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Estimating the Value of Brand Alliances in Professional Team Sports

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Brands often form alliances to enhance their brand equities. In this paper, we examine the alliances between professional athletes (athlete brands) and sports teams (team brands) in the National Basketball Association (NBA). Athletes and teams match to maximize the total added value created by the brand alliance. To understand this total value, we estimate a structural two-sided matching model using a maximum score method. Using data on the free-agency contracts signed in the NBA during the four-year period from 1994 to 1997, we find that both older players and players with higher performance are more likely to match with teams with more wins. However, controlling for performance, we find that brand alliances between high brand equity players (defined as receiving enough votes to be an all-star starter) and medium brand equity teams (defined by stadium and broadcast revenues) generate the highest value. This suggests that top brands are not necessarily best off matching with other top brands. We also provide suggestive evidence that the maximum salary policy implemented in 1998 influenced matches based on brand equity spillovers more than matches based on performance complementarities.

Key words: branding; brand alliances; sports marketing; matching model

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1. Introduction

Creating a brand alliance is a critically important marketing decision.¹ A brand alliance involves either short- or long-term associations of two or more individual brands, products, or other distinctive proprietary assets (Rao and Ruekert 1994). Familiar examples include brand alliances between Intel and Dell, NutraSweet and Diet Coke, and Michael Jordan and the Chicago Bulls. Despite the prevalence of brand alliances in practice, it remains empirically underexplored how brands form alliances. For instance, how do brands choose alliance partners? Does one brand add value to another brand's equity when the two form an alliance? What kinds of alliances generate the most value? In this paper, we empirically examine these issues in the context of alliances between professional athlete brands and team brands.

Professional team sports provide an ideal setting in which to study brand alliances. First, brand alliances matter in professional team sports such

as the National Basketball Association (NBA), the National Football League (NFL), the National Hockey League (NHL), and Major League Baseball (MLB). Star players attract fans to their teams, thus increasing their teams' brand equity. The value a star athlete can add to a team includes not only the increased productivity of the team's performance but also the appeal of this player to the fans beyond his on-court performance. At the same time, popular teams can enhance their players' popularity, the key determinant of an athlete's brand equity. When a player chooses a team, he considers not only the salary offered but also the value that the team will add to his brand equity; this value determines the player's other sources of income, such as endorsement deals. Second, the market lends itself well to rigorous analysis. In most other industries, it is challenging (if it is even possible) to construct an appropriate data set of brand alliances for a robust empirical study. In many cases, only a handful of potential brand alliance partners exist. Moreover, the set of these potential partners is often not well defined. In contrast, in professional team sports, the rules for team–player matching are known, the set of choices for both players and teams is well

¹ The term *brand alliance* is often interchangeably used with cobranding, comarketing, and cross-promotion.

defined, there are many players and many teams, and contracts are publicly observed.

To study the value of brand alliances, we estimate a two-sided matching model of player and team choices. A two-sided matching model posits that two types of indivisible discrete agents choose their partners strategically. Examples of such markets include marriage markets (Becker 1973, Choo and Siow 2006), labor markets (Jovanovic 1979), brand alliances (noted in Venkatesh et al. 2006), and free agent markets in professional sports.

We apply Fox's (2008) structural estimation method for two-sided matching models to player and team choices in free agent markets.² Solving a matching model with many agents is not trivial because one may have to examine an enormous number of possible matches to ensure that no agent has an incentive to deviate from the equilibrium match. Fox (2008) proposes using maximum score estimation (Manski 1975) to estimate a local production maximization condition, which is closely related to pair-wise stability in cooperative games. In our context, this model and estimation strategy give a consistent, computationally feasible estimate of the relative benefits of a given match while allowing endogenous transfers and nonassortative matching. In parameter estimation, we apply the differential evolution method, a global maximization route developed by Storn and Price (1997). This optimization method has been applied to find the global optimum for the nonlinear and nondifferentiable continuous space functions that may have many local optima (Fox 2008, Bajari and Fox 2009, Bajari et al. 2008).

The empirical matching model has two main advantages over standard random utility models such as logit and probit. First, the matching model accommodates rival choices. Random utility models typically assume that agents on two sides of a market (players and teams) make their partner choices independently. However, the observed partner choices result from the decisions of all agents from both sides; thus, their partner choices are determined interdependently. The two-sided matching model with maximum score estimation deals with the interdependence of all agents' choices. Second, using a maximum score in a matching model accommodates price endogeneity. In a matching game, the endogenous transfers that clear the market would be a function of factors unobservable to the econometricians. Random utility models typically use instruments to control for such correlation between the observed prices and omitted factors such as product attributes. In contrast, in the matching models the endogenous

transfers result from an equilibrium function of all agent characteristics. Consequently, the transfer data are not required in the empirical estimation of the matching models.

