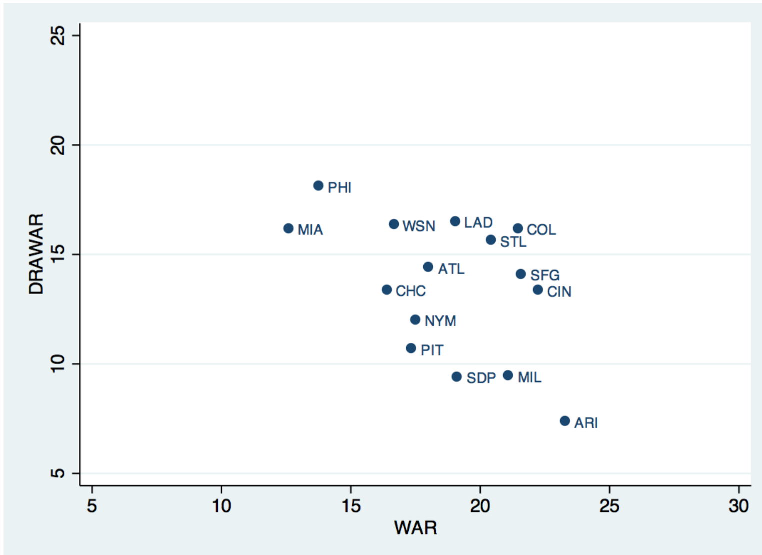

Figure 2.3: NL teams' current inputs combination to produce 50% wins

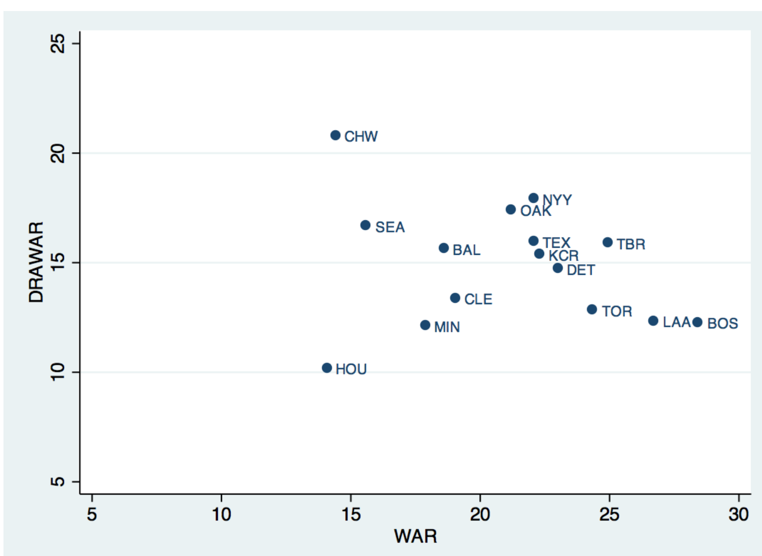

Figure 2.4: AL team's current inputs combination to produce 50% wins

nical inefficiency score of the two leagues in Figures 2.5 and 2.6, it seems that NL teams' efficiency scores are not much dispersed from the most efficient team in comparison to the AL where diversity can still be seen. This is consistent with the scatter plots in Figures 2.3 and 2.4 presented earlier. These might explain why the technical inefficiency is more statistically significant among the NL teams in comparison to the AL teams in the pooled regressions (because the outlier teams will be clearly considered as inefficient teams).

However, with the use of panel data, it seems that the AL, on average, suffers more with technical inefficiency problem, as indicates by a higher mean inefficiency score. Looking at Figures 2.7 and 2.8 that illustrate the trend in the inefficiency scores, the two leagues show an inverse trend. The inefficiency scores were quite stable in the past but have become bigger for teams in the NL in recent years. In the meantime, teams in the AL show a slightly improvement in efficiency. Hence, it can be concluded that inefficiency is bigger in the AL but the improvement can also be seen. On the contrary, in the NL, inefficiency is low and quite stable throughout the periods of this study, but teams have become less efficient in recent years. It should also be emphasized that inefficiency does not persist over the season on the same team but rather switching from team to team in different seasons. For example, the Seattle Mariners was least efficient team in the 2005 season, but was the third most efficient team in the league in the 2015 season.

2.3.2 Allocative Efficiency

The discussion in the previous section concentrates upon the direct estimation of frontier production function using only inputs-output relationship. It assumes that: first, there are given fixed input levels which the managers attempt to maximize output level accordingly; second, the managers try to maximize expected profit by selecting the levels of inputs and output.

In this section, it is assumed that the over all cost efficiencies can be decomposed into their technical and allocative components. The method accounts for factor-demand nature which makes it more realistic than the estimator derived from production function alone (Coelli et al., 1998, p. 32-33). Firms can be technically efficient while not being allocative efficient (Greene, 2011, p. 843-844). The production frontier provides the best outcome teams can achieve technically; the cost frontier, on the other hand, describes the best

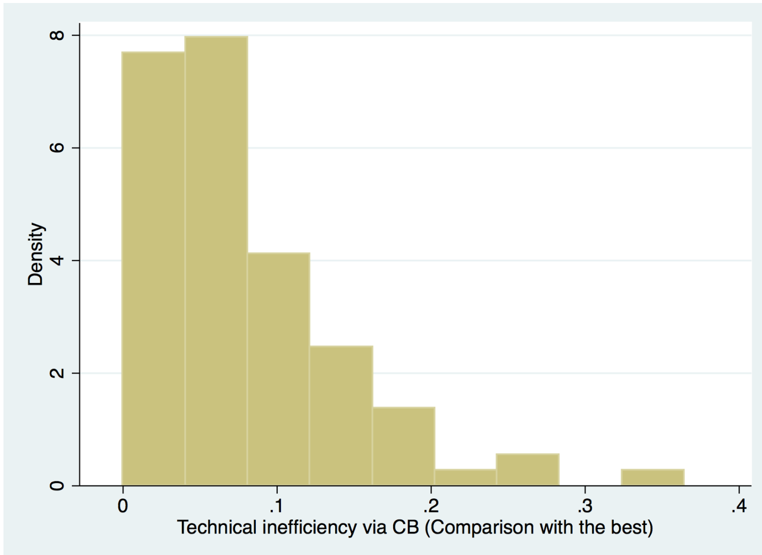

Figure 2.5: Histogram of technical inefficiency score in the NL

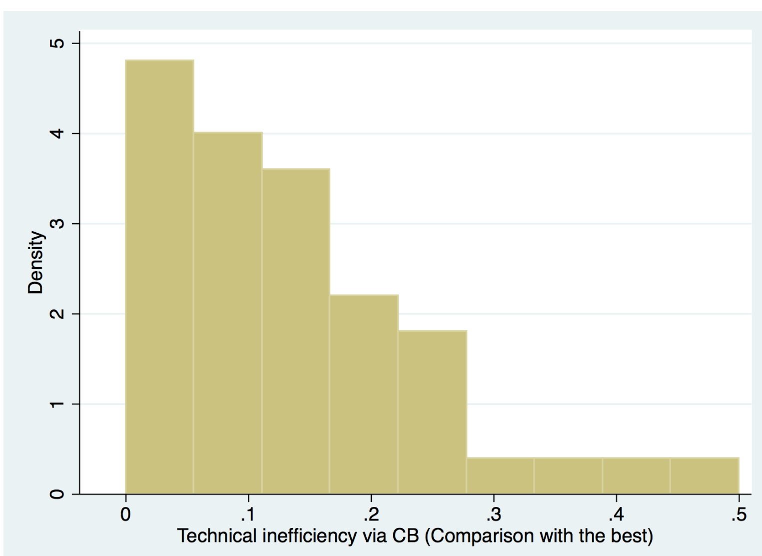

Figure 2.6: Histogram of technical inefficiency score in the AL

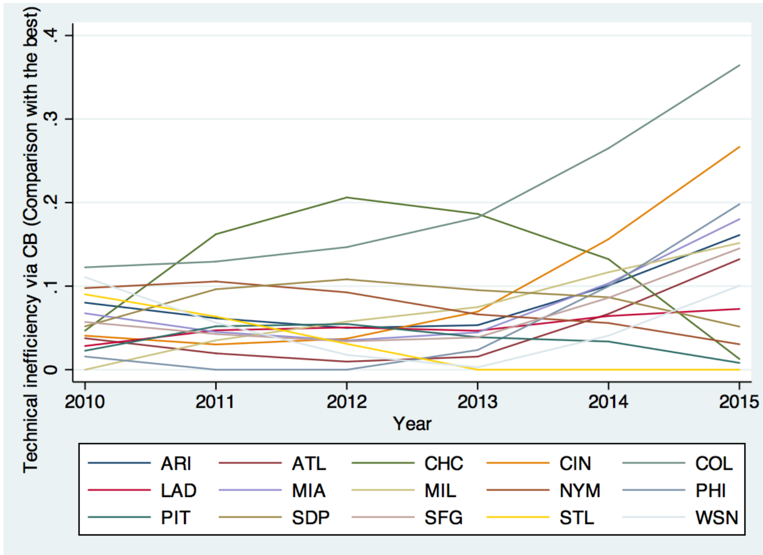

Figure 2.7: Trend of technical inefficiency in the NL

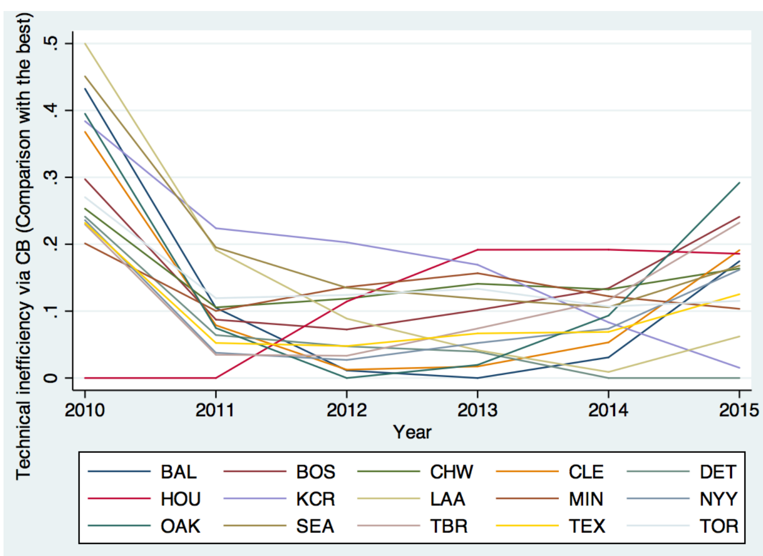

Figure 2.8: Trend of technical inefficiency in the AL

economically outcome since it involves a behavioral objective of cost-minimization as well (Kumbhakar & Lovell, 2000, p. 51).

The Cobb-Douglas cost function models are estimated in the following forms.

OLS: $\ln Payroll_i = \gamma_0 + \gamma_1 \ln P_{WARi} + \gamma_2 \ln P_{DRAWARi} + \gamma_3 \ln WINPCT_i + \epsilon_i$

SF: $\ln Payroll_i = \gamma_0 + \gamma_1 \ln P_{WARi} + \gamma_2 \ln P_{DRAWARi} + \gamma_3 \ln WINPCT_i + v_i - u_i$

FE: $\ln Payroll_{it} = \alpha_i + \gamma_1 \ln P_{WARit} + \gamma_2 \ln P_{DRAWARit} + \gamma_3 \ln WINPCT_{it} + v_{it}$

TFE: $\ln Payroll_{it} = \alpha_i + \gamma_1 \ln P_{WARit} + \gamma_2 \ln P_{DRAWARit} + \gamma_3 \ln WINPCT_{it} + v_{it} - u_{it}$

where $Payroll_{it}$ is team i's payroll in season t, P_{WARit} is team i's average input price of WAR in season t measured from team's total batters payroll divided by team's cumulative WAR, $P_{DRAWARit}$ is team i's average input price of DRAWAR in season t estimated by dividing team's total pitchers salary by team's cumulative DRAWAR, $WINPCT_{it}$ is team i's winning percentage in season t, v_{it} represents the symmetric disturbance of the error component and u_{it} is nonpositive value represents other errors contributed to higher production cost (cost inefficiency) independently distributed of v_{it}. The season-specific dummies were included in the pooled regressions but statistically jointly insignificant at the 5% level. The estimated individual effects of the panel regressions are not presented in the table to conserve space.

Table 2.3 reports the results of the four models. The results from the pooled regressions are similar to each other but different from those of the panel regressions, that are also similar to one another. The F-test against the null hypothesis that the coefficients of the team-specific dummies are equal to each other (no individual effects) is rejected at the 1% level ($F(28, 147) = 7.20$ and $p = 0.0000$). This implies that the team-specific panel analyses are more preferable for the study, like the production models.

The statistically significant constant terms can be viewed as the teams' fixed cost, which is higher for teams in the AL. The significance test of the inefficiency parameter rejects the null hypothesis in the NL group, but cannot reject the null hypothesis in the MLB and the AL. This implies that only the NL teams are cost inefficient. The effect of the input prices on team payroll is greater in the AL. This could be a result of the use of designated hitters in the AL (so they have higher batter to pitcher ratio). Still, it is cheaper for the AL teams to acquire wins in comparison to the NL teams. This also makes sense since, on average, batters produce more wins to team (as WAR is greater than DRAWAR for both league) and

Table 2.3: Regressions of $\ln(Payroll)$

	MLB				National League				American League			
	OLS	SF	FE	TFE	OLS	SF	FE	TFE	OLS	SF	FE	TFE
$\ln(P_{WAR})$	0.406***	0.406***	0.270***	0.270***	0.430***	0.454***	0.274***	0.274***	0.383***	0.383***	0.267***	0.266***
	(0.032)	(0.031)	(0.029)	(0.028)	(0.048)	(0.046)	(0.050)	(0.045)	(0.042)	(0.041)	(0.034)	(0.028)
$\ln(P_{DRAWAR})$	0.275***	0.275***	0.189***	0.195***	0.298***	0.312***	0.224***	0.224***	0.275***	0.275***	0.161***	0.167***
	(0.026)	(0.025)	(0.022)	(0.000)	(0.040)	(0.039)	(0.036)	(0.032)	(0.034)	(0.033)	(0.026)	(0.024)
$\ln(WINPCT)$	1.329***	1.329***	0.859***	0.982	1.325***	1.527***	0.906***	0.906***	1.368***	1.368***	0.844***	0.876***
	(0.128)	(0.127)	(0.112)	–	(0.194)	(0.218)	(0.192)	(0.172)	(0.170)	(0.166)	(0.132)	(0.120)
Constant	3.091***	3.091	8.229***		2.361	0.8 13	7.423***		3.316**	3.316	8.776***	
	(0.848)	(4.719)	(0.813)		(1.380)	(1.527)	(1.466)		(1.067)	(3.266)	(0.922)	
$\ln \sigma_v^2$		-2.927				-3.611				-2.992		
$\ln \sigma_u^2$		-16.017				-2.651				-17.509		
σ_α			0.210				0.197				0.229	
σ_u				0.258				0.000				0.0162
σ_v			0.166	0.000			0.182	0.163			0.150	0.093
ρ			0.615				0.538				0.700	
λ				0.000				0.000				0.000
Usigma				-2.711***				-38.116				-3.639***
				(0.105)				(32330533.394)				(0.831)
Vsigma				-40.833				-3.629***				-4.754***
				(461.356)				(0.149)				(0.791)
Observations	180	180	180	180	90	90	90	90	90	90	90	90
R^2	0.664		0.534		0.626		0.478		0.714		0.612	
Adjusted R^2	0.658		0.433		0.613		0.354		0.704		0.520	
Within R^2			0.534				0.478				0.612	
Between R^2			0.847				0.833				0.891	
Overall R^2			0.664				0.621				0.711	
Test of $\sigma_u = 0$		Do not reject				Reject				Do not reject		
Mean inefficiency		0.000		0.195		0.209		0.000		0.000		0.130

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$\sigma^2 = \sigma_v^2 + \sigma_u^2$; $\rho = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$; $\lambda = \frac{\sigma_u}{\sigma_v}$

price of WAR is cheaper. Hence, AL teams which use more batters can gain better benefit than the NL teams (that use one more pitcher, on average, more than the AL teams). The fact that the NL teams pay more for less could explain why the inefficiency is observed in the NL group in the SF model.

The fractions of variance due to the inefficiency (ρ) are bigger than the technical efficiency models. The fractions are more than 0.5 indicate that the variation in cost are more than 50% comes from inefficiency. The NL, however, still has lower average inefficiency score according to the TFE models. This is visually illustrated by the histogram of efficiency score in Figure 2.9 and the trend of inefficiency in Figure 2.10. From the entire period, only one team in the 2015 season is considered deviating from the frontier, although the observed inefficiency was very small. The AL, again, shows more diverse inefficiency scores through the histogram in Figure 2.11. The trend in Figure 2.12 indicates that the allocative inefficiency grows larger in recent years among the AL teams. The difference between the pooled and panel models is a good example of heterogeneity effect. With the different theoretical backgrounds of the models, it can be explained that there exist individual effects that are misinterpreted as inefficiency in the pooled regressions. Without the team-specific effects, none of the NL teams suffers from cost inefficiency, but the AL teams do.

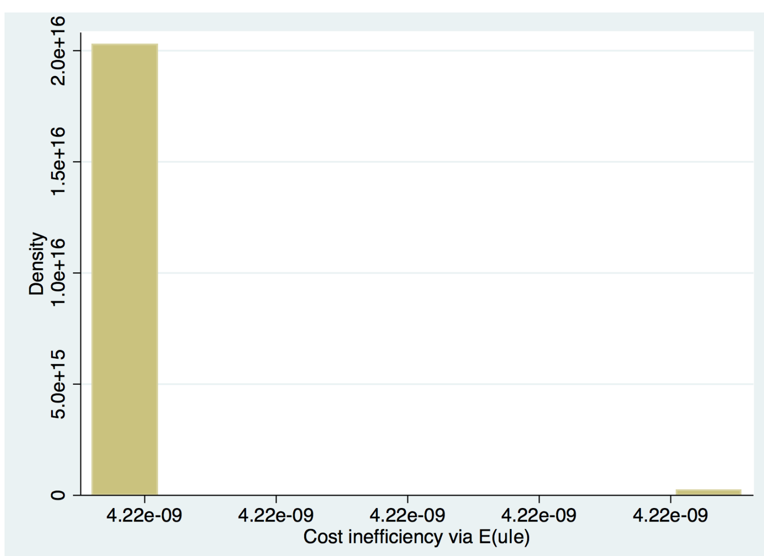

Figure 2.9: Histogram of allocative inefficiency score in the NL

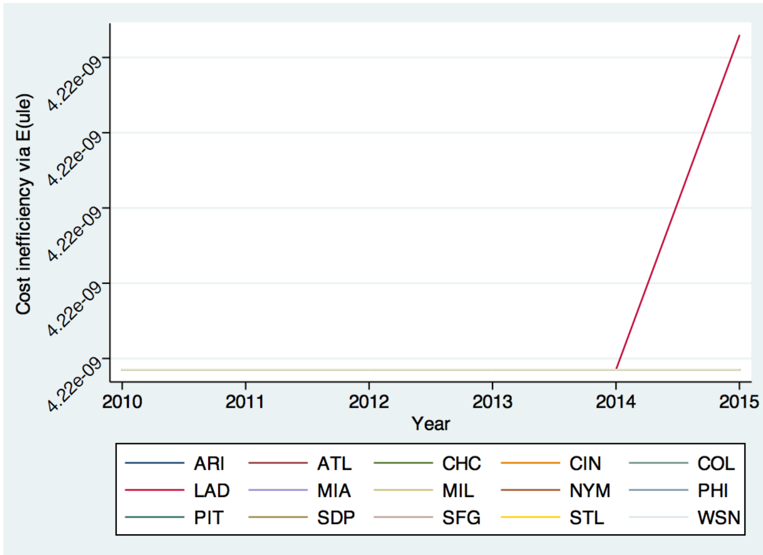

Figure 2.10: Trend of allocative inefficiency in the NL

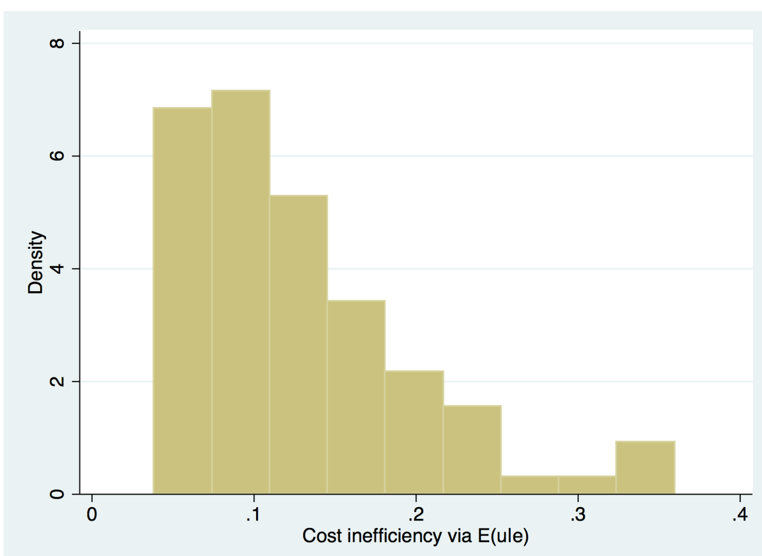

Figure 2.11: Histogram of allocative inefficiency score in the AL

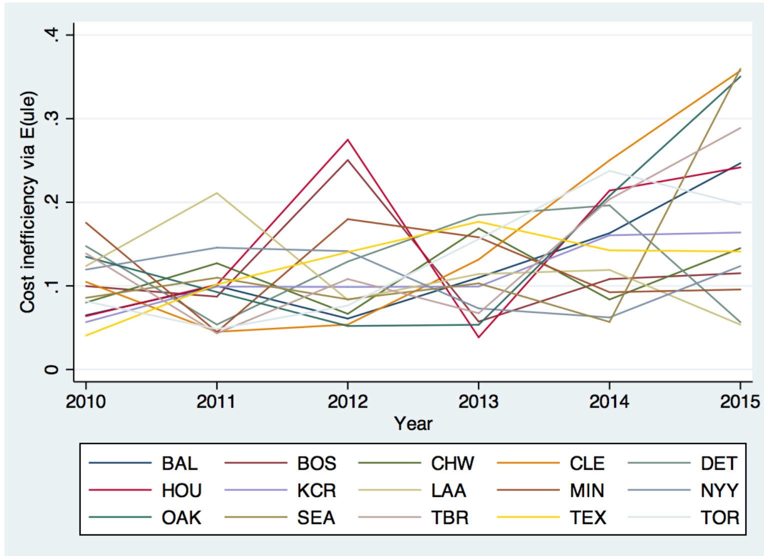

Figure 2.12: Trend of allocative inefficiency in the AL

The efficiencies of teams in both leagues can be ranked by their mean inefficiency scores. The ranks of mean technical efficiency scores presented in Table 2.4 are similar between the panel and the pooled stochastic frontier models.[8] The allocative inefficiency scores, however, shows some contrast. There is no difference in allocative inefficiency score obtained from the panel model of the NL group, but the inefficiency is observed in the pooled data. This is opposite to what found from the AL sample. With the knowledge about the significant individual effects, one can see that neglecting the teams' heterogeneity can lead to a fault conclusion.