Using data on the free agency contracts signed in the NBA during the four-year period from 1994 to 1997, we find that both older players and players with higher performance are more likely to match with teams with more wins. However, controlling for performance, matches between the most popular players and the highest revenue teams do not generate the highest brand alliance value. Instead, a brand alliance between high brand equity players (defined as receiving enough votes to be an all-star starter) and a medium brand equity team (defined by stadium and broadcast revenues) generates a higher value than an alliance between a high brand equity player and a high brand equity team and a much higher value than an alliance between a high brand equity player and a low brand equity team. This result indicates that the matching between player brand equity and team brand equity is not simply assortative.³ If controls for quality (performance) are included, brand equity matches become nonmonotonic. The most valuable matches are between brands of different relative strengths. The best player brands may be better off entering brand alliances with middle-level team brands because middle-level team brands gain the most from associating with a top player brand and are willing to pay for it. Interestingly, this result does not apply to low-value brands. Both partners need some brand equity to generate brand spillovers from a brand alliance.

Next, we examine what happens to brand alliances when the team brands are restricted from transferring some of the benefit of an alliance to the player brands. Specifically, in the 1998–1999 season, a change was made in the collective bargaining agreement (CBA) between the National Basketball Players Association and the NBA team owners. The new CBA included a maximum individual salary for players, thereby preventing teams from offering the top players their full value to the team.

We show that our estimated parameters on performance using pre-1998 data do a reasonably good job of predicting matches both before and after the CBA. In contrast, the parameters on brand equity only do a good job predicting matches before 1998. They predict the post-1998 out-of-sample matches poorly. We interpret this as suggesting that the 1998 CBA had a particularly large influence on matches driven by brand

² For reviews of structural methods in marketing, see Kadiyali et al. (2001) and Chintagunta et al. (2006).

³ Becker (1973) defines assortative matching as a monotonic relationship between the traits of matched players. His model suggests that in the marriage market, positive (negative) assortative matching occurs when men's traits monotonically complement (substitute for) women's traits.

equity spillovers. The results suggest that good performance may be equally valuable across teams and players; however, spillovers from player brands vary by team brand strength. We also provide a simple theory that shows that matches can change under a maximum salary restriction if the total surplus from a brand alliance cannot be realized because of a restriction on transfers from teams to players.

To the best of our knowledge, this is the first empirical paper to study the value of brand alliances at the firm level. Existing research in marketing has provided several alternative approaches to measure brand equity (e.g., Ailawadi et al. 2003, Goldfarb et al. 2009, Kamakura and Russell 1993, Simon and Sullivan 1993). However, this stream of research focuses on measuring the equity of individual brands rather than the equity created through the brand interactions. Notably, it is this value of brand interactions that underlies the partner choices in brand alliances. Thus, our paper contributes to the branding literature with new methods and knowledge for understanding brand alliances. We show that there can be large benefits to alliances between brands of moderately different relative strengths. There is a small literature that studies the value of brand interactions in an experimental setting (e.g., Park et al. 1996, Rao et al. 1999, Simonin and Ruth 1998) or through surveys (Venkatesh and Mahajan 1997). These studies examine how attitudes toward each individual brand are influenced by a brand alliance.⁴ In contrast, our paper uses field data from the NBA to examine the value of brand alliances at the firm level.

The remainder of this paper is organized as follows. We describe the data and provide industry background in §2. In §3, we explain the conceptual framework of brand alliances in professional team sports. We elaborate on athlete brands, team brands, and their relationship. In §4, we explain the two-sided matching model, empirical estimation procedure, and identification. We present the estimation results in §5 and study the impact of the maximum individual salary in §6. Section 7 concludes.

2. Data and Setting

2.1. Industry Setting

Our data come from the National Basketball Association (NBA), founded in 1946. It gradually expanded throughout the 1970s and began to boom in the early 1980s as superstars Larry Bird and Magic Johnson

dominated the league, followed by Michael Jordan in the late 1980s and the 1990s. League revenues have grown fairly steadily through the present day. Even though national television revenue is shared by all the teams (Fort and Quirk 1995), local TV and radio broadcasting and live gate revenues are not. Therefore, teams have strong financial incentives to compete for good players.

Before describing the details of data, we discuss some important institutional systems in U.S. professional team sports in general and in the NBA in particular: the free agency system, the draft system, and rookie-scale contracts.

2.1.1. Free Agency System. Initially, sports leagues such as the NBA, MLB, and the NFL used a reserve system. In a reserve system, teams have complete ownership of the players they drafted, and players had no control over where they played. Thus, players were exploited in a monopsony structure. Rottenberg (1956) reviewed this reserve system and speculated the outcomes under alternative institutional arrangements such as free agency for players and revenue sharing among team owners. Since then, free agency system was gradually introduced into the major U.S. sports leagues. In the NBA, the free agency system was added to the amendments of the CBA⁵ in 1976. Under the free agent system, players have the right to choose their teams once they become a free agent. Thus, the contract between a free agent and a team result from the choices from both sides. In this paper, we use two-sided matching model to study these contracts.

With the free agent system, athletes' salaries have increased rapidly as have teams' revenues, and the salaries of superstar players have climbed especially quickly (Scully 1989, MacDonald and Reynolds 1994). For example, the Chicago Bulls paid Michael Jordan more than \$33 million for the 1997–1998 season alone. To control the players' salaries, NBA team owners initiated a lockout in 1998. As a result, a new CBA between the NBA team owners and the players' association implemented a cap on individual players' salaries, which we label the "maximum individual salary policy." Because the 1998 CBA requires that the top players be paid almost the same money from every team, the value that a team adds to a player's brand equity (beyond salary) became more important after 1998 and the value that a player adds to a team's brand equity became less important. In this paper, we also investigate the impact of this maximum individual salary policy on the matching between players

⁴ Although they do not examine brand alliances, Kadiyali et al. (2000) has a similar underlying objective to our paper. They use a structural framework to separately identify channel power in retailer-manufacturer relationships. In other words, they also use structure to understand how cross-firm partnerships work.

⁵ The NBA and its players' association negotiate a CBA approximately every six years. One key purpose of the CBA is to regulate contract negotiations between players and teams, with restrictions such as minimum salary and maximum contract length.

and teams by simulating the counterfactual matching if the policy had not been implemented.

2.1.2. Draft System. The draft system has been the major way for players to enter the major professional sports leagues. However, the process to draft players in the NBA has evolved from a territorial-pick system in the early years to a coin-flipping system to today's lottery-pick system. Under the lottery system, the teams with worse won-lost records are rewarded with a higher probability of having a higher rank in the prospect draft. Prior to 1989, NBA teams would select players until they ran out of prospects. Thus, the drafts often ran many rounds; for example, the draft went 21 rounds in 1960. From 1989 onward, the drafts have been limited to two rounds, which gives undrafted players the chance to try out for any team. The draft system is used by sports leagues to increase the competitiveness of leagues. However, it often encourages some teams to lose to get higher talent in the draft (Taylor and Trogon 2002), which may contradict the spirit of sports. Massey and Thaler (2006) examine draft-related decisions from the NFL to show that teams often overvalue the top picks in their draft decisions. They suggest that the overvaluation could result from overconfidence, the winner's curse, or false consensus.

2.1.3. Rookie-Scale Contracts. Before 1995, rookie contract bargaining over salary and contract length was almost the same as free agent bargaining, even though rookies did not have the right to choose their teams. However, since 1995 the NBA has limited the contracts of the first-round draftees to specific rookie-scale contracts. In rookie-scale contracts, the first-round draftees are assigned salaries according to their draft positions. The rookie-scale contracts were initially for three years, and then a team option was added for the fourth year. Currently, they are two-year contracts with team options for the third and fourth year. The first-round picks are guaranteed a rookie-scale contract. However, the second-round picks are not guaranteed a contract. Because rookies do not have the right to choose their teams and also have almost no power to negotiate their contracts, our two-sided matching model does not apply to rookie-scale contracts. Thus, rookie-scale contract signings are excluded from our data.

2.2. Data Description

The data used in this paper consist of three main parts: *players*, *teams*, and their *matching*. We collected most of the player and team information from <http://www.basketball-reference.com/>. This website contains performance statistics for every player who ever played in the NBA and for every team that has ever been in the NBA. Team revenue data were

collected from other sources: *Financial World* (before 1996) and *Forbes* (after 1996). Unlike player and team data, no systematic matching (contract signing) data are available at a single website. We combine information from several websites to ensure the completeness and accuracy of the matching data. One source is *USA Today's* online salary database, which contains detailed salary information for players in each season. Another comprehensive source is a personal website, <http://www.eskimo.com/~pbender/index.html>, which documents all the contracts signed since 1994. In addition, we also use player information on the NBA website to cross-check a large number of the contracts to ensure accuracy.

Next, we describe each part of the data set in detail.