2.3.3 Payrolls and Efficiencies

Regular seasons success is an outcome of capability and managerial efficiency of the teams (H. F. Lewis et al., 2009). There are various ways to view capability, one of which is the resource capability or the ability to financially support the teams. Teams with higher budget can compensate managerial inefficiency with more resources, and vice versa. Teams with both capability and efficiency should be more successful.

Tables 2.5 and 2.6 provide pairwise correlation coefficients between efficiency scores,

[8]Table C.1 in Appendix C summarizes MLB teams and their abbreviations presented in Table 2.4.

Table 2.4: Efficiency ranking

Technical Efficiency		Allocative Efficiency		WINPCT	Payroll
Rank (FECSS)	Rank (SF)	Rank (TFE)	Rank (SF)	Rank	Rank
National League					
STL (0.031)	PIT (0.047)	PIT (0.000)	PIT (0.083)	STL (56.7)	LAD (176.0)
PIT (0.035)	STL (0.058)	SDP (0.000)	SDP (0.137)	LAD (54.5)	PHI (160.0)
ATL (0.047)	ATL (0.069)	MIA (0.000)	MIA (0.154)	SFG (53.5)	SFG (126.9)
LAD (0.052)	MIL (0.078)	ATL (0.000)	ATL (0.160)	ATL (53.1)	CHC (118.0)
WSN (0.055)	ARI (0.079)	WSN (0.000)	WSN (0.179)	WSN (52.7)	STL (111.0)
PHI (0.056)	LAD (0.081)	COL (0.000)	COL (0.192)	CIN (51.2)	WSN (107.0)
SFG (0.067)	WSN (0.082)	MIL (0.000)	MIL (0.196)	PHI (50.3)	NMY (107.0)
MIL (0.073)	PHI (0.086)	STL (0.000)	STL (0.196)	PIT (50.2)	CIN (96.9)
NYM (0.075)	SDP (0.088)	ARI (0.000)	ARI (0.210)	MIL (49.4)	MIL (94.8)
MIA (0.079)	SFG (0.088)	SFG (0.000)	SFG (0.218)	NYM (49.2)	ATL (94.6)
SDP (0.082)	NYM (0.090)	CIN (0.000)	CIN (0.244)	SDP (47.7)	COL (85.4)
ARI (0.085)	MIA (0.104)	LAD (0.000)	LAD (0.255)	ARI (47.7)	ARI (82.4)
CIN (0.100)	CIN (0.117)	NYM (0.000)	NYM (0.257)	CHC (45.6)	SDP (67.8)
CHC (0.124)	CHC (0.140)	PHI (0.000)	PHI (0.291)	MIA (45.4)	MIA (62.0)
COL (0.202)	COL (0.219)	CHC (0.000)	CHC (0.357)	COL (44.0)	PIT (60.3)
American League					
DET (0.065)	DET (0.050)	NYY (0.111)	NYY (0.000)	NYY (55.4)	NYY (212.0)
NYY (0.098)	NYY (0.055)	CHW (0.112)	CHW (0.000)	TBR (54.1)	BOS (166.0)
TEX (0.099)	TEX (0.0565)	KCR (0.113)	KCR (0.000)	TEX (54.0)	DET (143.0)
HOU (0.114)	CLE (0.065)	LAA (0.118)	LAA (0.000)	DET (53.7)	LAA (141.0)
TBR (0.120)	TBR (0.066)	BOS (0.120)	BOS (0.000)	OAK (51.6)	TEX (113.0)
CLE (0.120)	BAL (0.070)	TEX (0.124)	TEX (0.000)	BOS (50.8)	CHW (109.0)
BAL (0.126)	CHW (0.072)	BAL (0.124)	BAL (0.000)	BAL (50.4)	TOR (103.0)
MIN (0.137)	TOR (0.074)	MIN (0.124)	MIN (0.000)	TOR (50.3)	SEA (103.0)
TOR (0.145)	MIN (0.0756)	DET (0.128)	DET (0.000)	LAA (50.2)	MIN (97.8)
OAK (0.146)	OAK (0.078)	TOR (0.133)	TOR (0.000)	CLE (48.9)	BAL (94.0)
LAA (0.149)	HOU (0.078)	SEA (0.133)	SEA (0.000)	KCR (48.8)	KCR (77.3)
CHW (0.152)	BOS (0.081)	TBR (0.142)	TBR (0.000)	CHW (47.8)	CLE (71.7)
BOS (0.156)	LAA (0.089)	OAK (0.149)	OAK (0.000)	MIN (45.5)	OAK (67.5)
KCR (0.180)	SEA (0.095)	HOU (0.156)	HOU (0.000)	SEA (45.0)	TBR (65.8)
SEA (0.196)	KCR (0.102)	CLE (0.157)	CLE (0.000)	HOU (42.6)	HOU (63.2)

Mean inefficiency scores in parentheses.

Payrolls in $ million.

payrolls and wins, categorized by league. Figures 2.13 and 2.14 show the plots illustrated the same relationship as in Tables 2.5 and 2.6. They show that technical inefficiency contributes (negatively and significantly) to team success. Team payrolls have a significant positive correlation with wins.[9] Allocative efficiency, on the other hand, has no significant relationship with wins. The fact that the correlation between efficiency scores and winning percentage is modest is similar to a study conducted by Ruggiero, Hadley, and Gustafson (1996). This indicates that a team could win either with better players even if those skills are not efficiently used or with efficiently use of players although those players are not superior in talents.

Consider the technical efficiency ranking generated from the FECSS model, payrolls and winning percentages. One can see that successful teams from both leagues rank high in technical efficiency. The St. Louis Cardinals ranks first in efficiency and average wins. In the AL, the most successful team, the New York Yankees, ranks second for technical efficiency. Both teams appear to spend good amounts of money on players. Hence, the hypothesis is confirmed that teams with both capacity and efficiency should perform relatively better.

The Pittsburgh Pirates, in spite of ranking second in the league, ends up in the middle of wins ranking. Similar to the Houston Astros that ranks fourth in efficiency in its league but comes up at the last place in performance. These two teams share one common characteristic: they both spent the least on players in comparison to other teams in their leagues. On the other hand, teams with higher budget but lower efficiency such as the Chicago Cubs and the Boston Red Sox also finish in the middle of wins ranking. This supports the claims of the famous novel “Money Ball” (M. Lewis, 2004) and the study of Jewell and Molina (2004) that smaller teams can compete with bigger teams if they are more efficient. Unfortunately, efficiency alone cannot bring any team to the top spot. As for competitive balance issue, it is little relief that only larger pockets do not make a richer team an unbeatable champion.

There is no significant correlation between the technical and allocative efficiency in both leagues. However, a significant, strong, positive correlation between allocative inefficiency

[9]Although, this does not imply causality between payroll and wins and only indicates that the two variables are moving together in the same direction.

Table 2.5: Pearson's correlation matrix (National League)

	Technical Inefficiency	Allocative Inefficiency	Total Players Salary	Winning Percentage
Technical Inefficiency	1.000			
Allocative Inefficiency	-0.008	1.000		
Total Players Salary	-0.041	0.469***	1.000	
Winning Percentage	-0.611***	0.107	0.237**	1.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Pearson's correlation matrix (American League)

	Technical Inefficiency	Allocative Inefficiency	Total Players Salary	Winning Percentage
Technical Inefficiency	1.000			
Allocative Inefficiency	0.091	1.000		
Total Players Salary	-0.164	0.115	1.000	
Winning Percentage	-0.386***	-0.075	0.280***	1.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

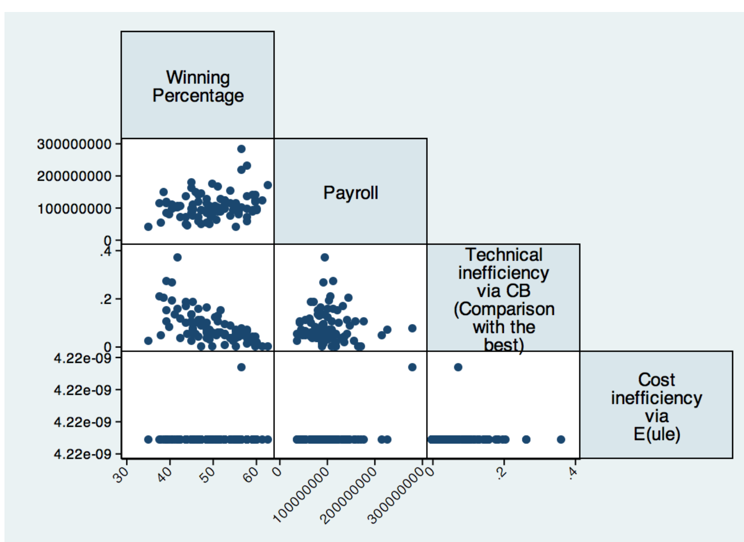

Figure 2.13: Correlation plots (National League)

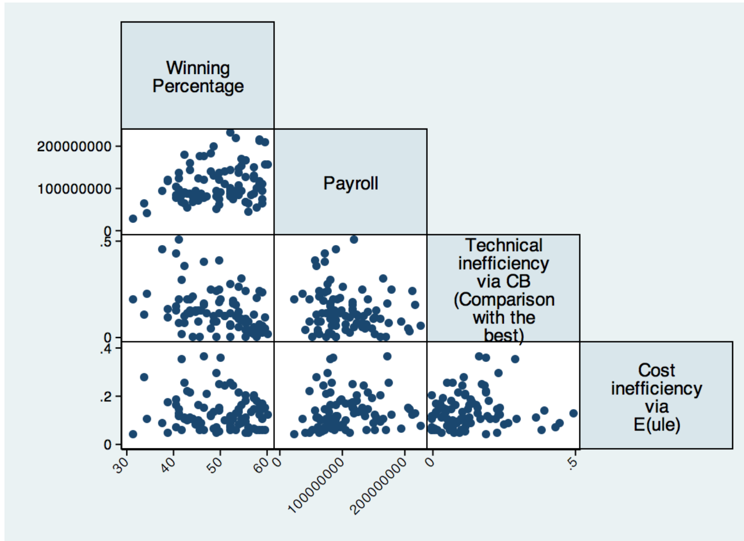

Figure 2.14: Correlation plots (American League)

and team payrolls is observed in the NL. This indicates that richer teams tend to be allocative inefficient (in the NL). This follows the findings of previous literature, such as Einolf (2004); Jewell and Molina (2004); H. F. Lewis et al. (2009, 2007). Despite the finding that allocative inefficiency does not deter team success, this finding still leads to a conclusion that the NL teams fail to efficiently allocate their budget. Consider the contribution to team wins between batters and pitchers, the NL teams can improve their efficiency by relocating their budget more toward batters. Another evidence supporting this idea is from the positive correlation between allocative inefficiency scores and DRAWAR in the NL group, which indicates that the inefficient teams tend to collect more talent pitchers (at the 30% significant level–the result is not included).

2.4 Conclusion

This study evaluates technical and allocative efficiency in the MLB using the data from the 2010 to 2015 seasons. The analyses perform stochastic frontier regressions, similar to the work of Porter and Scully (1982) that studied the same issue. The discontinuation of the stochastic frontier analysis study leads to a missing information to either support or against the findings on the MLB efficiency studies conducted by the DEA method. This study fills in this gap.

With the use of panel data, this study shows that there are some differences in technical efficiency among the MLB teams. On average, the NL teams do not suffer from allocative efficiency problem, although the technical inefficiency seems to grow larger in recent years. On the other hand, allocative inefficiency problem is growing in the AL.

A growing trend in inefficiency, both technical and allocative, is quite surprising especially in the context of sport tournament where spectators are focusing on teams' performance and owners are seeking for returns on investment. It also should be noted that baseball players' performance is quite consistent from season to season (50.74% significant correlation of current season and past season performance at the 1% level) which should make it less difficult for managers to plan their strategies and make contract offers. Furthermore, it should also be stressed that inefficiencies do not persist across the seasons on the same team, but rather switching from team to team on different seasons.

The Pearson's correlation tests indicate that allocative efficiency has no significant correlation with teams' success. Technical efficiency contributes the most to teams' average wins, follows by teams' average player salaries. Teams with both financial capacity and managerial efficiency success in the competition while teams that have one or another can somewhat substitute between the two, although they are more likely not be able to reach to the top spot.

Although, there is no significant different in efficiency scores of the NL teams in general, wealthier teams in the league show a significant positive relationship with allocative inefficiency, indicates budget management problem where teams unnecessarily spent too much money on wrong players, perhaps pitchers, who contribute less to team wins at the same cost as batters. For improvement, teams should pay more attention not only on the amount of money they put into the rosters, but also on the allocation of money.

Future research can look closer into the importance of relationship between teams and players, staffs and players and between players in order to find a more concrete reasons for the teams' success beyond just players' salaries aspect, which has been extensively discovered. This study only considers the conversion of inputs into output; it does not explore the production process of baseball teams. More thorough discoveries on specific techniques that teams use, which are now available in great detail, will, perhaps, fulfill the lack of details for technical efficiency in this study.

CHAPTER 3

THE WINNER'S CURSE IN THE MARKET FOR FREE-AGENT NBA PLAYERS

3.1 Introduction

In a common value auction with imperfect information, bidders offer their bids, individually and secretly for goods or services, estimated from their expected return. The winner is the one who offers the highest money and is also the most optimistic bidder in the auction war. Logically, the true value of the product should be closer to the mean value of offers. Since the winning bid is usually greater than the mean bid, the winners of the bid have greater tendency to pay more than the true value. In other words, the winners have greater chance to overvalue the product. This phenomenon is called a "winner's curse."

The winner's curse theory originates in natural resource economics, under the study of bidding war for oil fields (Capen, Clapp, & Campbell, 1971). It has also been applied to a number of studies in sport economics literature, many of which focus on the biddings for hosting mega sport events such as the Olympics, the FIFA World Cup, and the Super Bowl (Baade & Matheson, 2002, 2004, 2006; Burns, Hatch, & Mules, 1986; Mules & Faulkner, 1996; Ritchie, 1984; Ritchie & Aitken, 1984; Ritchie & Smith, 1991). The results are almost always pointing into the same direction–hosting countries (or cities) overspend on the events and make lower than expected return, or even negative returns. This implies that there is a winner's curse in mega sport event auctions.

In another respect, major league teams almost always involve in bidding wars for players due to a limited number of talented players. Salaries of major league players are one of the highest occupations in the United States. There are two possible causes for such high wages: monopoly power of players, either from super star power or from the player union, or bidding wars among teams.

Rosen (1981) is the first to present a theoretical framework on the *Economics of Superstars*. In this pioneer work, the author shows that superstars enjoy premiums of their superior talent. This reward is not linearly but multiplicatively related to talent. Audience have higher demand for talents, so players with more talents have bigger market they can sell their talents to. The bigger the market size, the more income the players get, because the teams that acquire such talents gain higher returns. Mathematically, the reward function is convex in talent in which the rate of return of talent depends on the functional form of the reward function. Furthermore, as demand expands, the concentration of income tends to be larger for the stars if the demand is elastic to talent.

There are various studies that explore the winner's curse in the player market. Blecherman and Camerer (1996), Burger and Walters (2008), and Cassing and Douglas (1980) use data from the Major League Baseball (MLB) from different time spans and different techniques; every study discovers the winner's curse in the teams' bidding for player process. Massey and Thaler (2013) study the same issue in the National Football League (NFL) drafting behavior of teams and discover a supportive evidence.

The National Basketball Association (NBA) is one of the most famous sport in the United States. Star players' salaries are tremendously high. Almost every team has at least one star player. In 2015, the average NBA player's salary is $5.15 million, with the highest pay of $23.5 million earned by Kobe Bryant of the Los Angeles Lakers. By far, the NBA players earn more than any other professional sport players.[1] Eschker, Perez, and Siegler (2004) explore the winner's curse problem in the NBA, focusing on the international players, and reveal that international players were overpaid by teams and there existed the winner's curse in the NBA during the 1996-97 and 1997-98 seasons, at the beginning of the influx of international players. The curse, however, disappeared afterward. Groothuis, Hill, and Perri (2009) find that there is a great uncertainty and false positives in players' performance from drafting system where teams overestimate the performance of players. They, however, conclude that this might not be a result of the winner's curse, rather it is because that there are very few talented players. If the teams want a chance to win over these players, they have to invest in them just like buying a lotto where they rely on the

[1] In 2015, the average MLB player earns $3.2 million, the NHL average earning is $2.4 million and the NFL average salary is $1.9 million.

accuracy of talent evaluation, but the chance is of winning the prize is still uncertain as well as the uncertainty of performance.

The aim of this study is to evaluate whether NBA teams can accurately predict the true value of their players or fall into the trap of the winner's curse. The finding from this study should provide some insightful information to teams' managers about their bid strategies. If such a curse persists, the managers should learn how to avoid the curse by discounting all bids accordingly. Also, it should help shed some light on the theory of winner's curse under the real world circumstance. The structure of this paper is as follows. The following section presents theoretical background of the winner's curse. Section 3 presents data sources and methodology implemented in this study. Fourth section provides empirical results. The conclusion and recommendation are in the last section.

3.2 Theoretical Background

Capen et al. (1971) brought the issue in the closed-envelop competitive bidding process to light, using an example of competitive bidding for petroleum field in the Gulf of Mexico. The authors present that the return on investment often does not meet the expectation of firms–the return was either lower than expected or even became negative, which made average return on investment become negative. Each bidder has different information, which leads to different expected return on investment. Even if the information is exactly the same, expectations are different among bidders due to different perceptions. This leads to varying expected return, which can be too high or too low, and almost no chance of being exactly the true value of the object in the auction. The winner firm of the competitive bidding is the firm that has highest expected return or overestimates the true value because the firm is less likely to win the bid if it was to undervalue the object. This is the so-called the "winner's curse." From the simulation method of an expected winning bid probabilistic model presented in Capen et al. (1971), it seems that the expected winning bids tend to be higher when there is more information, when there is more uncertainty about true value, and when there are more bidders. The author suggests that once bidders realized the existence of the winner's curse, they should lower their bids accordingly.

Thaler (1988) defines the winner's curse into two versions: the winner receives negative return on investment and the winner receives less than expected return on investment.

Both versions of the curse leave the winner disappointed. Thaler further explains that economic theories normally assume rationality, while it is difficult in such a competitive bidding setup because the expected value of an investment is indeed conditioned on winning the auction. Firms tend to bid more aggressively as number of bidders increases. Meanwhile, winning an auction war against more bidders increases the chance of the firm overestimating the true value.

The early experiment on the winner's curse was conducted by Bazerman and Samuelson (1983). A coins-filled jar worth \$8 was the auction object while subjects, 419 MBA students in 12 microeconomics class at Boston University, did not know the true value of the object. The study discovered that in the closed-envelop auction environment, the mean estimated value of the object was approximately \$3 below the true value. Nevertheless, the mean winning bid was \$2 above the true value of the object. This serves as evidence of the winner's curse.

Several experimental studies followed such as those of Kagel, Harstad, and Levin (1987), Kagel and Levin (1986), and Samuelson and Bazerman (1985). The results point in the same direction that there exists winner's curse. Although the curse is realized and can be eliminated as bidders gain more experience and knowledge, it is difficult to avoid such a curse due to complexity of valuation of the product's true value and bidding competition. However, laboratory studies usually face criticisms about the realism. Hence, various field experiments were conducted; most encounter evidence of the winner's curse (Hendricks & Porter, 1988; Roll, 1986; Varaiya, 1988; Varaiya & Ferris, 1987).

Cassing and Douglas (1980) study the winner's curse theoretically and explore real world phenomena using the Major League Baseball (MLB) data. The authors develop a theoretical study base on a noncompetitive environment where teams bid for talent from a player who is the monopoly of his own talent that has the marginal revenue product (MRP) equal to $B/2$.[2] The teams' expected value of the MRP is assumed to have a uniform distribution with the range between 0 and B. In other words, sometimes the MRP will be underestimated and sometimes be overestimated. If there is only one team that bids for

[2]This is an adaptive model of Capen et al. (1971) to the free-agent player market. The probabilistic model of the curse is exactly the same as that of Capen et al. (1971) except that the authors assume that the product's (in this case, player's) true value has a uniform distribution where the original work uses exponential distribution.

players several times, on average, the bidding offers will be equal to the players' MRP. In competitive environments with more than one team that are involved in the bidding war, on the other hand, teams that correctly estimated the true value are usually not the winner. The winners are usually the teams that overestimate the MRP. Although teams have identical information about players, they can still offer different bids due to some human element in digesting information.

Assume that there are n bidding teams where every team has an identical uniform distribution for MRP on the interval [0, B] with mean $B/2$ and in order to win the bid, the winner must offer \$$x$ to player. This means that there will be $n-1$ teams that lose the bidding war. Hence, the probability that all but one team bids less than x is $(x/B)^{n-1}$. Given K is a constant necessary to make $h(x)$, the p.d.f. of the winning bid, integrate to 1, $h(x) = K(x/B)^{n-1}(1/B)$. In the case where $K = n$, we can write an equation of the expected winning bid (EWB) as

$$EWB = \int_0^B xh(x)dx = \int_0^B n(x/B)^n dx = [n/(n+1)]B. \tag{3.1}$$

It can be seen that EWB will equal to MRP ($B/2$) only when there is one team in the bid and exceeds MRP when $N \geq 2$. The size of EWB increases and approaches B as n increases. In conclusion, free-agent players tend to be paid more than their true value under competitive bidding environment and the size of extra pays tend to be bigger as the number of bidding teams increases.

Cassing and Douglas find that teams overpay players. However, the authors conclude that selection bias of samples could result in such finding. Only better players tend to switch teams, and vice versa. As a result, players with uncertain performance, who are not represented in the samples, tend to stay with their former team; the good ones are the ones that move and create higher value for their new teams. Burger and Walters (2008) use a newer data set and a more sophisticated technique to measure performance and discover the same issue. The authors conclude that, with available information on players, especially about risk, teams still fail to avoid the winner's curse when they are faced with complex valuation problems such as talent; teams continued to overvalue players. Massey and Thaler (2013) similarly study the same problem in the National Football League (NFL) teams' drafting behavior. The finding follows those of the MLB studies that performance is also overvalued in the NFL.

L. M. Pepall and Richards (2001) use a game theoretical framework to explain such phenomena under a Bertrand duopolistic setup where two teams, i and j, are competing downstream in a price competition of output that involves the usage of a superstar and upstream where the two teams compete in a bidding war for a superstar. At equilibrium, if the ticket price of one team is positively correlated with the present of a star in another team, a price war begins and both teams are worse off. If the ticket price is negatively affected by the present of a star in another team, star player softens competition and both teams benefit, except that the team which hires the star receives less profit. In other words, there is a tendency for the winner's curse to occur in the market where price of end product negatively corresponds to the present of stars.

3.3 Data and Methodology

Winner's curse in the player market occurs if the winner of the bid has an expected value of a player that is greater than his real value. The expected value of a player is the return the team estimated that they will get from hiring that particular player. For any rational team, the pay will not exceed the player's expected generated income. In mathematical expression,

$$w_i(MP_{Li}) \leq MRP_i \tag{3.2}$$

where $w_i(MP_{Li})$ is the offered player's salary based on his expected marginal product of labor (MP_L) which, in sports, is the marginal win produced by player, and MRP_i is player's marginal revenue product or his contribution to team income in dollar term ($MRP = MR \times MP_L$). However, there is an uncertainty about the true value of the player's production that makes some teams, although rational, more likely to overvalue the player and offer a wage that is above his MRP. A team falls a victim of the winner's curse if they win the bid while their expected value (E(MRP)) of the player more than the true (average) value (MRP).

$$E(MRP_i) > MRP_i \tag{3.3}$$

In bidding process with almost identical information, the expected value of a player should be similar between teams. Hence, the distribution of expected value is known to the bidders. The bid distribution does not reveal the underlying true distribution of MRP. To guarantee that they will be able to sign a player, teams, with no information about other teams' offers, teams have to offer their best possible contract they can under the profit-maximizing condition. The offered salary needs not be equal to the player's expected value, but it needs to be above other teams' offers in order to win. Some teams might offer bids that are lower than the true value, and vice versa, but on average, the bids should be close to the true value. In other words, the part of player's salary that is determined by expected marginal product (E(MP)), must be equal to player's expected value (E(MRP)) perceived by the competitive auction bidders. The winners' E(MRP)s, as a result, are usually higher. It is important to stress that the wage mentioning here is only a partial wage that is determined by player's expected production and not the actual wage that may include other aspects of the player such as age, experience, charisma, union power, team power, hedging against the winner's curse, and so forth.

$$w_i | E(MP_{Li}) \leq E(MRP_i) \tag{3.4}$$

From labor economic theories, $w = MC \times MP_L$ for profit maximizing business in competitive market. Since $MRP = MR \times MP_L$, one can rewrite the previous equation as

$$MC \times E(MP_L) \leq MR \times E(MP_L) \tag{3.5}$$

From Equation (3.5), divide both sides of by $E(MP_L)$:

$$MC \leq MR \tag{3.6}$$

The salary is less than or equal to expected marginal revenue product, hence, marginal cost is less than or equal to marginal revenue. This is true either under the perfect competitive environment or the noncompetitive environment where the bargaining power of the players and the teams are equal and cancel out each other. The true value of a player cannot be directly observed because it involves many perspectives; some of which cannot be measured, for example, leadership, personality, and so forth. However, the the estimated marginal revenue product (MRP) can be predicted if MR and MP are known. As a result, this study assumes that teams have information about players' the mean marginal product and its distribution. Although, teams still face uncertainty of performance due to the variance in performance, which is different from player to player. Also, teams already have a plan on how to use the players in their games, for example, they have expectations about how much time the players will be put on the court throughout the contract period.

Previous studies of the winner's curse in bidding for players almost always compare singular wages with MRP of players to justify whether there exists the winner's curse or not. As mentioned earlier, considering that there are many factors determining wage and the conclusion about winner's curse drawn from the fact that wage is greater than MRP might not be realistic. As a result, this study focuses on the evaluation of MC and MR of wins that are contributed by players to reach the conclusion about the winner's curse. There are three main steps of the estimation. The data used in each steps must be chosen carefully to best fit the methodology. The data can be separated into team level and individual player level data. The descriptive statistics of the data used in this study is in Table 3.1.

Table 3.1: Summaries of statistics from the 2004/05 to 2014/15 NBA Seasons

Variables	Obs.	Mean	Std. Dev.	Min	Max
Individual					
Salary ($)	691	6,741,807	4,929,465	304,897	23,239,562
Win Score (games)	691	3.65	3.94	-3.33	23.65
Variance of WS (games)	691	8.79	10.86	0.00	76.14
Height (in.)	691	78.64	3.69	65	87
Weight (lb)	691	216.13	27.33	135	325
Experience (year)	691	8.56	2.62	6	18
Age (year)	691	30.02	3.02	24	40
All Star	50				
Position, center	115				
Position, power forward	111				
Position, point guard	136				
Position, small forward	127				
Position, shooting guard	124				
Team					
Total Revenue	330	13,200,000	40,000,000	54,000,000	307,000,000
Team Payroll	330	66,738,678	12,562,757	23,380,124	126,610,272
Win82	330	40.99	12.66	9	67
Population	330	5,347,834	4,847,263	987,535	20,182,305
Stadium Capacity	330	19,103.430	1,046.442	16,867	21,165
Playoff	330	0.533	0.500	0	1

3.3.1 Evaluation of Players' Contribution to Wins

The first step of the analysis is the calculation of players' contribution to teams' wins. The win score (WS) method introduced by Berri (2008) is implemented in this study. The main advantage of WS is that it measures players' production in term of numbers of wins generated to team which makes it possible to summarize players' performance into one unit of tangible measurement, wins. The method involves two main steps: the calculation of players' action on court and the actual win contribution of each player to his team in each season. It shall be noted that win score is selected in this study not because it best predicts player performance nor does it highly related to wages; it is chosen mainly because it directly illustrates players' contribution as number of wins produced which is more suitable for the study of MRP. Appendix D describes the full steps of WS calculation. In the steps of evaluation of players' action, team-level data are used. The individual performance statistics are required for the following steps.

Both team-level and individual-level performance data for the NBA 2004/2005 season through the 2014/2015 season are obtained from `www.basketball-reference.com`. It should be noted that players who appeared less than 20 games per season or spent time on court less than 12 min per game were excluded due to their minimal impact on the games. A total of 1,410 qualified players, free agents, and not-free agents, are included in the first step of WS evaluation. This is to get the most accurate values of players' actions, since every player shares some part of contribution in games. Every analysis after the evaluation of WS only uses 691 free-agent players with multiyear contracts because they can better represent the competitive market that is the main focus of this study. As for team-level data, since there are 30 teams across 11 seasons, the total of 330 observations are used.

It is important to understand that in the Berri (2008)'s version of WS, players' contributions are evaluated only for each particular season. Despite being a useful tool to evaluate player's production, the season-specific nature of the variable is a drawback for cross-season studies. In this study, WS will need to be compared across season. As a result, some adjustments are necessary.

In the final step of the calculation for WS, Berri divides player's Wins Produced per 48 min played (WP48), which is calculated from performance statistics, by 48 and multiplies by the actual minutes played (MP) to get the win score, WS. For the analysis of this study, WP48 for every player for each season are estimated and averaged across the years of contract, player-by-player. So, the WP48 used in this study is the contract-length average WP48 of each player.[3] The variance of WS is calculated per player from the contract-length average WS.[4] There are 804 free-agent players whose names appeared in the roster for the 2004/2005 to 2014/2015 season that are qualified from the selection criteria. However, in order to calculate the variance of performance which is crucial to this study, only players who signed multiple-year contracts are included and the sample size reduces to 691.

Figure 3.1 is the histogram of contract-length average WP48 of free-agent players. The distribution is symmetric which indicates that player's performance are normally distributed. This is consistent with the normal quantile plot in Figure 3.2. However, the actual contribution comes from the amount of time each player spent on court. In this study, it is assumed that teams know the average WP48 and variance of WP48 of each player as they can observe performance of every player across several seasons, and that they also know how much time each player will be placed on court. After dividing the contract-length average WP48 by 48 and multiply by contract-length average minutes played of that player, the expected WS of each player is obtained and assumed to be known by team prior to bidding process.[5]

To ensure that the use of expected WS in this study will be consistent with the actual WS (denote as AWS) calculated for each player for each season from Berri (2008) method, the correlation between WS and AWS for 691 free agents is calculated. It appears that there is a 90.28% significant relationship between the two variables. The scatter plot in Figure 3.3 illustrates this relationship. As a result, the implementation of expected WS in this study should not significantly impact the results.

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[3] Contract-length average $WP48_i = \frac{\sum_{t=1}^{n} WP48_{it}}{n}$, where n is number of years in contract.

[4] $VarWS_i = \frac{\sum_{t=1}^{n}(WS_{it} - \overline{WS_i})^2}{n}$, where n is years in contract.

[5] $WS_i = (WP48_i/48) \times \overline{MP_i}$.

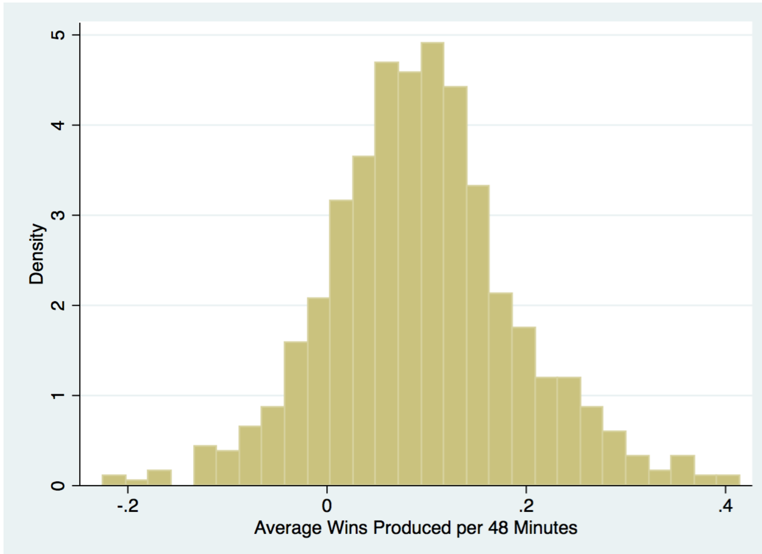

Figure 3.1: Histogram of free-agent players' contract-length average wins produced per 48 min

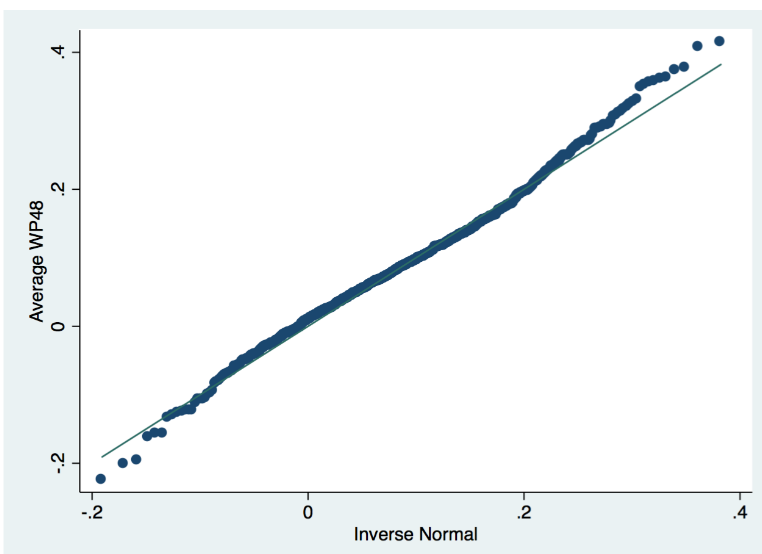

Figure 3.2: Normal quantile plot of free-agent players' contract-length average wins produced per 48 min

Figure 3.3: Scatter plot of free-agent players' actual and expected win score

Figure 3.4 is the histogram of expected win score of free-agent players.[6] The distribution is right-skewed. The shorter left tail implies that there are not many "bad" players among the free-agent NBA players. The longer right tail indicates that superstars are hard to find. Figure 3.5 is the normal quantile plot of the expected WS. It shows that distribution of WS deviates severely from normal. Hence, Figures 3.1 and 3.4 indicate that greater wins contributed to team does not come solely from superior performance as measured by WP48, but also from longer minutes played.

Figure 3.6 shows that the variance of WS is very right skewed. This implies that there are only a small amount of players with inconsistent WS. This is in line with the 70% correlation of players' WS from one season to another season that implies the consistency of players' performance across the seasons.

3.3.2 Evaluation of Marginal Cost of Win

The marginal product of each free-agent player, namely expected win score (WS), from the previous steps are used for the calculations of marginal cost (MC) and marginal rev-

[6]As mentioned earlier, win score is calculated from actual performance in particular season multiply by the actual time on court. Meanwhile, expected win score is estimated from contract-length average performance multiply by the actual time on court.

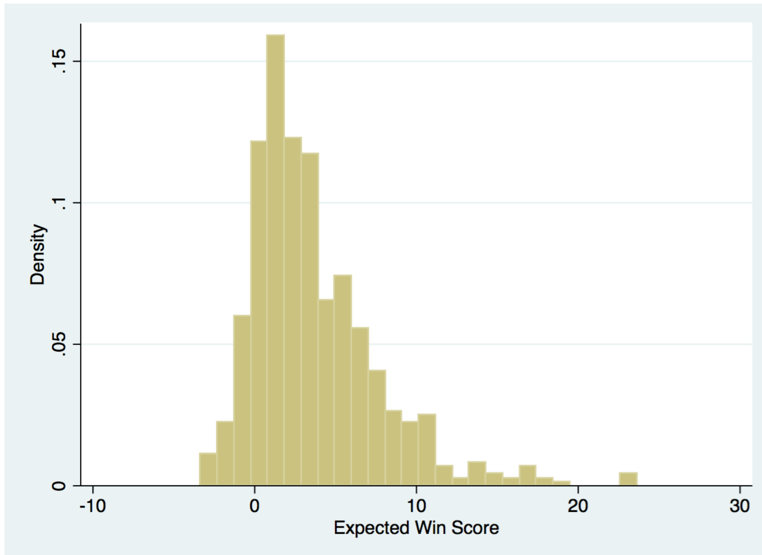

Figure 3.4: Histogram of free-agent players' expected win score

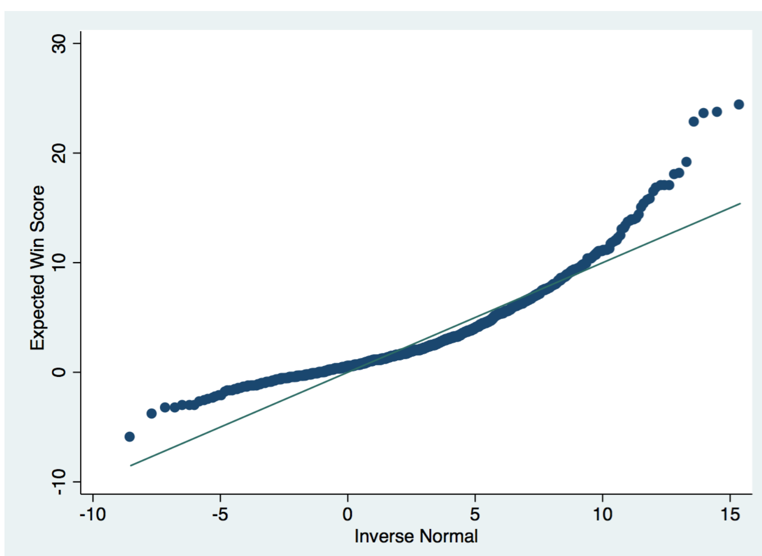

Figure 3.5: Normal quantile plot of free-agent players' expected win score

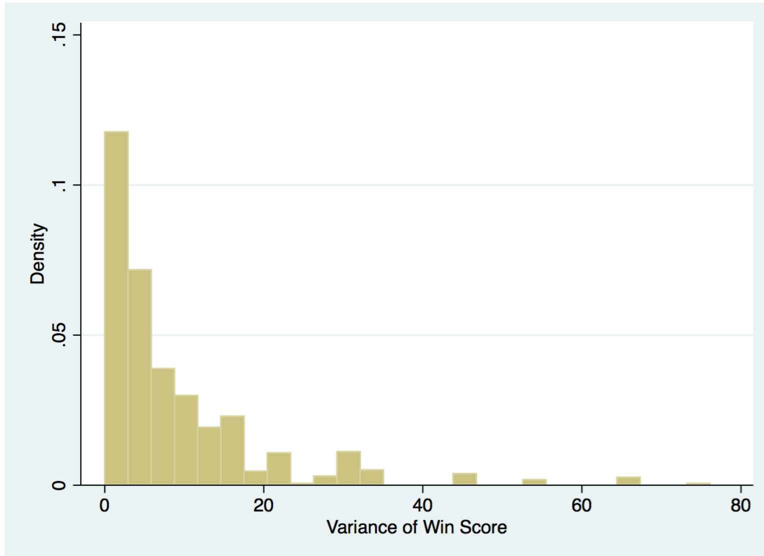

Figure 3.6: Histogram of variance of free-agent players' expected win score

enue (MR) of win. The MC of wins is defined as the amount of money teams spent in order to win one extra game. Since teams use players to produce victories, salaries of player determine the MC. As teams only have limited spots in the roster, in order to win more games, rather than a higher quantity, quality of player is required. Better players cost more to team. This study assumes that MC of WS is constant. The salary data come from `www.basketball-reference.com`. Since many players sign multiyear contracts, the contract-length average salary is used for the analysis for simplicity. Other costs associated with wins are neglected as we only consider the cost of wins the teams spent on players.

As expected WS presents the expected production of wins each player produced, it is the expected marginal product ($E(MP_L)$) of that player. Once the MP is calculated, the "MRP realized wage," the base salary that is determined by player's MRP or $w|E(MP_L)$ can be determined. The use of WS especially the assumption that the realized MP is known prior to the contracts were signed might not be realistic. However, as stated in Capen et al. (1971) that a better technology used for estimating the true value of product, in this case WS, might narrow the uncertainty but it does not necessarily change the expected value.

To control for other characteristics of players that might affect the salary negotiations, a regression of salary as a function of player's MP, controlling for other player's characteristics, can be performed using the following equation.

$$w_k = \alpha_0 + \alpha_1 WS_k + \alpha_2 VarWS_k + \sum_{m=3}^{n} \mathbb{Z}_{mk}\alpha_m \tag{3.7}$$

where w_k is player's salary; WS_k is player's expected win score, $VarWS_k$ is variance of player's win score that captured uncertainty in the marginal product of player, $\mathbb{Z}_k$ is other characteristics of player's: age, age-squared, experience, height, weight, position played, and superstar status (measure by all-star game appearance). The estimated coefficient α_1 is the MC of wins. While WS and VarWS comes from the previous step, the rest of the information is from `www.basketball-reference.com`.

Consider the histogram of free-agent salary in Figure 3.7, one can observe a right-skewed distribution. This indicates that only a small portion of players receive higher pay. The Lorenz Curve in Figure 3.8 shows that there is evidence of inequality in pay among NBA free-agent players. Although not presented here, the inequality is also observed in the all NBA player sample, which includes both free-agent and not free-agent players. The inequality seems to be worse for the whole sample. This is understandable since numerous not-free agents receive lower pay contracts than the free agents, especially the rookies that usually get paid at the minimum wage.

Figure 3.9 show a positive relationship between salary and expected performance of free-agent NBA players. Although the plots show no strong correlation, the direction of the relationship in both graphs indicates that teams do realize players' contributions and reward them accordingly. There is 39.56% significant correlation between the two variables.

3.3.3 Evaluation of Marginal Revenue of Win

The next step of this study is to evaluate the value of player as the contribution that each player makes to the teams' revenue. The pioneer work on monetary valuation of wins is a study of Scully (1974). The calculation involves the estimation of marginal revenue (MR), or in the specific term for sport teams, marginal wins value (MWV) for each team. The MWV is the revenue the team expected to gain from winning one extra game. Rascher and Rascher (2004) indicate that team's revenue is a function of market characteristics and team characteristics. Overall, one can say that there are various factors determining revenue of a team.

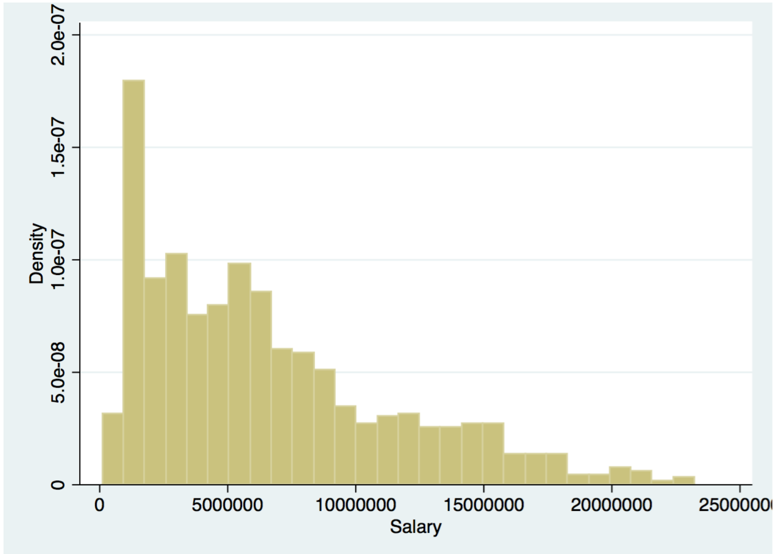

Figure 3.7: Histogram of free-agent players' salary

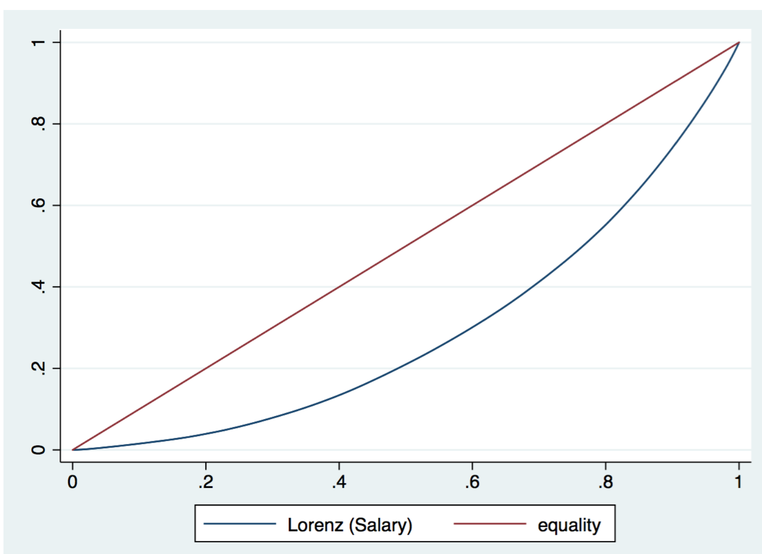

Figure 3.8: Salary cumulative distribution in the NBA free-agent market

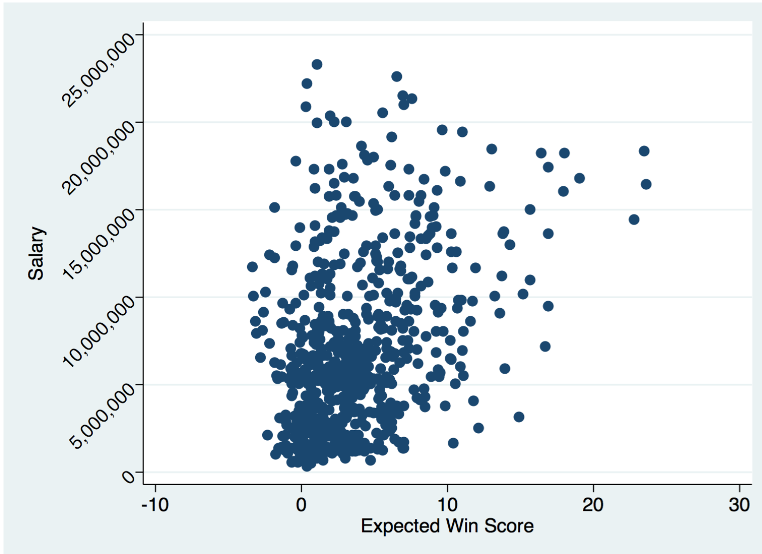

Figure 3.9: Scatter of salary and expected win score

To study this topic, we need team-level data. There are many factors contributing to revenue. The most important factors are winning percentage of current and previous season. Other determining factors include extra game played after the regular season (measured by playoff appearance), market size (measured by population in the metropolitan area where the franchise located), stadium capacity, and year-specific dummies to account for economic impact such as inflation and industry growth. The winning percentage data are gathered from the NBA official website (`www.nba.com`). The population data are collected from `http://www.census.gov` and `http://www.statcan.gc.ca`. The stadium capacity data are published at `https://en.wikipedia.org/wiki/List_of_National_Basketball_Association_arenas`. The revenue data are collected from the 2004/2005 to 2014/2015 seasons, which are available at `www.forbes.com/teams`.

With our main focus on winning, we can regress a total revenue function from the following model.

$$TR_i = \beta_0 + \beta_1 Win82_i + \sum_{j=2}^{n} \mathbb{X}_{ij}\beta_j \tag{3.8}$$

where TR_i is team's total revenue, $Win82_i$ is number of games won per 82 games played calculated by multiplying team's winning percentage by 82, $\mathbb{X}_i$ is a vector of external factor affecting team's total revenue, and β_1 is the MWV or the MR.

Figure 3.10 is the histograms of teams' total revenue from the 2004/05 to 2014/15 NBA season in nominal term.[7] Total revenue distribution skews to the right in every season indicating that there is a small number of teams that generate higher revenue than others.

Due to disagreements between players and teams, the 2011/12 regular NBA season was shorter than the usual 82 games. To make the analysis of marginal revenue consistent, winning percentages are converted to Win82. It is defined as numbers of games won out of 82 games played, which only differs from observed wins in the 2011/12 season.[8] Figure 3.11 shows that wins in the NBA are normally distributed. The normality is also observed in the distribution of team win score, which is simply the summation expected WS of every player in the particular season's roster, as presented in Figure 3.12.[9] The team that has highest WS in the sample is the Golden State Warriors in the 2014/15 season which won the NBA championship in that season. A 90.18% significant correlation between the team WS and Win82 indicates that the expected performance is highly correlated with the actual performance. Figure 3.13 shows a scatter plot between the two variables.

Figure 3.14 illustrates a positive relationship between team revenue and its performance. This indicates that teams with higher revenue usually win more often, although the correlation is only 25.39%. On the other hand, 21.56% correlation is predicted for team's total revenue and Team WS. This implies that there is a slight positive relationship between teams' revenue and the cumulative expected performance of players in the rosters. Figure 3.15 presents this relationship. The weak correlation may be a result of outliers in the sample. As can be seen at the upper left corner of both figures, there are teams that, despite having high revenue, suffer from poor performance. There are two possible reasons: fan royalty keeps the team revenue high even the teams do not perform well; or these teams have poor resource allocation and spend too much money on bad players. Since the correlation do not imply causality, the outliers can be from either cause.

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[7] The figure does not take in consideration the inflation because economy-wide inflation has remained quite low throughout the sample period.

[8] It should be noted that $Win82$ and WS are numbers of victories per season. While $Win82$ denotes team's actual wins, WS is estimated wins contributed by a player. By adding up roster players' WS, team WS can be estimated.

[9] $Team\ Win\ Score_{it} = \sum_{j=1}^{k} WS_{jt}$, where player j to k play for team i in season t.

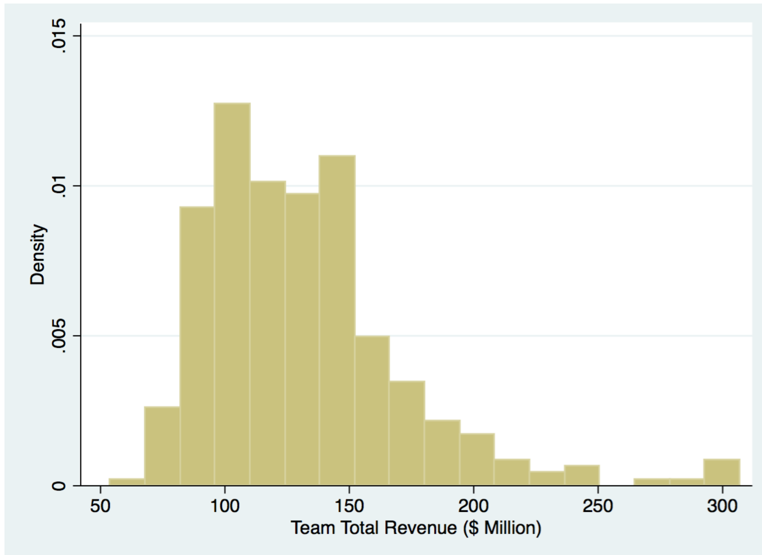

Figure 3.10: Histogram of NBA teams total revenue

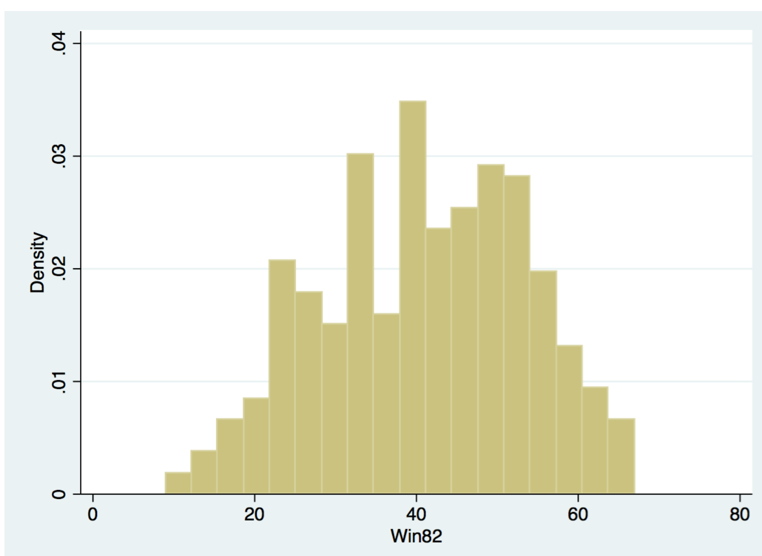

Figure 3.11: Histogram of win82 in the NBA

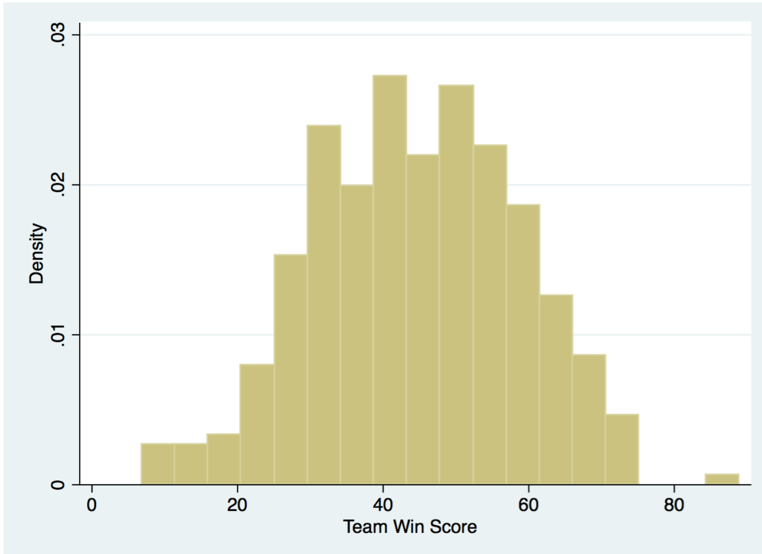

Figure 3.12: Histogram of team win score

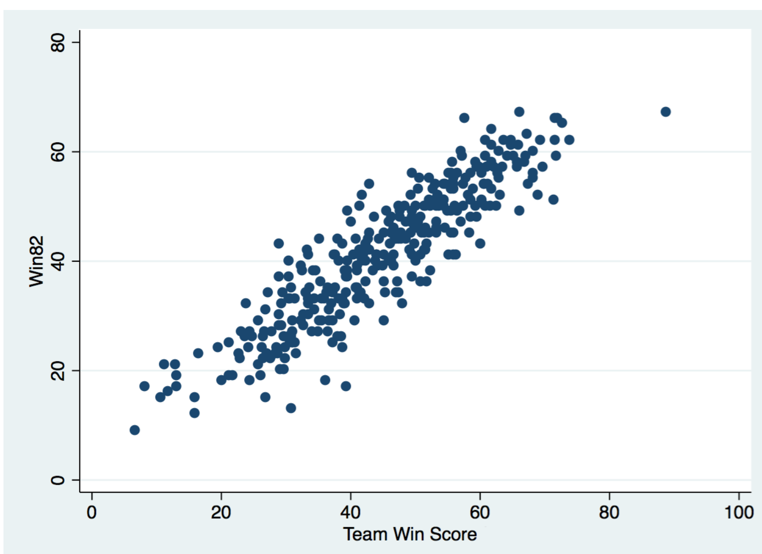

Figure 3.13: Scatter plot of NBA teams' expected and actual performance

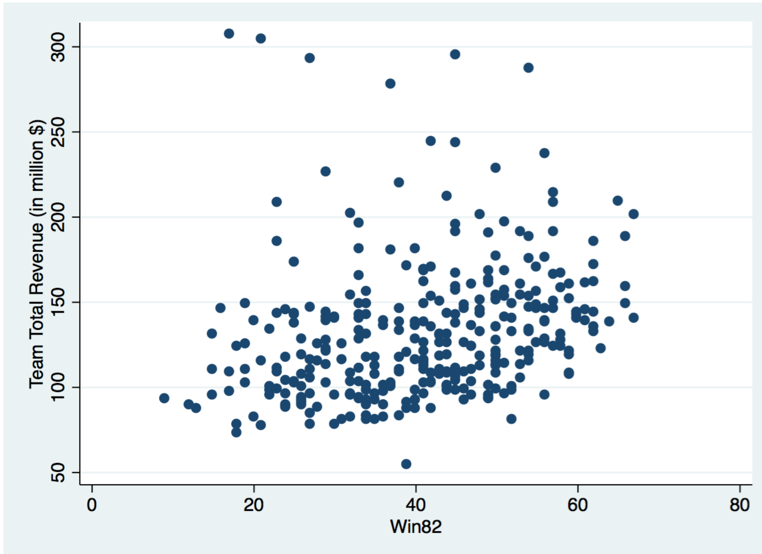

Figure 3.14: Scatter plot of NBA teams' revenue and win82

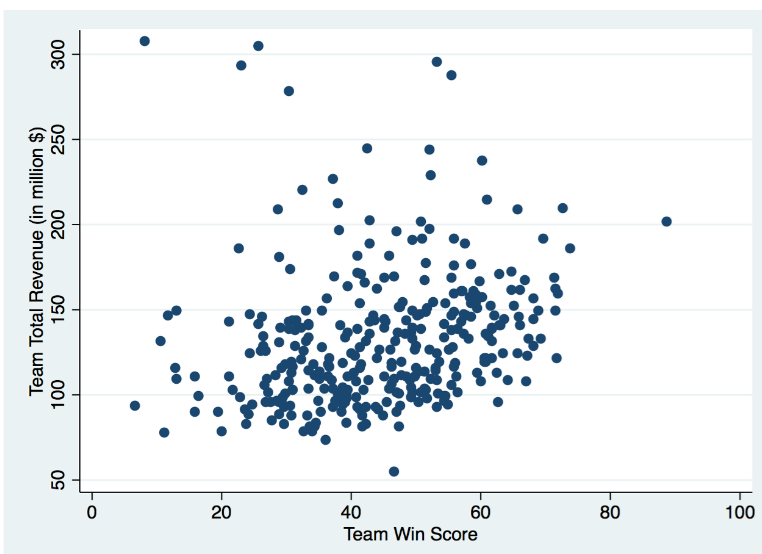

Figure 3.15: Scatter plot of NBA teams' revenue and teams' win score

The winner's curse appears if MC is greater than MR. In other words, if α_1 from the estimation in salary equation (Equation 3.7) is greater than β_1 in the revenue equation (Equation 3.8), then there is an evidence of the winner's curse.

3.4 Results

3.4.1 Marginal Cost of Win

This study applies win score (WS) of Berri (2008) as the performance measurement of players. The main reason is because it is directly measuring the contribution to wins of each player that can be directly interpreted as player's marginal product. In the process of calculation for WS, WP48 is estimated. WP48 is defined as wins produce per 48 min and is evaluated from performance statistics. A player's WS is the actual wins produced by that player in that season which is WP48 divided by 48 and multiplied by the actual minutes played. [10]

The performance of current season and the season before of NBA players are significantly correlated with each other (70% for WS and 72% for WP48). In this study, the contact-length average WP48 is used for calculation of expected WS and is assumed to be common knowledge among teams. Teams are also assumed to have already planned ahead of the season how much time each player will be playing. As a result, WS is known to teams. The variance of performance is assumed to be common knowledge, but the uncertainty in actual performance remains.

The offered wage is a function of performance, variance of performance, and other players' characteristics.

$$\begin{aligned} Salary_i = &\beta_0 + \beta_1 WS_i + \beta_2 VarWS_i + \beta_3 (WS_i \times Star_i) + \beta_4 Age_i + \\ &\beta_5 Age_i^2 + \beta_6 Exp_i + \beta_7 Ht_i + \beta_8 Wt_i + \delta_0 Star_i + \\ &\sum_{j=1}^{4} \delta_j Pos_i + \sum_{k=1}^{10} \delta_k Year_i + \sum_{m=1}^{29} \delta_m Team_i \end{aligned} \tag{3.9}$$

where *Salary* is player's salary, *WS* is expected win score calculated from average WP48, *VarWS* is variance of win score, *Age* is player's age at the beginning of the season when the contract was signed, *Exp* is experience in the major league at the beginning of the

[10] For the complete steps, see Appendix D.

season when the contract was signed, *Ht* is player's height in inches, *Wt* is player's weight in pounds, *Star* is the dummy variable for star player (= 1 if player appeared in the roster of the all-star game during the contract at least once), *Pos* is dummies for positions (where power guard is the base group in this study), *Year* is the year at which the contract was signed, and *Team* is the team-specific dummy. The heteroskedasticity is observed, and hence, the robust standard errors are implemented.[11] The result of the regression is presented in Table 3.2. The estimated coefficient of *Year* and *Team* are not presented in the table to conserve space.

The model can explain approximately 45.35% of the the variation in salary. This indicates that there is an ample room for other factors considered by team when determining players' wage. The use of salary to compare with the marginal revenue product of players in earlier studies of the winner's curse, hence, might not be appropriate.

From the regression, *Age*, *Weight*, and *Position* dummies except for center are not statistically significant. On average, as nonstar player's win score increases by one game, all else being equal, his salary is expected to increase by $236,315. To explicitly focus on the "super star," the players who received sizable contracts, the *Star* dummy is included into the model along with the WS-Star interaction term. The estimated coefficient of both terms are statistically significant. Star players receive a premium of $9,693,614, on average. However, they are exploited on their superior performance as the WS-Star interaction term shows a significant negative sign. Average star players produce 5.41 more wins than average nonstar players.[12] One can calculate that an average star player receives a total of $7,510,094 as premium after discounting for their superior performance.

The variance variable is statistically significant and has a positive value. This follows the winner's curse theory that a greater uncertainty in the expected value of the product leads to a higher bid. The correlation of WS and VarWS is positive significant at 53.90% indicating that better players seem to be more inconsistent. In other words, there is a performance streak for better players.

Age is statistically insignificant but Age^2 is significant and negatively affect salary; this

[11] The Breusch-Pagan/Cook-Weisberg test's chi-square is 148.35 at the 52 degree of freedom and $p = 0.000$.

[12] Average star player's WS is 8.67 and average regular player's WS is 3.26.

Table 3.2: Regression of salary with robust standard errors

Variable	Coef.	Std.Err.	t	$p > \|t\|$
Win Score	236,314.77***	54,626.18	4.33	0.00
Variance of Win Score	51,626.88**	20,885.17	2.47	0.01
Win Score × Star	-403,608.18***	135,941.31	-2.97	0.00
Age	967,098.58	811,076.98	1.19	0.23
Age^2	-27,940.96**	13,737.09	-2.03	0.04
Experience	682,977.51***	146,176.40	4.67	0.00
Height	231,392.35**	91,257.41	2.54	0.01
Weight	18,639.30	12,446.69	1.50	0.13
Dummy, star	9,693,614.43***	1,200,673.88	8.07	0.00
Dummy, center	-2,215,828.92**	1,052,580.50	-2.11	0.04
Dummy, power forward	-1,520,160.86	925,184.45	-1.64	0.10
Dummy, small forward	-795,136.81	708,917.63	-1.12	0.26
Dummy, shooting guard	43,710.89	553,666.29	0.08	0.94
Constant	-25,727,118.36*	14848176.30	-1.73	0.08
R^2	0.4535			
Observations	691			

indicates that older players receive lower pay which should be a result of lower expected performance. The correlation of age and performance is -14.96% for the regular players (but not significant for star players). Experience is positively significant. Height also have a positive significant effect on wage.

3.4.2 Marginal Revenue of Win

One game produced by an average player is equal to a game produced by a star player. As a result, the returns on wins for a team should be the same no matter who generates wins. Hence, team-level data are used for the calculation of marginal wins value (MWV), in contrast to the individual player data used in the calculation of the marginal cost. Heteroskedasticity was encountered but was corrected after using robust standard errors.[13] The model for estimation is

$$\begin{aligned} TR_{it} = &\alpha_0 + \alpha_1 Win82_{it} + \alpha_2 Win82_{it-1} + \alpha_3 Pop_{it} + \alpha_4 Cap_{it} + \\ &\gamma_0 Playoff_{it} + \gamma_1 Champion_{it} + \sum_{j=1}^{10} \gamma_j Year_i \end{aligned} \tag{3.10}$$

[13]The Breusch-Pagan/Cook-Weisberg test's chi-square with 15 degree of freedom is 395.03 and p = 0.000.

where TR_{it} is team total revenue, $Win82_{it}$ is number of wins per 82 games,[14] $Win82_{it-1}$ is the number of wins per 82 games from the previous season to capture the long-term effect of wins, Pop_{it} is the market size measured by the population in the metropolitan area where the team located, Cap_{it} is stadium capacity, $Playoff_{it}$ is a dummy variable for postseason appearance, $Champion_{it}$ is the dummy variable for winning the championship in that season, and $Year_i$ is the dummies for years in the sample capturing the inflation and industry growth (2005 is the base year). The regression output is in Table 3.3.

About 58% of the variation in team total revenue can be explained by the model. Most of the explanatory variables are statistically significant. Market size and stadium capacity both have positive influence on total revenue. Being in the playoff does not affect team revenue. Team performance does have a positive impact on team revenue across both current and the immediate following seasons.

The marginal effect of Win82 on team revenue from the previous season is even more valuable as that of the current season. The present value of the expected return calculated from

$$\frac{\partial(TR)}{\partial(Win82)} = 486,640 + \frac{583,242}{1+\delta} \tag{3.11}$$

where δ is the discount rate. Assume that the discount rate is 5%, an extra win generates \$1,042,109 to the team per season.

3.4.3 Is There a Winner's Curse in the NBA Players Market?

To discover the winner's curse, previous studies usually compare player's MRP to his salary. If salary exceeds MRP, they conclude that the winner's curse exists. For NBA players, the MRPs can be calculated by multiplying WS with MWV of \$1,042,109. Using a one-sided paired t-test for the null hypothesis that salary is equal to MRP against the alternative hypotheses that salary is smaller and greater than MRP, respectively, we reject the null hypothesis that salary is equal to MRP, but rather is greater than MRP (p = 0.0000); but cannot reject the null hypothesis that salary is equal to MRP when the alternative hypothesis states that salary is less than MRP (p = 1.0000). As a result, using salary-MRP

[14]To capture the impact of the lockout in the 2011/2012 season that shortened the regular season to only 66 games.

Table 3.3: Regression of total revenue with robust standard errors

Variable	Coef.	Std.Err.	t	$p > \|t\|$
Win82_t	486,639.74**	207,166.45	2.35	0.02
Win82_{t-1}	583,242.03***	121,586.33	4.80	0.00
Market size	3.90***	0.61	6.40	0.00
Stadium capacity	4,944.86***	1,121.24	4.41	0.00
Dummy, playoff	959,399.98	4,858,958.04	0.20	0.84
Dummy, champion	15,825,753.89***	4,596,913.50	3.44	0.00
Dummy, 2015	61485814.93***	8,377,452.17	7.34	0.00
Dummy, 2014	51,790,882.02***	6,582,970.97	7.87	0.00
Dummy, 2013	44,244,788.11***	7,048,305.76	6.28	0.00
Dummy, 2012	15,216,538.08***	5,888,741.08	2.58	0.01
Dummy, 2011	24,573,270.88***	5,939,553.02	4.14	0.00
Dummy, 2010	19,850,993.00***	5,814,125.03	3.41	0.00
Dummy, 2009	19,204,125.18**	5,911,644.16	3.25	0.00
Dummy, 2008	18,612,060.54**	5,827,442.17	3.19	0.00
Dummy, 2007	12,427,629.88**	5,878,378.59	2.11	0.04
Dummy, 2006	5,834,063.22	5,741,423.71	1.02	0.31
Constant	-53,074,811.83**	22,471,120.37	-2.36	0.02
R^2	0.5799			
Observations	329			

comparison, the conclusion follows previous literature that the winner's curse does exist in the free-agent NBA players market.

Consider the cost-revenue of WS by comparing the marginal cost and marginal revenue, the conclusion is different. The marginal cost of WS is the amount of money teams spend to acquire an extra win generated by players. It is the same as the marginal effect of WS on player's salary. The marginal revenue is the return in dollar term a team would earn if they win one more game in the season. It is the marginal effect of Win82 on team's total revenue which is calculated to be $1,042,109 per win.

The estimated coefficient of WS from the regression is tested against a null hypothesis that $\beta_{WS} \leq 1,042,109$. At the 5% level, we fail to reject the null hypothesis (p = 1.0000). As a result, teams, on average, spend less than what they get from an extra win. In other words, teams actually realized the true value of players and can eventually exercise their monopsony power to lower the salary below players' actual value.

Since teams determine salaries by including the uncertainty component, namely variance of WS into consideration, one should not draw any conclusion about winner's curse without taking in consideration this factor. The median of variance of WS is 8.79 means than, for an average player with regular variance in performance, the winner's curse occurs if $\beta_{WS} + 8.79\beta_{VarWS} > 1,042,109$. At the 5% level, the single tail t-test for the null hypothesis that $\beta_{WS} + 8.79\beta_{VarWS} \leq 1,042,109$ fails to reject the null hypothesis (p = 0.9550). Again, with the inclusion of uncertainty variable, there is still no evidence that teams are victims of the winner's curse.

Average star player receives \$8,748,409 as a premium while the 5.65 extra wins generated by an average star player provide his team $1,042,109 \times 5.65$ = \$5,887,916. One might conclude that the winner's curse does exist here. However, star players normally not only generate revenue to his team only through extra wins created. Autographs, souvenirs, jerseys, and so forth. of star players can create more money to the team. Due to the lack of detailed information about team revenue, this part of income cannot be estimated. However, it is likely that another 42% of the revenue that cannot be explained by marginal revenue model in this study will include star player indirect revenue. With this in mind, the winner's curse has less probability to occur under this circumstance.

The two findings are in conflict. Comparing only MRP and salary, teams fall in the winner's curse trap. However, it might not be reasonable to conclude that teams overestimate the value of players since another evidence suggests that they actually realize the true value and even pay players less than they should. The reason that salaries are greater than expected benefit of players can be because of other nonperformance player's characteristics and negotiation from the player union. Berri, Leeds, and von Allmen (2015) present that players are paid for something else besides wins, namely bargaining power. This power comes from the player union that has been successfully negotiating over team's fixed revenues such as those from broadcasting rights, a portion that is not included in the revenue function. The estimated bargaining power is computed by subtracting player's average salary by estimated MRP. In this study, the estimated bargaining power of free-agent players is \$2,938,109, less than the estimation of \$3,877,737 by Berri et al. (2015). This is supported by another regression of the a function, $\ln(Team\ Payroll)_{it} = \beta_0 + \beta_1 \ln(Team\ Revenue_{it})$.[15] A 1% increase in team revenue, all else equal, is expected to

[15]The result is not reported.

increase team's payroll by 0.37%.

Berri et al. (2015) argue that the bargaining power equalized salaries with MRP. In this study, although the estimated bargaining power is almost 50% smaller than what was presented in Berri et al. (2015), the effect of the labor union and its bargaining power seems to be greater beyond just equalizing salaries to MRP. Instead, it raises salaries above MRP. This might sound illogical that team owners would allow this to happen. However, consider that players do not only create revenue through wins. Star players can bring more fans to the stadium. Their numbers on the jersey, their signatures, their photographs, and so forth, can be sold as team merchandise. These also generate dollars to team. As a result, the real bargaining power should be even less than the figure estimated.

It is also possible that the estimated bargaining power of the free agents comes from exploitation of wins generated by the not-free agent players. Many players in the roster have less than 6 years of experience and are bonded with contracts that are usually compensated at the minimum wage. As of the 2015/16 season, a rookie's minimum salary is \$525,093 and the minimum salary for a player with 5 years of experience is \$1,100,602. If a player generates only 1 win to his team, his value should at least be \$1,268,327 if teams set wages equal to his MRP. The average nonstar player in this study is \$5,932,277. Considering this possibility, a part of the extra pay players receive as free agents is to compensate the exploited salary when they were not-free agents. This lowers the dollar gains from bargaining power even further.

There are other costs necessary to generate wins beside payrolls such as managerial expenses, stadium maintenance costs, and so forth. As a result, the estimated MC of wins might be too low. However, this part of the cost is beyond the responsibility of players; although, teams could pass these costs onto players and lower their pays.

3.5 Conclusion

This study examines the market for free-agent NBA players whether there is a winner's curse problem or not. The characteristics of NBA free-agent player market deem appropriate for the study of the winner's curse. Previous studies on the winner's curse in major sports industry often compare salaries with MRPs. Most conclude that salary is greater than MRP, and hence, the winner's curse exists.

In labor economics, it is assumed that wage is equal to marginal cost of labor and that a firm will maximize benefit by equalizing marginal cost to marginal revenue product of labor. While the latter part of this assumption is still theoretically correct, in the real world, the former part is not applicable as wages are normally determined by many factors. This study argues that salaries of NBA players are not solely determined by performance, but also other players' characteristics. As a result, it is not appropriate to directly compare salary with MRP, which is only estimated from the player's performance. Instead, the comparison between marginal cost and marginal revenue of win is applied.

Using the traditional method of salary-MRP comparison, it follows previous literature that the winner's curse exists. However, using the MC-MR comparison, this study discovers that teams indeed reward players less than the revenue they generated to teams, even after include the tendency for winner's curse such as the returns to variance of performance. Although there is no clear evidence, it seems likely that it is the same for star players. The winner's curse theory indicates that the winner of the bidding war "overestimated" the true value of product. As evidence presented in this study suggests, there is no evidence of such overestimation. Hence, this study concludes that there is no winner's curse problem in the bids for NBA free-agent players.

There still exists a positive difference between salary and MRP. One possible reason is that a part of the salary is determined by other players' characteristics that do not directly contribute to wins, such as age, experience, height, super star status, and so forth. Another possible factor is the bargaining power over team's fixed revenue, for example, TV broadcasting right income, that is, by agreement of the league and the NBA labor union, shared between teams and players. The extra wage above MRP can be a form of compensation that teams provide to players for a lower-than-MRP salary paid when players are not yet free agents. Teams could also pass other costs necessary to generate wins besides players such as managerial cost onto players and lower their wages.

Despite seemingly not being the cause of the winner's curse, star players are exploited from their contributions. The better performance of the star players, the more exploitation persists. This contradicts the economics of superstars theory by Rosen (1981), that return on performance increases in a nonlinear fashion. Future research can focus on the discovery of the relationship between player's characteristics to wins or performance, that has always been assumed to be constants. This will enable the possibility of monetary evaluation of player's characteristics that helps improve the precision of the estimation for player's marginal revenue product besides just from performance. It could, in turn, yield a more precise conclusion about the winner's curse through a more accurate expectation of benefit teams would have gained from players, since not every position requires same type of player.

CHAPTER 4

ADVERTISING BEHAVIOR IN THE U.S. SKI INDUSTRY: AN APPLIED CONJOINT ANALYSIS METHOD

4.1 Introduction

The interest of advertising behaviors in business has been studied in numerous advertising research, although, in the past thirty years, this field of study has not received much attention from economists. Moul (2006) suggests that the omission of advertising can cause substantial biases in estimation of factors determining market demand.

Advertising is one of the marketing tools used to compete for consumers' attention. Nowadays, the expansive usage of customer and market research makes customers' preference predictability more accurate. However, the market is competitive and there are several firms that are trying to reach out to customers. The approach and timing of communication has become the main sources of sale expansion. These are all depending on the ability of the firms to advertise. Competition for customers leads to a more intense advertising competition.

Comanor and Wilson (1974) state that the content of advertising is not as important as the fact that a product or brand is well advertised. This reflects in customers choosing a well-known, highly advertised, but expensive brand over an unknown, little advertised, cheaper one. Nelson (1970, 1974) and Grossman and Shapiro (1984) explain that this could be the result of the change in demand elasticities which depend on the range of alternative products for which quality of information is available. In a market where quality of product cannot be observed, advertising is a tool to persuade customers to believe that the advertised product is the better one. Prasad and Sethi (2004) explain that firms advertise in order to maximize their profit while also considering the actions of the competitor dynamically, due to the carry-over effect of advertising (the advertising spending today will continue to influence sales several months down the line).

The U.S. ski industry is selected as a case study for this research. Although there are many branches of businesses under the snow sports industry, this study pays attention only to ski and snowboard resorts. The ski resort industry is highly competitive. The concentration ratio of industry is considered to be at a medium level. Vail Resorts Inc. is the leader in the market with a market share of 29.3%, followed by the Intrawest Corporation (10.0%), Boyne Resorts (8.7%), and the Powdr Corporation (5.7%). The rest 46.3% goes to other small operators. The industry has been consolidated as large operators continue buying individual resorts or send small operators out of business. Accessibility to capital becomes an obstacle to small business since ski resorts have to deal with the uncertainty of weather condition, requiring the cost of installing snow making equipment. The ski resort industry is characterized by significant barriers to entry because of high initial costs, high capital intensity, and limitation of ski areas, which is constrained by environmental regulations. It is expected that over the next five years, the number of small operators will decline, while the bigger companies enjoy the benefits from economies of scale (Yang, 2012).

Approximately 8% of the total revenue of ski resorts goes to marketing expenses including advertising (Yang, 2012). The advertising performance depends on the media used, the message delivered, the markets targeted, and the dollar invested (Strategic Marketing & Research, Inc, 2013). Since it is costly, advertising is expected to be able to raise the demand (L. Pepall, Richards, & Norman, 2005, Chapter 20). The difference in size of capital between firms can impact the ability of the firms to expand their advertising and can, in turn, constrain the ability to compete in the business. According to Kaldor (1950), advertising scales economies exist and big firms are better able to finance large advertising expenditure, which promotes greater industry's concentration.

This study tries to examine differences in advertising behavior by focusing on two groups of ski resorts, big and small, around the U.S. especially on the differences in advertising behavior due to the ability to access to capital between the two sample groups. The main purpose is to explore whether advertising ability could be one of the reasons for industry consolidation or not.

This study is a supply-side study and the analysis involves the decision-making process of the resorts, instead of a demand-side study which pays attention to consumers' behavior, which is an area that has long been neglected. The following section describes the methodology and sample used in this study. The third section provides results of the study. The conclusion and recommendation are in the last section.

4.2 Approach

4.2.1 Methodology

This study applies the choice-based conjoint analysis (CBC) or discrete conjoint model. The CBC conjoint analysis is adapted and used to study the behavior of firms instead of consumers. The estimation used in this study is multinomial logit analysis (MNL). More details on the conjoint analysis and the MNL estimation can be found in Appendix E.

4.2.2 Sample

The respondents in this study are ski resorts' experts or persons in charge of making advertising decisions. Since the study pays attention to the advertising behavior of the firms, the marketing managers, advertising managers, or general managers are in the focus group. The identity of each resort and respondent is coded and kept confidential to ensure anonymity of participants.

There were 482 ski resorts under 340 businesses in the U.S. as of year 2012 (Yang, 2012). The questionnaire was sent to 152 individuals who are in charge of making the advertising decisions of each ski resort and are reachable by e-mail. The conjoint tasks were performed and the data were collected using third-party software (Sawtooth). At the end of the survey, 22 responses were received, of which only 19 are valid.

Based on the data screening criteria suggested in Hair, Black, Babin, Anderson, and Tatham (2005), 2 respondents were eliminated because both answered the questions using "straight line" pattern (always selected choice 1). This corresponds with the data obtained by the software used in this study that both of them spend approximately 3 s per task which does not seem possible considering the amount of information presented in each task.

Out of the remaining qualified 17 respondents, 4 did not complete the entire survey. However, these respondents were kept in the utility estimation. Only the 13 respondents who completed the entire survey were used in the calculation of the "hit rate," which is the test for checking the accuracy of predictions.

4.2.3 Conjoint Tasks

The respondents were asked to answer general questions related to their businesses, such as the size of their resorts, services provided in their resorts, location of their resorts, and so forth.[1] In Appendix F, the characteristics of the resorts that participated in this analysis is summarized.

A total of 15 choice tasks were presented to each respondent after completing the general questions. Each task contained three conjoint profiles. The question asked at the beginning of each conjoint task was: *"If you were considering increasing your business' advertisement for this year and these were the only situations you face, which would be the most likely scenario that you will choose to advertise more?"*

The choice for not choosing to increase advertising was included in every choice set as dual response task.[2] This made the tasks more realistic without losing information and the ability to estimate absolute and relative effects of each attribute (Haaijer, Kamakura, & Widel, 2001).

After in-depth interviews with industry's experts (n = 7), four attributes are considered in this study. A low number of attributes could lead to an unrealistic the conjoint task. However, in-depth interviews with ski resorts' representatives and experts in the industry suggest that these are the only factors the ski resorts pay attention to when it comes to advertising decisions. Each attribute is divided into five levels based on in-depth interviews and industry reports (Yang, 2012) to be as realistic as possible as listed in Table 4.1. These levels are used in the factorial designed profiles and estimated separately as individual variables.

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[1] See Appendix G.

[2] First, the respondents were asked to choose the best choice among the presented profiles. After that, they were asked whether the respondents will really choose to increase advertising if the situations in that choice sets really are only situations in real world where they have an option of not increasing advertisement.

Table 4.1: Attributes and levels used for the conjoint analysis

Attributes	Levels
Total revenue of last season compared to the season before (TR)	Increased by 3% Increased by 10% Decreased by 3% Decreased by 10% Did not change
Snow quantity of the resort compared to average snow falls this season (SQ)	3 in. above average 5 in. above average 3 in. below average 5 in. below average Same as average
Number of times you see advertisement of competitors in the current season compared to last season (RA)	Increases by 20% Increases by 50% Decreases by 20% Decreases by 50% Does not change
Average cost of advertising media that the resort is currently using or planning to use this season compared to last season (CA)	Increases by 10% Increases by 25% Decreases by 10% Decreases by 25% Does not change

Total revenue is one of the main factors affecting the advertising expenditure decision. In this study, total revenue means the total revenue of last season in comparison to the season before. It has two possible causalities: an increase in total revenue raises the possible budget for advertising, or an increase in advertising expenditure brings about a higher total revenue. Lambin (1976) finds that the latter causality flow dominates the former one. Brand advertising shows a positive impact on a brand's current and future sales and/or market share. This conclusion is consistent with previous literature, such as Nerlove and Waugh (1961) and Telser (1962). Although, Lambin also finds that there is a strong evidence of a decreasing return to advertising factors.

There are two possible hypotheses regarding total revenue. First, if the firms set advertising expenditures as a proportion of total revenue of last season, total revenue should have a positive relationship with the possibility of an increase in advertising expenditures. Second, a negative relationship should be observed if the firms react to a decline in total revenue of last season by expanding advertising expenditures. According to resorts representatives, many resorts have pretty stable marketing expenses overtime. As a result, it is more reasonable to predict that the latter hypothesis will be more likely the case.

Snow condition of each season is said to be one of the most important factors in advertising, according to in-depth interviews. Some ski resorts claim that the ability to make artificial snow by snowmaking technology could reduce the uncertainty in snow conditions so they do not make advertising decisions based on snowfall. However, the majority of resorts state that snow quantity plays a significant role in advertising decisions. So, it is possible that the region where ski resorts are located determines the advertising behavior in regard to snowfall. The prediction is that, since big operators have better technology and an ability to afford the cost of snowmaking, they will not be as sensitive to snow conditions as small resorts are.

Lambin (1976) finds a negative relationship between rival brand advertising on the firm's sales or market share. He concludes that there are competitive tendencies in advertising. Unlike cartel prices, agreement on advertising behavior is difficult to secure. Also, positive advertising reaction elasticities are observed, which indicates the interdependence among brand advertising policies (Clarke, 1973; Grabowski & Mueller, 1971; Lambin, 1976; Telser, 1962). The reason is that advertising makes consumers less loyal to a brand (Telser, 1964). As a result, the rivals' advertising attribute is included into this model. To be more specific, instead of using rivals' expenditure on advertising, which is unknown to the resorts, according to representatives from ski resorts, the change in numbers of rival resorts' ads seen by the company is used in this study. The assumption is that if an operator sees that his or her competitors increase their advertising, he or she should do the same to avoid losing market share, if he or she thinks that it is possible to compete with them. In other words, if the competitors are of the same size of business, the competition among resorts should be more intense. On the other hand, some representatives from small ski resorts state that there is no point for them to compete with bigger ski resorts by advertising because they do not have the same capital as the bigger resorts do. As a result, the hypothesis on the rival's advertisement for this study is that the big resorts should be more competitive than the small resorts due to a more flexible capital.

Since this research focuses on decision-making process of the firms, the principles of microeconomic theory suggest that costs of production are main factors affecting the supply–including the supply for advertising (L. Pepall et al., 2005, Chapter 20). It should be noted here that the cost of advertising means the cost of particular channels of communication the resorts use to send their messages to the customers, for example, the cost of prime time in radio advertising. It is the cost of advertising media that each resort is currently using or planning to use if the cost is to be lower. These channels can be different among resorts since some of them might spend more on radio advertising, some on magazines, some on online social networks and some on television channels. It is expected that the smaller businesses would be less cost sensitive than the bigger ones since they mostly rely on cheap social network, local newspaper, or radio advertising while the big businesses invest more in costly advertising channel, such as television and global magazines.

4.3 Estimations and Results

In this study, two estimation approaches are conducted: counting analysis and multinomial logit estimation (MNL). Out of the 15 tasks asked to each respondent, 3 tasks are exactly the same while other 12 are randomly assigned to each respondent. The difference tasks presented to each respondent helps increase the information about preferences. The results presented in this section are estimated using 12 random tasks. The 3 tasks which are called "holdouts" are used later on to test the validity of the models.

4.3.1 Counting Analysis

The counting method is a quick way to summarize the results of choice data. The number of times an attribute level was chosen as a ratio of the number of times it was available in choice tasks will show the preference of each level in the same attribute. It provides the information that is closely related to the conjoint utilities. Although it should be noted that random imbalances in the design can distort count ratios if the sample size is small, which is the main problem of this study.

The 2-way and 3-way interaction effects from the counting analysis are also estimated but none of them are statistically significant and, hence, are not considered for the analysis. The null hypothesis is that the resorts do not make their advertisement base on the presented factor. In other words, when making decision, resorts pay attention on each factor separately. Table 4.2 summarizes the main effect results. The second column demonstrates the counting ratio, the number of times each level was chosen over the number of times it appeared as an option, of the whole sample.

Consider the chi-square statistics for each attribute, only the "cost of advertising" attribute is statistically significant at the 1% level. The null hypothesis is that the difference between the counting ratio of each level within the same attribute is equal to zero. The preference between levels in the cost of advertising attribute is statistically different from one level to other levels. For other attributes, the counting ratio shows that there are no significant difference in the preference of each level in the same attribute. In other words, there is no significant difference in the number of times an attribute level was chosen as a ratio of the number of times it was available in choice tasks.

The last two columns present the counts of two separated groups of ski resorts, categorized by the size of the resorts.[3] The two groups of resorts have similar results as the aggregated one. The chi-square statistics point out that the cost attributes are statistically significant at the 5% level for the small size group and significant at the 1% level for the big size group. Other attributes are all statistically insignificant.

It can be interpreted that, for ski resorts, either big or small, all the levels of last season's total revenue, the quantity of snow, and the amount of competitors' advertising are equally important for the ski resorts to take in consideration when they are making advertising decisions. The change from one level to another within the three attribute does not significantly change the advertising decisions. It worth mentioning here that the conjoint analysis builds on the assumption that every attribute included in the model is important. As a result, an insignificant statistic of the difference between the levels in each attribute does not mean that the attribute is not an important factor when making decisions.

The main factor that affects the advertising behavior of ski resorts is the cost of advertising media. Both groups, small and big resorts, show that a decrease in cost of advertising raises the possibility of an increase in advertising. The greater the reduction in cost of advertising channels, the higher probability for small ski resorts to raise their advertising.

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[3]NSAA uses vtf/h (lift capacity per hour) to classify ski resorts into 4 sizes. In this study, the small and medium small size resorts are combined and called small resorts while the medium-large and large resorts are grouped as big resorts. There are 12 small resorts and 5 big resorts according to this categorization.

Table 4.2: Counting analysis

Variable	Counting Ratio		
	Total (17)	Small (12)	Big (5)
Total revenue of last season compared to previous season			
Increased by 3%	0.371	0.342	0.393
Increased by 10%	0.333	0.342	0.333
Decreased by 3%	0.330	0.295	0.375
Decreased by 10%	0.333	0.356	0.400
Did not change	0.301	0.333	0.182
Within Attribute Chi-Square	*0.743*	*0.496*	*3.137*
D.F.	*4*	*4*	*4*
Significance	*not sig*	*not sig*	*not sig*
Snow quantity of this season compared to average			
3 in. above	0.240	0.263	0.194
5 in. above	0.299	0.347	0.219
3 in. below	0.370	0.316	0.467
5 in. below	0.434	0.395	0.452
Same as average	0.323	0.346	0.345
Within Attribute Chi-Square	*6.421*	*2.133*	*5.990*
D.F.	*4*	*4*	*4*
Significance	*not sig*	*not sig*	*not sig*
Rivals' advertisement in this season compared to last season			
Increases by 20%	0.364	0.355	0.387
Increases by 50%	0.408	0.392	0.467
Decreases by 20%	0.306	0.316	0.276
Decreases by 50%	0.299	0.282	0.333
Does not change	0.286	0.316	0.200
Within Attribute Chi-Square	*3.213*	*1.645*	*3.756*
D.F.	*4*	*4*	*4*
Significance	*not sig*	*not sig*	*not sig*
Cost of advertising in this season compared to last season			
Increases by 10%	0.212	0.213	0.194
Increases by 25%	0.165	0.231	0.121
Decreases by 10%	0.469	0.382	0.633
Decreases by 25%	0.505	0.500	0.483
Does not change	0.327	0.347	0.267
Within Attribute Chi-Square	*27.161*	*12.439*	*16.714*
D.F.	*4*	*4*	*4*
Significance	$p<.01$	$p<.05$	$p<.01$

A smaller decline in the cost of advertising, on the other hand, seems more tempting for big resorts to increase their advertisement in comparison to their smaller counterparts. This could be because the bigger resorts spend more on expensive advertising media and, thus, a small decrease in percentage means a big drop in dollar term for them.

4.3.2 Multinomial Logit Analysis

There are 4 attributes with 5 levels each, as a result, $5 \times 4 = 20$ path-worth utilities are estimated. The last level of each attribute are dropped off to prevent the problem of perfect collinearity. Hence, only $20 - 4 = 16$ dummy variables representing 16 levels are included in the model. Also, the "none" response is included as another dummy variable in order to correct the magnitude and reduce the bias of estimators. As a result, $16 + 1 = 17$ parameters are estimated. It should be noted here that the path-worth utilities that are calculated and rescaled so that the summation of all utilities in the same attribute will be zero. This makes it possible to find the path-worth utilities of all the drop-off variables.[4]

One might worry about the overfitting problem because of the small sample size. However, in the MNL estimation, each choice task is treated as one sample. As a result, the total observation for this study is approximately equal to the number of respondent multiplies by the number of random tasks $17 \times 12 = 204$.

Tables 4.3, 4.4, and 4.5 provide information from MNL regressions of the whole sample, small resorts group, and big resorts group, respectively. The chi-square statistics of the three models for any iteration[5] pass the significance test (all greater than the critical values), which suggests that the models provide a good fit to the data, and thus, the model is valid. The null hypothesis for the test is that the explanatory variables are together not explaining the explained variable.

The estimated coefficient parameter of each level (in the "Effect" column) can be interpreted as an average path-worth utility for the sample group. This is based on the assumption that the respondents are homogeneous. For the whole sample, 5 parameters reject the

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[4]For more information about the MNL regression, see Appendix E.

[5]An iteration is a selection of the first attribute level used to begin the MNL estimation. For more information, see Appendix E.

Table 4.3: Multinomial logit estimation (aggregated)

Number of Respondents	17		
Iteration	*Chi-Square*	*RLH*	
1	74.2168	0.3190	
2	77.0228	0.3209	
3	77.0415	0.3209	
4	77.0415	0.3209	
Log-likelihood for this model	-267.1207		
Log-likelihood for null model	-305.6414		
	38.5207		
Percent Certainty	12.6032		
Consistent Akaike Infor Criterion	644.0544		
Chi-Square	77.0415		
Relative Chi-Square	4.5319		
Variable	Effect	Std Error	*t* Ratio
Total revenue of last season compared to previous season			
Increased by 3%	0.2233	0.1808	1.2352
Increased by 10%	-0.0670	0.1884	-0.3558
Decreased by 3%	-0.0107	0.1838	-0.0580
Decreased by 10%	0.1146	0.1858	0.6168
Did not change	-0.2602	0.1851	-1.4059
Snow quantity of this season compared to average			
3 in. above	-0.3733	0.1974	-1.8912
5 in. above	-0.0342	0.1925	-0.1777
3 in. below	0.2688	0.1779	1.5114
5 in. below	0.3550*	0.1698	2.0908
Same as average	-0.2163	0.1828	-1.1829
Rivals' advertisement in this season compared to last season			
Increases by 20%	0.0994	0.1751	0.5676
Increases by 50%	0.2581	0.1724	1.4967
Decreases by 20%	-0.2480	0.1898	-1.3069
Decreases by 50%	0.0063	0.1881	0.0334
Does not change	-0.1157	0.1893	-0.6114
Cost of advertising in this season compared to last season			
Increases by 10%	-0.5122*	0.2076	-2.4670
Increases by 25%	-0.8138**	0.2247	-3.6210
Decreases by 10%	0.6622**	0.1726	3.8365
Decreases by 25%	0.6810***	0.1665	4.0915
Does not change	-0.0172	0.1812	-0.0948
None	0.9526***	0.1663	5.7294

Table 4.4: Multinomial logit estimation (small resorts)

Number of Respondents	12		
Iteration	*Chi-Square*	*RLH*	
1	51.0264	0.3193	
2	52.9677	0.3211	
3	52.9702	0.3211	
4	52.9702	0.3211	
Log-likelihood for this model	-191.9761		
Log-likelihood for null model	-218.4612		
	326.4851		
Percent Certainty	12.1235		
Consistent Akaike Infor Criterion	488.1606		
Chi-Square	52.9702		
Relative Chi-Square	3.1159		
Variable	Effect	Std Error	*t* Ratio
Total revenue of last season compared to previous season			
Increased by 3%	0.1688	0.2098	0.8046
Increased by 10%	-0.0085	0.2247	-0.0380
Decreased by 3%	-0.1540	0.2188	-0.7041
Decreased by 10%	0.0361	0.2269	0.1590
Did not change	-0.0423	0.2125	-0.1992
Snow quantity of this season compared to average			
3 in. above	-0.2693	0.2287	-1.1777
5 in. above	0.0780	0.2270	0.3434
3 in. below	0.0885	0.2194	0.4034
5 in. below	0.3101	0.2030	1.5276
Same as average	-0.2072	0.2168	-0.9556
Rivals' advertisement in this season compared to last season			
Increases by 20%	0.0621	0.2100	0.2959
Increases by 50%	0.1402	0.2046	0.6850
Decreases by 20%	-0.1122	0.2248	-0.4991
Decreases by 50%	-0.0998	0.2335	-0.4273
Does not change	0.0097	0.2172	0.0446
Cost of advertising in this season compared to last season			
Increases by 10%	-0.4586	0.2475	-1.8530
Increases by 25%	-0.6445*	0.2578	-2.5006
Decreases by 10%	0.3462	0.2094	1.6531
Decreases by 25%	0.6409**	0.1920	3.3383
Does not change	0.1160	0.2126	0.5456
None	1.1347***	0.1943	5.8396

Table 4.5: Multinomial logit estimation (big resorts)

Number of Respondents	5		
Iteration	*Chi-Square*	*RLH*	
1	49.0584	0.3870	
2	54.8832	0.4045	
3	55.3018	0.4058	
4	55.3064	0.4058	
5	55.3064	0.4059	
Log-likelihood for this model	-59.5270		
Log-likelihood for null model	-87.1802		
	27.6532		
Percent Certainty	31.7196		
Consistent Akaike Infor Criterion	207.2781		
Chi-Square	55.3064		
Relative Chi-Square	3.2533		
Variable	Effect	Std Error	*t* Ratio
Total revenue of last season compared to previous season			
Increased by 3%	0.4517	0.4439	1.0176
Increased by 10%	-0.3305	0.4176	-0.7915
Decreased by 3%	0.4352	0.3939	1.1048
Decreased by 10%	0.6739	0.4054	1.6622
Did not change	-1.2302*	0.4944	-2.4883
Snow quantity of this season compared to average			
3 in. above	-0.6745	0.4686	-1.4395
5 in. above	-0.6838	0.4830	-1.4157
3 in. below	0.9130*	0.4230	2.1583
5 in. below	0.7528	0.3881	1.9398
Same as average	-0.3075	0.4084	-0.7531
Rivals' advertisement in this season compared to last season			
Increases by 20%	0.3102	0.3697	0.8392
Increases by 50%	0.8082*	0.3921	2.0613
Decreases by 20%	-0.8118*	0.4134	-1.9638
Decreases by 50%	0.2342	0.4283	0.5469
Does not change	-0.5408	0.4546	-1.1896
Cost of advertising in this season compared to last season			
Increases by 10%	-0.3551	0.4589	-0.7738
Increases by 25%	-1.6798**	0.5819	-2.8868
Decreases by 10%	1.7495***	0.4078	4.2901
Decreases by 25%	1.1253**	0.4207	2.6750
Does not change	-0.8400	0.4327	-1.9410
None	0.8049*	0.3698	2.1765

null hypothesis that the attribute level individually does not contribute to the probability of the resorts increasing their advertising and are statistically significant (excluding the none option which is only included into the model for correcting the magnitude of utility prediction): one from snow quantity attribute and four from cost of advertising attribute.

Snow quantity of the resort in the current season compared to average snowfall plays an important role in advertising decisions only if it is 5 in. below average, *ceteris paribus*. Although the other levels in this attribute are not statistically significant, the order of estimated parameters provides some valuable information. On average, the resorts will raise their advertising investments when the snow quantity is below average. This implies that ski resorts use advertising to persuade skiers to come to their resorts during bad weather condition periods rather than providing information about snowfall. In other words, it seems that skiers find information about snow falls from other sources rather than the resorts' advertising. This is consistent with the information obtained from the in-depth interviews that most resorts advertise more when there is little snow fall during the season, meanwhile, there is no need to advertise when there is a good quantity of snow since skiers will come to the resorts anyway.

The other 4 significant attribute levels are all from the cost of advertising attribute, consistent with the result of counting analysis. The most influential level is when the cost of advertising declines by 25%, followed by a 10% decrease, 10% increase, and 25% increase, respectively. The order of estimated utilities illustrate a negative relationship between the cost of advertising and the probability of increasing advertisements following the law of demand.

Take a closer look at only the small resort group ($12 \times 12 = 144$ observations); only two levels in the cost of advertising attribute are statistically significant: a 25% increase in cost and a 25% decrease in cost. This implies that the advertising decisions of the small resorts are quite arbitrary when it comes to other attributes beside cost. For the cost of advertising, only a dramatic change in cost significantly impacts the advertising decisions.

It is a little more complicated for the big resorts' advertising decisions ($5 \times 12 = 60$ observations). There are 7 variables that significantly affect the probability of resorts to increase their advertising. All the attributes are taken into consideration at a different degree. Last season's total revenue becomes statistically significant only if it remained stable from the season before. If the revenue of last year did not change the big resorts tend to lower their advertising. As for snow quantity, 3 in. below average brings about higher advertising. This could be because of two possible reasons: first, the resorts advertise more to increase the number of visitors in bad weather conditions when not many people want to go skiing; second, they use snowmaking machines during bad weather periods and want more income from skiers to compensate for the cost of making snow. The reason that the "5 in. below average" level is not statistically significant could be that the big resorts can take advantage of economies of scale if they have to make more artificial snow.

The number of competitors' advertisements, although does not affect the small resorts advertising decisions, positively influences the number of advertisement of the big resorts. This illustrates an advertising competition behavior among big operators. The resorts tend to increase their advertising when their rivals increase their ads by 50%. They do not pay attention to a slight increase in number of competitors' ads. As for a declining in advertisement of competing resorts, it seems that the big operators only pay attention when their rivals slightly reduce their ads and neglect a large change. This is somewhat consistent with the information obtained from in-depth interviews that the advertising budgets are quite stable. Although their rivals cut down the amount of advertisement, big operators still continue publishing their ads as before. However, if they see a significant increase in competitors' advertisement, they tend to increase their advertising as well in response.

The estimation for the cost of advertising parameters yields a similar result to those of small resorts. A negative relationship is observed. A decrease in the cost of advertising increases the chance for resorts to increase their ads. A big increase in advertisement probability, due to a small drop in cost of advertising, could be that the cost of advertising is more expensive for big operators as explained earlier. More evidence that the bigger resorts have less financial constraints is that they do not pay much attention to a small increase in the cost of advertising (a 10% increase in cost is statistically insignificant, all else equal). Also, the magnitude of the estimated path-worth utilities for the significant levels are all greater for the big resorts in comparison to those of the small resorts. However, there is not enough information to explain why they prefer the "decreases by 10%" level to "decreases by 25%" level. One explanation could be that there is a decreasing return to advertising factors as suggested by Lambin (1976). The big resorts will keep on increasing their ads when the return on advertising is positiive until the return becomes zero. Another possible explanation is that they do not need to increase expenditure much when cost becomes lower while they can still increase ads.

From the preference score for each attribute presented in Table 4.6, the cost of advertising attribute is again the factor considered to be the most important for both sample groups.[6] Although, for the big resorts, the cost of advertising is not as important as for the small resorts. There is not much difference for the total revenue attribute among the two sample groups. However, it can be seen that the big resorts pay more attention to snow quantity and the amount of competitors' ads. There are two implications here. First, the big resorts tend to use advertising more than the small resorts when there is a change in snow conditions. Combining with the path-worth utility found earlier, it seems that the big resorts use advertising as a tool to increase customers when the snowfall is below average. This could be because it is costly for them to use snowmaking equipment so they need to increase the revenue to compensate the expense. Second, the big resorts are more competitive than the small resorts and advertising is one of the tools used in competition. This finding is consistent with the hypothesis made about the competitors' advertising attribute.

4.3.3 Prediction Ability of the Models

As mentioned earlier, 3 conjoint tasks among the 15 tasks assigned to each respondent are the same. For utility estimations, only 12 random tasks are used. The 3 holdouts are used for calculating the "hit rate," which is a tool to check the precision of the model. The basic idea is that the respondents should choose the profile that gives highest total utility in each task. The total utility of each profile can be calculated from Equation 4.1.

$$\hat{u}_A = \hat{u}_i TR_A + \hat{u}_i SQ_A + \hat{u}_i RA_A + \hat{u}_i CA_A; i = 1, 2, 3, 4, 5 \tag{4.1}$$

where $\hat{u}_A$ is the predicted total utility of profile A and $\hat{u}_i$ is the estimated path-worth utility of level i of each attribute found from the MNL regression assigned to profile A.

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[6] For more detail about preference score, see Appendix E.

Table 4.6: Preference scores

Attribute	Preference scores		
	Total	Small	Big
Total Revenue	19.96	22.22	22.27
Snow Quantity	19.76	11.56	18.68
Rivals' Ads	12.41	13.68	18.95
Cost of Advertising	47.86	52.54	40.11

The 3 holdouts were combined in the same format as other random choice tasks and are the same across the respondents. The profiles in each task are used for utility estimations. Only 13 respondents completed all the holdouts, which are used in the calculation of hit rates.

The profile that gives the highest utility among the 3 profiles in each task should be selected by the respondent. The MNL assumes homogeneity, hence, the estimated utilities are the same for the whole sample. Since the holdout tasks are the same for every respondent, the predicted choices are also the same. For example, in holdout task number 1, regardless of characteristics of ski resorts, the model predicts that every resort will choose profile 2 which has the highest estimated utility.

If the respondent chooses the profile predicted by the model in the actual conjoint task, it is counted as a "hit," otherwise it is a "miss." After the utility is computed, it is compared to the utility of the "none" dual-response option to calculate the hit rate for the "none" option.[7] If the utility of the "none" option is higher than the utility of the highest-utility profile, the respondent is forecasted to choose the "none" option after selecting one of the three profiles thought to be the best choice for them.

The hit rates are presented in Table 4.7. The model has the prediction ability at 38.46% after average across the 3 holdout tasks. The model best predicts the last holdout but worst predicts the first holdout. On average, the model, although not very successful, has higher predictability than one-third or 33.33% if the profile is to be chosen randomly.

As for the "none" responses, the model has a high hit rate for the second holdout (84.61%). For the first and the third holdouts, the model also correctly forecasts the choice

[7]The utility for the none option is also calculated during the process of utility estimation but not interpreted because there is no meaning of the none response by itself.

Table 4.7: Hit rates

Task	Hit Rates
Holdout_1	30.77%
Holdout_2	38.46%
Holdout_3	46.15%
Average	38.46%
None_1	46.15%
None_2	84.61%
None_3	38.46%
Average	56.41%

at a higher than 25% rate (if the "none" response are to be chosen randomly, the respondent will have a choice of choosing profile 1, 2, 3, and a "none" option). On average, the model 56.41% correctly predict the "none" response.

It should be noted here that the prediction abilities of the models are not very high due to a small number of respondents and the homogeneity assumption. However, it correctly predicts both profile selections and "none" response more than the randomly-choose method.

4.4 Conclusion and Recommendation

This study aims to explore the differences in advertising behaviors of the U.S. ski resorts using an applied CBC method. The conjoint tasks were designed based on in-depth interviews with ski industry's experts. The attributes included are total revenue of last season, snow quantity, competitors' advertisement, and cost of advertising media. Each attributes are divided into 5 levels based on information gathered during the interviews and industry reports. The resorts are separated into 2 groups, small and big, based on vtf/h (lift capacity per hour).

The counting analysis suggests that there is no significant difference in the selection ratio between levels within attributes of all the including attributes except for cost. This indicates that all levels are selected with the same proportion for all attributes except cost. Within the cost attribute, the lowest cost level (decreases by 25%) was chosen the most often for the whole sample and the small ski resorts. Big resorts, however, select the "decreases by 10%" the most often.

The results of the multinomial logit regressions reveal quite similar conclusions. There is no difference in the preference score of total revenue attribute of the two resort groups. Meanwhile, the cost of advertising significantly impacts the advertising decisions for both groups of sample. A negative cost-advertising possibility relationship is observed. The small resorts pay more attention to cost of advertising than the big resorts do. For the small resorts, only 2 levels of the cost attribute's estimators are statistically significant. Both are when there is a dramatic change in the cost of advertising. For the big resorts, 3 out of 5 levels of the cost attribute are statistically significant. There is a sign of a decreasing return to advertising factors follows the finding of Lambin (1976). As for an increase in cost of advertising, the big resorts only react to a large increase in cost (25%).

The big resorts seem to pay attention to various factors besides cost. They pay attention to snow quantity when it is 3 in. below average. The higher probability of increasing their advertisement when snow quantity is low could be that because the snowmaking technology is costly and the resorts will need to compensate the cost with more customers. They, however, do not pay much attention when the snow quantity is 5 in. below average. The reason could be that because, although costly, snowmaking technology has economies of scale and the resorts can produce artificial snow at a lower cost.

Furthermore, the preference score on rivals' advertising indicates that the big resorts pay attention on advertising competition while the small resorts do not. This follows the hypothesis made prior to the estimation. According to the in-depth interviews, smaller operators indicate that there is no need for them to pay attention to rivals' advertising behavior because they cannot raise their capital to compete in such competition anyway.

In conclusion, this study proves that size of ski resorts contribute to different advertising behaviors. The big resorts seem to face a lower budget constraint and are more likely to use more expensive advertising media. They also tend to be more competitive than the small resorts. The small resorts have higher budget constraints, are more sensitive to cost changes, and cannot freely change their advertising decisions when there are changes in important business factors such as snow quantity or amount of competitors' advertisement. However, there is no clear evidence that the expansion of big ski resort operators will be harmful to competition in the industry in the perspective of advertising, except only if the lack of advertising competition drives small operators out of business.

The “hit rates” are calculated from 3 holdout tasks. The result suggests that the model can better predict the choice than the randomly-choose method. The Chi-Square statistics used for testing the validity of the model also suggest that, no matter which iteration used for the estimation process, the model is valid. In other words, the independent variables (attribute levels) can together statistically significantly explain the change in the dependent variable (probability of an increase in advertisement).

In this study, the sample were only asked about the choice they would choose from the sets of situations, which might not be realistic enough, since the real world phenomena is a lot more complex than just four attributes and five levels. Also, the decision or intention of the respondents might not be followed in the real situation. However, similar concerns have also been taken in consideration in the marketing research field. Fortunately, it is shown in many studies that the results of the conjoint analysis are quite accurate (Orme, 2013; Sawtooth Software, Inc., 2001), valid and reliable (Green & Srinivasan, 1978).

The main problem of this study is the issue of small sample size. Most of the ski resorts do not want to provide the data or participate in the survey for various reasons. This problem constrains the analysis in this study to only focus on the size of resorts instead of other characteristics that might be important, such as region of the resorts. The future research, if there is any, should probably be conducted by the ski industry itself or by government to guarantee the higher participation rate. The future research can apply other estimation methodologies, for example, hierarchical Bayes (HB) estimation, which allows heterogeneity between businesses, which is widely used in recent conjoint analysis (Howell, 2009). If the number of participating resort increases, more analyses, such as factor analysis or cluster analysis, could be conduct in order to see the affect of advertising of the big resorts on the small resorts. This could help clarify the anticompetitive perspective of advertising which is the main concern that has not been answered in this study.

APPENDIX A

STOCHASTIC FRONTIER ANALYSES

Consider a firm that produces only one output (y) using a vector of inputs ($\mathbf{x}$), one can write the input requirement set, the set of all input bundles that produce at least (positive) y units of output, as followed.

$$V(y) = \{\mathbf{x}\ in\ R^n_+ : (y, -\mathbf{x})\ is\ in\ Y\}. \tag{A.1}$$

The production function of a one-input firm can be defined as an inverse of input requirement frontier.

$$f(\mathbf{x}) = \{y\ in\ R : y\ is\ the\ maximum\ output\ associated\ with\ -\mathbf{x}\ in\ Y\} \tag{A.2}$$

A production plan y in Y is "technologically or technically efficient" if there is no y' in Y such that $y' \geq y$ and $y' \neq y$. In other words, there is no way to produce more output with the same inputs or to produce the same output with less inputs than an efficient production plan. From a production function, "isoquant" can be derived. This implies that every input bundle on the isoquant is technological efficient.

The isoquant which gives all input bundles that produce exactly y units of output is the technological efficient frontier. It can be defined as

$$Q(y) = \{\mathbf{x}\ in\ R^n_+ : \mathbf{x}\ is\ in\ V(y)\ and\ \mathbf{x}\ is\ not\ in\ V(y')\ for\ y' > y\}. \tag{A.3}$$

In an industry where different firms have different technologies (and production functions), the industry production function is the most efficient production function. It is considered the frontier of input requirement. Other (less efficient) production functions are "output distance functions," production technology of which output can still be radially expanded at a given inputs level. Mathematically expressed, the production function is $f(\mathbf{x}) = y/\mu^*$ where $\mu^* = 1$ for the efficient production on the isoquant (industry production function) and $\mu^* < 1$ for the inefficient production (output distance function).

Denote that $\mathbf{w}$ is a vector of input prices, the cost function is the minimal cost at the input prices and output level, $c(\mathbf{w}, y) = \mathbf{wx}(\mathbf{w}, y)$. Consider a cost minimization problem for a firm with a Cobb-Douglas technology $y = Ax_1^a x_2^b$.

$$c(\mathbf{w}, y) = \min_{\mathbf{x}}\{\mathbf{wx} : \mathbf{x} \in V(y)\} \tag{A.4}$$

The cost function is

$$\begin{aligned} c(w_1, w_2, y) &= w_1 x_1(w_1, w_2, y) + w_2 x_2(w_1, w_2, y) \\ &= A^{\frac{-1}{a+b}}\left[(\frac{a}{b})^{\frac{b}{a+b}} + (\frac{a}{b})^{\frac{-a}{a+b}}\right] w_1^{\frac{a}{a+b}} w_2^{\frac{b}{a+b}} y^{\frac{1}{a+b}}. \end{aligned} \tag{A.5}$$

This expression implies that, at a given factor prices combination and a specific output level, there will be an input combination that yield a lowest possible cost of production (the cost efficient input combination). A firm that uses input combination that minimizes cost of production is considered allocative efficient. Graphically, the cost-minimizing input combination is the tangency point between the isoquant and the isocost. Recall that every point on the isoquant is technologically efficient, there is only one tangency point along the curve; hence, it is possible that a technologically efficient firm is not allocative efficient if the acquired input combination is not at the tangency point.

For a technically inefficient firm, there exists a firm's isoquant (which shall not be confused with the industry isoquant) derived from the output distance function. A technically inefficient firm can be allocative efficient if it uses an input combination at where the firm's isoquant is tangent with the given isocost.

If the cost frontier $c(y, \mathbf{w})$ is differentiable with respect to input prices, then Shephard's lemma states that

$$x(y, \mathbf{w}) = \nabla_{\mathbf{w}} c(y, \mathbf{w}). \tag{A.6}$$

As a result, the vector of cost-minimizing input demand equation can be obtained as the factor price gradient of the cost frontier. In other words, an allocative efficient firm produces on the cost frontier where $\mathbf{w}x = c(y, \mathbf{w})$ and $x = x(y, \mathbf{w})$, while an allocative inefficient firm operates above the cost frontier where $\mathbf{wx} > c(y, \mathbf{w})$ and $\mathbf{x} \neq x(y, \mathbf{w})$.

Figure A.1 illustrates examples of the four cases of efficiencies. Every point on the industry isoquant is considered "technically efficient." As a result, both firm A and B are technically efficient by definition, while firm C and D are technically inefficient. However, only firm A uses a cost-minimizing input combination and is considered "allocative

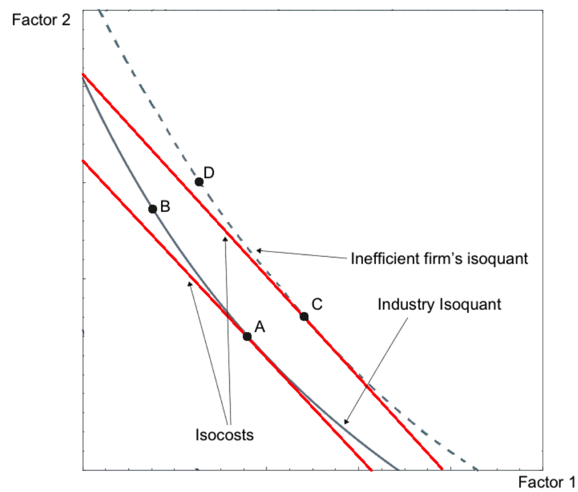

Figure A.1: Four scenarios of efficiency

efficient". Therefore, A is both technically and allocative efficient while B is technically efficient but not allocative efficient. Assume that firm C and D share the same (output distance) production function that have the same isoquant. Only C operates where the isoquant and isocost is tangent with each other. Hence, C is, although technically inefficient, allocative efficient. Meanwhile D is neither technically nor allocative efficient. It should be noted that the isocosts have the same slope, which implies that factor prices are the same on both lines, firm A still operates at a lower production cost that C even though both of them are allocative efficient. This is because A is more technically efficient and uses less inputs than C to produce the same level of output.

APPENDIX B

STOCHASTIC FRONTIER REGRESSION USING STATA

The statistical software Stata provides several functions to estimate data using the stochastic frontier regression of both stochastic production and cost frontier models. For more details about the frontier analysis see Kumbhakar and Lovell (2000).

The `frontier` command (`xtfrontier` and `sfpanel` for panel data) in Stata follows the development of stochastic frontier problem in production. The most basic components consist of: the most efficient firm produces the maximum output using the same level of inputs and is considered as the "frontier" of production; other firms that produce lower output level due to random error or a degree of inefficiency.

Mathematically expression is as follows.

$$q_i = f(z_i, \beta)\xi_i exp(v_i) \tag{B.1}$$

where q_i is output which assumes to be strictly positive, z_i is a vector of inputs, ξ_i is the level of efficiency which must be in the interval (0, 1]–the efficient firm will have ξ_i equals to 1, and v_i is the random shocks component.

After taking the natural log, one should get

$$\ln q_i = \beta_0 + \sum_{j=1}^{k} \beta_j \ln z_{ji} + v_i - u_i \tag{B.2}$$

where u_i is $\ln(\xi_i)$. In this expression $u_i \geq 0$ which implies that $0 < \xi_i \leq 1$.

By performing an analogous derivation in the dual cost function problem, the cost frontier can be written as follows.

$$\ln c_i = \beta_0 + \beta_q \ln q_i + \sum_{j=1}^{k} \beta_j \ln p_{ji} + v_i - u_i \tag{B.3}$$

where c_i is cost and p_{ji} are input prices. Inefficiency in cost requires either the output level is lower at the same cost or the expenditure is higher at the same output level.

The frontier model is rewritten in the form of

$$y_i = \beta_0 \sum_{j=1}^{k} \beta_j x_{ji} + v_i - su_i \tag{B.4}$$

given s = $\begin{cases} 1, & \text{for production functions} \\ -1, & \text{for cost functions} \end{cases}$

where $y_i = \ln(q_i)$, and $x_{ji} = \ln(z_{ji})$ for a production function; and $y_i = \ln(c_i)$, and $x_{ji} = \ln(p_{ji})$ for a cost function. The term v_i is the idiosyncratic errors independently $N(0, \sigma_v)$ distributed over the observation. In this study the inefficiency component is assumed to be independently half-normally $N^+(\mu, \sigma_u^2)$ distributed.

Stata version of stochastic frontier regression maximizes the log-likelihood function by using the Newton-Raphson method (and Jondrow et al. (1982) for sfpanel). The log-likelihood functions for a normal/half normal model is

$$\ln L = \sum_{i=1}^{N} \left\{ \frac{1}{2} \ln\left(\frac{2}{\pi}\right) - \ln \sigma_S + \ln \Phi\Big(- \frac{s\epsilon_i \lambda}{\sigma_S}\Big) - \frac{\epsilon_i^2}{2\sigma_S^2} \right\} \tag{B.5}$$

where $\sigma_S = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\lambda = \sigma_u / \sigma_v$, $\epsilon_i = y_i - x_i\beta$, and $\Phi()$ is the cumulative distribution function of the standard normal distribution. The estimated variance-covariance matrix is calculated as the inverse of the negative Hessian.

To estimate u_i, the mean of the conditional distribution $F(u|\epsilon)$ is

$$E(u_i|\epsilon_i) = \mu_{*i} + \sigma_* \Big\{ \frac{\phi(-\mu_{*i}/\sigma_*)}{\Phi(\mu_{*i}/\sigma_*)} \Big\}. \tag{B.6}$$

The technical efficiency (s = 1) or cost efficiency (s = -1) is estimated by

$$\begin{aligned} E_i =& E\{exp(-su_i)|\epsilon_i\} \\ =& \Big\{ \frac{1 - \Phi(s\sigma_* - \mu_{*i}/\sigma_*)}{1 - \Phi(-\mu_{*i}/\sigma_*)} \Big\} exp\Big(- s\mu_{*i} + \frac{1}{2}\sigma_*^2 \Big) \end{aligned} \tag{B.7}$$

where $\mu_{*i} = -s\epsilon_i \sigma_u^2 / \sigma_S^2$ and $\sigma_* = \sigma_u \sigma_v / \sigma_S$.

The efficiency scores used in this study are efficiency scores which can be obtained via $E\{exp(-su_i)|\epsilon_i\}$. The scores are between (0, 1] interval for production functions where the score of 1 indicates that the firm is on the frontier. On the other hand, for cost functions, the efficiency scores are in the range of $[1, \infty)$ where the score of 1 indicates the minimum cost which is the frontier where the efficient firm locates. The efficiency scores then compare with the frontier efficiency to calculate the “inefficiency” scores that illustrate how far the inefficient firms are from the frontier production (cost-minimization).

APPENDIX C

MLB TEAMS' ABBREVIATIONS

Table C.1: MLB teams' abbreviations

Team	Abbreviation	League
Arizona Diamondbacks	ARI	NL
Atlanta Braves	ATL	NL
Baltimore Orioles	BAL	AL
Boston Red Sox	BOS	AL
Chicago White Sox	CHW	AL
Chicago Cubs	CHC	NL
Cincinnati Reds	CIN	NL
Cleveland Indians	CLE	AL
Colorado Rockies	COL	NL
Detroit Tigers	DET	AL
Houston Astros	HOU	AL
Kansas City Royals	KCR	AL
Los Angeles Angels	LAA	AL
Los Angeles Dodgers	LAD	NL
Miami Marlins	MIA	NL
Milwaukee Brewers	MIL	NL
Minnesota Twins	MIN	AL
New York Mets	NYM	NL
New York Yankees	NYY	AL
Oakland Athletics	OAK	AL
Philadelphia Phillies	PHI	NL
Pittsburgh Pirates	PIT	NL
San Diego Padres	SDP	NL
San Francisco Giants	SFG	NL
Seattle Mariners	SEA	AL
St. Louis Cardinals	STL	NL
Tampa Bay Rays	TBR	AL
Texas Rangers	TEX	AL
Toronto Blue Jays	TOR	AL
Washington Nationals	WSN	NL

APPENDIX D

WIN SCORE

The calculation of win score appear in this paper follows the steps presented in Berri (2008). The computation includes information from both free-agent and not-free agent players. However, in order to be qualified as samples, players must appear in at least 20 games per season and have time spent on court more than a minimum of 12 min per game. There are 1,410 qualified players in this study. Team statistics used to evaluate the marginal value of each action are statistics per game while individual performance are regular season performance.

D.1 Player's Performance and Scoring

Each player contributes differently to his team's victories base on his actions on court. As a result, it is important to estimate the value of each action he performed on court to determine his real contribution.

For a team to have a chance to score, they need to have a possession to the ball. Possessions a team acquires (PA) are from

$$PA = DTO + REBD + REBTM + DFGM + d_1 DFTM \tag{D.1}$$

where DTO is the number of turnovers made by the opponent team, $REBD$ is the number of teams's defensive rebounds that can be credited to a specific player, $REBTM$ is the number of defensive rebounds that cannot be credited to an individual player, $DFGM$ is the number of field goals made by opponent and $DFTM$ is the number of free throws made by opponent. It should be noted that other circumstances beside free throws made by opponent guarantee that the team will acquire a possession of the ball. However, it is only a fraction of free throws made by opponent that the team will acquire a possession of the ball. In other words, $0 < d_1 < 1$.

In addition to PA that gives the possession of the ball to a team by rules, the team can obtain the ball from offensive rebounds (REBO). Once the team has a possession of the ball, a field goal attempt shall be made, except only if there is a turnover (TO). We can say that the field goal attempt (FGA) is in the equation:

$$FGA = DTO + REBD + REBTM + DFGM + d_1 DFTM - TO + REBO - f_1 FTA \quad \text{(D.2)}$$

where free throw attempts (FTA) are equal to a fraction of field goal attempts, since more than one free throw can be taken on a given possession and $0 < f_1 < 1$. Rearrange Equation (D.2), we get

$$FGADIF = d_1 DFTM - f_1 FTA \quad \text{(D.3)}$$

given that $FGADIF = FGA - (DTO + REBD + DFGM - TO)$. With the 2004/05 to 2014/2015 seasons' data available from the NBA, the estimated value of d_1 and f_1 are presented in Table D.1. Provided that the constant term serves as possession-changing team rebounds that is missing in the estimation of field goal attempts, $REBTM = 4.571 + e_{it}$. After substituting the estimated coefficient of DFTM back into Equation D.1, we get:

$$PA = DTO + REBD + REBTM + DFGM + 0.454 DFTM. \quad \text{(D.4)}$$

Turn to efficiency in scoring, offensive efficiency is the ability for teams to score once they have a chance to score (that is, possession employed). The possessions employed (PE) of any team can be calculated from the number of times the team attempted to shoot, no

Table D.1: Estimation of field goal attempt difference

Variable	Coefficient
Constant	4.571***
	(15.14)
DFTM	0.454***
	(-37.58)
FTA	-0.429***
	929.45)
Adjusted R^2	0.831
Observations	330

t-statistics in parentheses

matter whether it is successful or not, plus the chance that is missing, such as turnovers. Offensive rebounds shall not be double-counted. In equation form,

$$PE = FGA + 0.429FTA + TO - REBO \tag{D.5}$$

where FGA is the number of field goal attempt, FTA is the number of free throws attempt (the coefficient 0.429 comes from Table D.1), TO is the number of team's turnovers and $REBO$ is the number of offensive rebounds.

We can say that points scored (PTS) is determined by the number of possessions the team acquired multiply by point(s) per possession employed.

$$PTS = \frac{PTS}{PE} \times PA. \tag{D.6}$$

This is equivalent of saying that PA = PE (although in this dataset the average PA = 91 and the average PE = 95). This idea applies to the opponent team as well. Hence,

$$DPTS = \frac{DPTS}{DPE} \times DPA. \tag{D.7}$$

D.2 Scores and Wins

In a game, two competing teams alternate possessions with each other. So, at end of the game, each team would have about the same number of possessions Oliver (2004) (in this data $\overline{PE} = \overline{DPE} = 95$ and $\overline{PA} = \overline{DPA} = 91$). Since the number of possessions a team employed and acquired is virtually identical to the number of the opponent's possessions employed and acquired, PA, a factor that positively impacts wins, must cancel a factor that negatively impacts wins, DPA. Also, DPE is virtually equivalent to the team's PA. We can connect team's offensive and defensive efficiency to wins by estimating

$$Wins = \alpha_0 + \alpha_1 OE + \alpha_2 DE \tag{D.8}$$

where $Wins$ is the team's winning percentage, OE is the team's offensive efficiency ($\frac{PTS}{PE}$), and DE is the team's defensive efficiency ($\frac{DPTS}{DPE}$ or $\frac{DPTS}{PA}$). The regression result of Equation D.8 using data from season 2004/05 to 2014/2015 is in Table D.2.

From our data, the mean of PTS = 98.931, the mean of DPTS = 98.929, the mean of PE = 95.031, and the mean of PA = 90.548. After taking the derivative of wins with respect to PTS, PE, DPTS, and PA, respectively, the marginal values of player and team factors in term of wins are calculated as presented in Table D.3.

From Table D.3, Equation D.4, and Equation D.5, we can compute the marginal value of player and team defensive factors as presented in Table D.4.

D.3 The Missing Components

Other three actions that are not on the list yet are personal fouls, blocked shots, and assists. When a player commits a personal foul, free throws are rewarded to the opponent team. Although not all personal fouls lead to free throws, it is fair to distribute percentages of opponent free throws from Table D.4 to each player according to the percentages of their personal fouls. Since not every personal foul leads to free throw made by opponent, the impact of personal fouls on free throw made by opponent can be found from a regression of personal foul (PF) on opponent's free throw made (DFTM). The results is in Table D.5.

Each free throw made by the opponent costs the team 0.016 wins.[1] As a result, each personal foul costs the team $1.093 \times 0.016 = 0.018$ wins.

Block shots reduce the chance of opponent gaining two-point field goal. As a result, we can determine the value of a block shot by regressing opponent's two-point field goal made on blocked shot (BLK) and field goal attempt (DFGA). The result is in Table D.6.

Since one two-points field goal made by the opponent team costs the team $(0.032 \times 2) - 0.035 = 0.031$ wins, and one blocked shot reduces the chance of a two-points field goal by 32.3%, each blocked shot is worth $0.031 \times 0.323 = 0.010$ wins.

The only missing component so far is the value of assists. As noted in Berri, Schmidt, and Brook (2007), the value of assist is not always statistically significant in determining players' wins produced and in the models that it is statistically significant, the marginal effect is small. Hence, for simplicity, the marginal value of 0.022 as found in Berri et al. (2007) is used.

Given all the marginal value of each actions on court, we can summarize the value of a player's actions on court in Table D.7.

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[1] Since every point made by opponent costs the team 0.032 wins (DPTS = -0.032) and every free throw attempt by the opponent uses up a chance of the opponent team (and benefit the team) by 0.016 wins, each free throw made cost the team *0.032 - 0.016 = 0.016* wins

Table D.2: Estimation of offensive and defensive efficiency

Variable	Coefficient
Constant	0.649***
	(5.96)
PTS/PE	2.934***
	(44.64)
DPTS/PA	-2.933***
	(-42.37)
Adjusted R^2	0.931
Observations	330

t-statistics in parentheses

Table D.3: Marginal value of offensive and defensive efficiency

Variable	Marginal Value
Points	0.031
Possessions Employed	-0.032
Points Surrendered	-0.032
Possessions Acquired	0.035

Table D.4: Marginal value of player and team defensive factors

Player Factor	Marginal Value
PTS	0.031
FGA	-0.023
FTA	-0.014
RBO	0.032
TO	-0.032
RBD	0.035
STL	0.035
Team Defensive Factor	Marginal Value
DPTS	-0.032
DFGM	0.035
DFTM	0.016
DTO-STL	0.035
RBTM	0.035

Table D.5: Determining the value of a personal foul

Variable	Coefficient
PF	1.093***
	(32.56)
Adjusted R^2	0.880
Observations	330

Dummy variables for each team and year were included in the model. t-statistics in parentheses.

Table D.6: Determining the value of a blocked shot

Variable	Coefficient
BLK	-0.323***
	(-3.78)
DFGA	0.500***
	(18.54)
Adjusted R^2	0.837
Observations	330

Dummy variables for each team and year were included in the model. t-statistics in parentheses.

Table D.7: Marginal value of player and team defensive factors

Player Factor	Marginal Value
Three-point field goal made (3FGM)	0.060
Two-point field goal made (2FGM)	0.030
Free throw made (FTM)	0.017
Missed field goal (FGMS)	-0.032
Missed free throw (FTMS)	-0.014
Offensive rebound (REBO)	0.032
Defensive rebound (REBD)	0.035
Turnovers (TOV)	-0.032
Steal (STL)	0.035
Opponent's free throw made (DFTM)	-0.018
Blocked shot (BLK)	0.010
Assist (AST)	0.022
Team Defensive Factors	**Marginal Value**
Opponent's three-point field goal made (D3FGM)	-0.062
Opponent's two-point field goal made (D2FGM)	-0.029
Opponent's turnover (DTOV)	0.035
Team rebound (REBTM)	0.035

D.4 Evaluation of Player's Production

A player's production can be evaluated from marginal values presented in Table D.7. This can be expressed in the equation form as follows.

$$\begin{aligned} PROD48 = & [(3FGM \times 0.060) + (2FGM \times 0.030) + (FTM \times 0.017) + \\ & (FGMS \times -0.032) + (FTMS \times -0.014) + \\ & (REBO \times 0.032) + (REBD \times 0.035) + (TOV \times -0.032) + \\ & (STL \times 0.035) + (DFTM \times -0.018) + (BLK \times 0.010) + \\ & (AST \times 0.022)] \times (48/MP) \end{aligned} \tag{D.9}$$

where the list of variables is in Table D.7 and MP is minutes played. It should be emphasized that the calculation converts player's production to production per 48 min played in order to equalize the difference in time spent on court.

Since basketball is a team sport, teammates actions also affect player's performance. In order to adjust for teammates environment, accumulated block shots, and assists of each team are calculated and compared with the league average, in the particular season, per 48 min played.

$$\begin{aligned} MATE48 = & [(BLKTM \times 0.010) + (ASTTM \times 0.022)] - \\ & [(BLKLG \times 0.010) + (ASTLG \times 0.022)]/MPTM \times 48 \end{aligned} \tag{D.10}$$

where BLKTM is team's accumulated block shots, ASTTM is accumulated team assists, BLKLG is the league average block shots, ASTLG is the league average assists, and MPTM is team's total minutes played.

Player's sole production per 48 min (P48) can be found through

$$P48 = PROD48 - MATE48. \tag{D.11}$$

There are five positions in basketball; some positions are capable of scoring more than others. In order to correct for this imbalance, each P48 is adjusted for player's position. Average P48 of each position for each season is observed and subtracted from player's P48 to get P48 by Position (Adj.P48)

$$Adj.P48 = P48 - Position\ Average\ P48. \tag{D.12}$$

The missing components at the bottom part of Table D.7 are team defensive performance factors that cannot be traced back to any individual player. Since these are teams' performance, we can distribute the contribution across the players, according to the minutes the player was placed on court. The team defensive adjustment is calculated relative to league average defensive adjustment to capture the comparative team performance that the players belong to. It is then added to player's Adj.P48 so that

$$RelativeAdj.P48 = Adj.P48 + DEFTM48 \tag{D.13}$$

where DEFTM48 is team defensive adjustment per 48 min relative to league average (DEFTM = League Average Defensive Adjustment - Team Defensive Adjustment) and team defensive adjustment is calculated from the value in Table D.7 (plus team's blocked shot, BLKTM) and team's performance statistics.

$$\begin{aligned} DefensiveAdjustment =& [(D3FGM \times -0.062) + (D2FGM \times -0.029) + \\ & (DTOV \times 0.035) + (REBTM \times 0.035)]/MPTM \times 48 \end{aligned} \tag{D.14}$$

The average winning percentage is 0.500 games. Since there are five players on court at a time, we can say that one player produces *0.500* $\div$ *5* $=$ *0.100* wins per 48 min. However, teams sometimes play overtime games and the actual average wins produced per 48 min is 0.099 instead of 0.100. Once added the Relative Adj. P48 to average player's performance of 0.099, player's wins produced per 48 min is determined

$$WP48 = RelativeAdj.P48 + 0.099). \tag{D.15}$$

In the final step, by dividing player's WP48 by 48, and multiply it by the actual minutes played, the actual win score of each player can be obtained

$$WS = WP48/48 \times MP. \tag{D.16}$$

APPENDIX E

CONJOINT ANALYSIS

E.1 Choice-Based Conjoint Analysis Experiment

The conjoint analysis is widely used in the field of psychology and marketing (Green & Srinivasan, 1978; Gustafsson, Herrmann, & Huber, 2007). The most commonly used type of conjoint analysis nowadays is the choice-based conjoint (CBC) method (Orme, 2013, p. 39).

In market research that uses CBC, the main goal is to find the path-specific utility or preference of each characteristic of product or option for a population or an individual (Taneva, Giesen, Zolliker, & Mueller, 2008). More details on path-specific utility will be discussed later.

The characteristics considered to influence purchasing decisions of consumers are mostly selected from interviews of sample group of customers. Each characteristic is called an "attribute" and will be divided into "levels" with the minimum of two levels per attribute. For example, package color could be considered as one of the attributes, its levels could be black, yellow, and red. The number of levels must not be too large nor too small. Instead, it must be big enough to present a realistic situation and not too small to gather necessary information (Hair et al., 2005, p. 495). To avoid multicollinearity bias, the chosen attributes should not linearly correlate with each others (Hair et al., 2005, chapter 4). Also, to avoid the information overload problem during the experiments, it is suggested that any choice-based conjoint analysis should not consist of more than 6 attributes (Green & Srinivasan, 1990; Hair et al., 2005).

"Profiles" or "cards" are designed by putting together combinations of levels from every attribute by a process called "factorial design." In this process, levels from every attribute are randomly put together to assure that each of them will be presented on the profiles at approximately an equal number of time (level balance). It is worth mentioning that, although, the levels are said to be “randomly” put together, they are carefully chosen so that each profile will be unique to each other and can represent each attribute as much as possible. This also helps reducing the psychological contexts and order effects, in which some respondents may only pay attention to the attribute that is presented first in each profile (Sawtooth Software, Inc., 2001). This can be done by the conforming to the following principles: “Minimal overlap” requires each attributes level to be presented as few times possible in a single task. “Orthogonality” requires that attribute levels are chosen independently of other attribute levels (Sawtooth Software, Inc., 2001).

The respondents will be asked to perform “choice tasks”. In each task, they will be presented with two or more profiles (so-called “choice set” or “stimulus”) at a time and asked to choose only one profile that they think is the most preferable combination. The minimum number of choice tasks can be as little as one task, depending on the number of respondents. The maximum number of choice sets for any research, however, should not exceed 30 stimuli. This is the suggested number that is proven to be the best number of choice set, not too large to overwhelm the respondents, nor too small to gather the necessary information (Sawtooth Software, Inc., 2003). It should be noted that some stimuli must be considered with close attention. Some sets of cards might not provide any information and should not be included in the task. For example, a profile with superior level in every attribute should not be presented together with a profile with all inferior level of attributes (Orme, 2013, Chapter 6).

E.2 Estimation of Path-Worth Utilities and Preference Scores

The data observed will be estimated using econometric tools, such as multinomial logit estimation (MNL) and hierarchical Bayes estimation (HB). The selection of methodology used depends on the purpose of the researcher and the suitability of data. The researcher will be able to determine the “path-worth utility” of each level of all attributes the consumers put on the product or option from such estimations.

Multinomial logit estimation (MNL) is used in this study. In CBC studies, MNL model is commonly used with the aggregate model. It seeks weights for attribute levels which are analogous to utilities in the conjoint analysis. The sum of weights can be compared to the total utility of the attribute and is related to respondents' choices among concepts. The completed steps of utility estimation can be found in Rao (2014). As stated earlier, the main goal of the conjoint analysis is to find the "path-worth utility" of each level of attributes. First, it is assumed that

$$\tilde{u}_k = v_k + \epsilon_k \tag{E.1}$$

$$v_k = \sum_{j \in T} \beta_{jk} x_{jk} \tag{E.2}$$

where $\tilde{u}_k$: Individual's random path-worth utility of attribute k

v_k: Individual's deterministic path-worth utility for attribute k

ϵ_k: Individual's random component of the utility for attribute k

x_{jk}: Dummy variables represented the observed value (characteristic) of level j of attribute k

T The numbers of variables included in the model.

In each choice task, respondents must choose the most preferable profile. For simplicity, let's assume that there are two profiles, j and m, presented at a time. Hence, the probability of choosing profile j (express as $P[y_j]$)can be derived as follows:

$$\begin{aligned} P[y_j = 1] &= P[\tilde{u}_j \geq \tilde{u}_m; m \in S] \\ &= P[v_j + \epsilon_j \geq v_m + \epsilon_m; m \in S] \\ &= P[\epsilon_j - \epsilon_m \geq v_m - v_j; n \in S] \\ &= P[\epsilon_m \leq v_j - v_m + \epsilon_j; m \in S] \\ &= \frac{\exp v_j}{\sum\limits_{m \in S} \exp(v_m)} = \frac{1}{1 + \sum \exp(v_m - v_j)} \end{aligned} \tag{E.3}$$

The probability of choice of level k of attribute j can be written as:

$$P_j = \frac{1}{1 + \sum\limits_{m \in S} \exp(v_m - v_j)} \tag{E.4}$$

From Equation E.2,

$$P_j = \frac{1}{1 + \sum\limits_{m \in S} \exp\big[\sum\limits_{k \in T} \beta_{jm}(x_{jm} - x_{jk})\big]}. \tag{E.5}$$

The only unknown parameter is β which can be estimated. Then, the marginal effects can be found by $\frac{\partial P_j}{\partial x_j}$.

For example, let's assume that a market research aims to study the demand for product X in the market. According to the interviews from sample group of customers, characteristic A and B are considered as the only two attributes consumers care about when making purchasing decisions. Both attributes can be divided into two levels: 1 and 2. The researcher can put these levels together and comes up with $2 \times 2 = 4$ profiles:

- Profile 1: A1 and B1
- Profile 2: A1 and B2
- Profile 3: A2 and B1
- Profile 4: A2 and B2

Assume that the researcher decides to show two profiles at a time in each task, he will have the total of $\frac{4!}{2!(4-2)!} = 6$ tasks possible:

- Task 1: Profile 1 and Profile 2
- Task 2: Profile 1 and Profile 3
- Task 3: Profile 1 and Profile 4
- Task 4: Profile 2 and Profile 3
- Task 5: Profile 2 and Profile 4
- Task 6: Profile 3 and Profile 4

It should be noted here that it is not necessary to present every task to each respondent. The number of task presented to each respondent shall be selected based on the number of respondent and the amount of information contained in each task. The respondents will be asked to choose one of the two profiles in each task. The probability of choosing will be 1 for the selected profile. If all possible tasks in this example are to be asked in the conjoint tasks, a total of six observations will be obtained from each respondent. These observations will be used in the estimation of path-worth utilities, follows the mathematical derivation presented previously.

Let's assume that respondent Z chooses Profile 1 over Profile 2 in his first choice task. This, by assumptions, means that he prefers Profile 1 over Profile 2; hence, his utility of Profile 1 is greater than his utility of Profile 2. His utility of Profile 1 comes from his utility of attribute level A1 and B1 together. Meanwhile, his utility of attribute level A1 and B2 add up to the utility of Profile 2. In mathematical expression, it can be written as $u_{A1} + u_{B1} > u_{A1} + u_{B2}$, where u_i is respondent Z's path-worth utility of attribute level i.

In the process of estimation, the dependent variable is the probability of choosing a particular profile (1 if choosing or 0 if otherwise). The independent variables consist of dummy variables representing attribute levels presented in the choice task (1 if presented or 0 otherwise). Since each task is unique to others, in other words, every task has its' own model, the regular logit or probit estimation cannot be done.

Each task will be considered as one observation. In this case, one respondent completes six tasks. As a result, six observations will be observed. If five respondents were asked to perform the conjoint tasks, a total of $6 \times 5 = 30$ observations will be used in the estimation. The individual's deterministic path-worth utility of each attribute level will be estimated using Equation (5), in which β coefficients are the utilities. Since, we only compare two unique profiles at a time, it is possible that the respondent might choose Profile 1 over Profile 2, Profile 2 over Profile 3, but Profile 3 over Profile 1. As a result, the estimation can begin from any task or any "iteration." However, no matter which iteration the researcher chooses to begin with, the results should be similar.

After the path-worth utility of each attribute level is estimated, the utilities of different levels in the same attribute will be added up as respondent Z's deterministic path-worth utility for that particular attribute. In our example, u_{A1} and u_{A2} are estimated, after adding them up, the utility of attribute A (u_A) can be calculated. This will be the same for calculating the path-worth utility of attribute B. Assume that there are five respondents in this study, the utility of each level of attribute A will be estimated using all of the responses (in this case $5 \times 6 = 30$) and the utility of the attribute will be calculated in the same manner as in one respondent case.

Since the utilities are estimated attribute by attribute, there could be a magnitude problem in which the estimated utility of one attribute is far greater than others. This does not mean that the attribute with higher utility is more preferable than others. The estimated values only represent the probability of choosing one attribute level in comparison to others. As a result, the estimated utilities are normally rescaled for the purpose of interpretation. The most common way is "zero-center rescaling" method. The estimated utilities in each attribute will be rescaled so that the total utility value within each attribute is equal to zero. A higher (rescaled) utility implies a higher preferable, however, a level with 200 utils does not mean it is double preferable than a level with 100 utils. Also, a negative utility does not mean that the level is not preferable, it is only the effect of zero-centered rescaling as mentioned earlier. Furthermore, since the utilities are rescaled within each attribute, it shall not be used to compare across the attributes, for example, A1 level in our example happens to have a higher utility than B2 but it does not mean that A1 is more preferable than B2.

The estimated path-worth utilities help providing some insights into preference of each respondent on each characteristic of the product. The firm can launch the product containing the characteristics that best match the target consumers' demand at the right price using this information (Orme, 2013, Chapter 9).

In the conjoint analyses, "preference scores" are the main concerns. After path-worth utilities for all the levels in every attribute are calculated, the preference score for each attribute can be found by the following formula:

$$Preference\ Score\ of\ attribute\ k = \frac{max_k u - min_k u}{\sum_{i=1}^{k}(max_i u - min_i u)} \tag{E.6}$$

These preference scores (or average importance) will be between 0 and 1, which are normally converted into 0-100 scales for simplicity. This tells the relative importance each person gives to an attribute, relative to other attributes.

The advantage of the CBC conjoint analysis is that it is more realistic than rating or ranking the products (which is done in the traditional conjoint analysis) since people are always facing trade-off situations in everyday life (Louveire & Woodworth, 1983). The "interaction effect" can also be estimated to see the decisions made by respondents when they base their choices on the combination of products' characteristics. This is an advantage of the CBC conjoint analysis over the traditional conjoint analysis that only presents the "main effect" by adding up the utilities of each attribute (Sawtooth Software, Inc., 2001). For example, in a market research which the researcher wants to study the preference of color and shape of the product, in the study that uses main effect, the utility of "round and blue" product can be found by simply add up the path-worth utility of "round" and the path-worth utility of "blue". In comparison, the interaction effect allows the researcher to directly estimate the utility of the "round and blue" as an attribute, which might be more accurate in studying the preference of customers.

APPENDIX F

PARTICIPATING RESORTS' CHARACTERISTICS

Table F.1: Participating resorts' characteristics

Characteristics	Total (19)				
VTF/H [000]	0-2,999 (10)	3,000-5,999 (4)	6,000-11,999 (2)	12,000+ (3)	
Visitor/year [000]	<100 (10)	100-250 (6)	250-550 (2)	>550 (1)	
Skiable acreage	80 (8)	250 (3)	800 (3)	1900 (2)	n.a. (2)
Snow making acreage	40 (10)	100 (3)	150 (1)	330 (3)	n.a. (2)
Days open	90 (7)	100 (5)	130 (3)	150 (4)	
Owned by government		Yes (3)	No (16)		
Have ski school		Yes (19)	No (0)		
Have restaurant(s)		Yes (17)	No (2)		
Have lodge(s)		Yes (16)	No (3)		
Have ski shop(s)		Yes (17)	No (2)		
Night ski service		Yes (16)	No (3)		
Nursery service		Yes (7)	No (12)		
Operate off-season		Yes (10)	No (9)		
Proximity to the major airport by road	<1 Hr (11)	1-2 Hrs (5)	2-3 Hrs (3)	>3 Hrs (0)	
Region	Northeast (6)	Southeast (0)	Midwest (6)	Rocky Mountain (4)	
		Pacific South (0)	Pacific North (3)	More than one (0)	
Target group of customers		National (3)	Regional (9)	Local (7)	
Size of competitors' resorts (check all that applied)		Smaller (6)	Same size (7)	Bigger (14)	

APPENDIX G

QUESTIONNAIRES

If you were considering increasing your business' advertisement for this year and these were the only situations you face, which would be the most likely scenario to cause you to advertise more?
Choose by clicking one of the buttons below:

Note: *Point the mouse over the variables on the left column to see descriptions.*

(1 of 15)

Snow quantity	5 inches *below* average	Same as average	3 inches *above* average
Approximate number of competitor's ads	*Decreases* by 20% from last season	*Decreases* by 50% from last season	Does not change from last season
Cost of your resort's current advertising medium	*Decreases* by 25% from last season	*Increases* by 25% from last season	*Decreases* by 10% from last season
Last season total revenue	Did not change from the season before	*Increased* by 10% from the season before	*Decreased* by 10% from the season before

Given what you know about your resort's competitive startegies, would you really advertise more under the scenario you chose above?

- Yes
- No

Figure G.1: Example of a conjoint task

Which of these can best describe the characteristics of the resort(s) you are in responsible for making advertising decisions? (If you are responsible more than one resort then please use the total number of all the resorts.)

VTF/H [000]	0-2,999 ◯	3,000-5,999 ◯	6,000-11,999 ◯	12,000+ ◯
Visitor/year [000]	<100 ◯	100-250 ◯	250-550 ◯	>550 ◯
Skiable acreage	80 ◯	250 ◯	800 ◯	1900 ◯
Snow making acreage	40 ◯	100 ◯	150 ◯	330 ◯
Days open	90 ◯	100 ◯	130 ◯	150 ◯
Owned by government		Yes ◯	No ◯	
Have ski school		Yes ◯	No ◯	
Have restaurant(s)		Yes ◯	No ◯	
Have lodge(s)		Yes ◯	No ◯	
Have ski shop(s)		Yes ◯	No ◯	
Night ski service		Yes ◯	No ◯	
Nursery service		Yes ◯	No ◯	
Operate off-season		Yes ◯	No ◯	
Proximity to the major airport by road	<1 Hr ◯	1-2 Hrs ◯	2-3 Hrs ◯	>3 Hrs ◯
Region	Northeast ◯	Southeast ◯	Midwest ◯	Rocky Mountain ◯
		Pacific South ◯	Pacific North ◯	More than one ◯
Target group of customers		National ◯	Regional ◯	Local ◯
Size of competitors' resorts (check all that applied)		Smaller ☐	Same size ☐	Bigger ☐

Figure G.2: Example of general questions

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