2.2.1. Player Information. For each player, we have three types of information: player characteristics (age and position), popularity, and on-court performance. Popularity is measured by the number of all-star votes a player receives in the all-star ballot. Based on the number of votes, five players per conference, including two guards, two forwards, and one center, are elected to the all-star game as starters. Each year, the NBA reveals only the top 10 vote getters at each position on the all-star ballot. Therefore, the number of all-star votes is truncated and available only for those players on the top 10 list. We use these data to construct our player brand equity measure based on relative ranking in this voting. In the NBA, an individual player's performance is recorded in many dimensions, including points, rebounds, assists, steals, turnovers, and blocks. Combined, these numbers measure a player's on-court contribution to team performance. We construct a simple one-dimensional index to measure a player's performance defined as follows:

$$\begin{aligned} \text{player performance} = & \text{points} + \text{rebounds} + \text{assists} \\ & + \text{blocks} + \text{steals} - \text{turnovers}. \end{aligned}$$

This is a performance-per-game measure and it ranges from 1 to 47.8, with a mean of 15.9 and standard deviation of 8.32. In the estimation, the *player performance* is rescaled to the range from 0 to 1 to make the results easier to interpret. Our player performance measure is similar to the additive structures commonly used in the existing research on NBA players' productivity (e.g., Bellotti 1988, Berri 1999, Berri and Schmidt 2002). Of course, this is one of many possible ways to summarize a multidimensional attribute. However, this simple additive index is likely to be highly correlated with the alternatives. Because our focus is on the matching between player brand and team brand, and because player performance is used as a control variable only, we expect the impact of choosing a different performance formula on our main results to be minimal.

2.2.2. Team Information. For each team in the NBA, our data contain the population of the team's host city,⁶ the team's winning percentage, the team's roster, and revenue from live attendance and local and national broadcasting. Unfortunately, we do not have data on any of the smaller revenue sources such as food at the stadium and sales of licensed clothing. Therefore, in our analysis, we assume that total revenue is highly correlated with revenue from attendance and broadcasting. In §4.3, we will divide the teams into categories according to their revenues as a measure of team brand equity.

2.2.3. Player–Team Matching Information (Contracts). Our original data that we have collected cover almost all the contracts signed including both free agent signings and rookie contracts from the 1994–1995 season to the 2004–2005 season. Because our model is a two-sided matching model, the contracts should result from two-sided matching process. However, all the rookie-scale contracts, minimum salary contracts, and those contracts signing very low performance players do not result from a two-sided matching process. Therefore, we exclude such contracts from our analysis. In addition, because of the lock-out in 1998, there was no all-star game in the 1998–1999 season, so we exclude those contracts signed in 1999 because of the missing data for all-star votes. Second, if a player did not play for the NBA in the season prior to signing a contract, his contract is also excluded from the estimation because of the lack of performance data.

As a result, we use 199 matching records (contracts) from the 1994–1995 season through the 1997–1998 season to estimate our model. We also use 157 contracts signed in 1998–1999 and from 2000–2001 to 2004–2005 to understand the impact of the maximum salary restriction. Each contract identifies the matching parties—the player and the team and the signing date as well as a variety of other details. These 199 matching records represent all non-rookie contracts for players who earn above the minimum salary and achieved a minimum level of performance in the previous season.⁷ We do not have information about those contracts offered but not signed. Such data would be useful to validate our estimates of brand alliance values.

⁶ Population is based on data from the 2000 U.S. Census and 2001 Canadian Census.

⁷ We drop players with very low performance because they are unlikely to hold any brand equity. Specifically, using the performance measure defined above, we drop all centers with a performance level below 0.2 and all guards and forwards with a performance level below 0.3. Results change little if they are included.

3. Athlete Brands, Team Brands, and the Alliances

In this section, we conceptually discuss athlete brands (player brands) and team brands, and how they can add value to each other's brand equity through brand alliances. In the marketing literature, there are many approaches to measure brand equity. Keller and Lehmann (2006) divide these measures into three categories. The first category uses financial market outcomes. For example, Simon and Sullivan (1993) use incremental cash flows to estimate brand equity at both the firm and individual brand levels. The second category is from the consumer's perspective. This approach often uses survey data to assess the awareness, attitudes, associations, attachments, and loyalties that consumers have toward a brand (e.g., Keller 1993, Park and Srinivasan 1994). The third category takes the firm's perspective and uses product-market outcomes such as price premium and market share to measure brand equity (e.g., Ailawadi et al. 2003, Goldfarb et al. 2009).

In this paper, we are interested in brand-level decisions to form alliances but do not have data on cash flows or financial value. Therefore, we take the firm's perspective—the teams and the players—using an approach similar to Ailawadi et al. (2003). For teams, we measure brand equity as the team's revenue from paid attendance and from local and national broadcast rights. For players, we measure brand equity by all-star votes in all-star balloting. This measure can be seen as an aggregate measure of fans' attitudes toward the athletes. Because our primary interest is in brand spillovers rather than how performance affects matching, in the structural analysis that follows we examine how brand equity influences team and player matches *over and above* observable measures of performance (in the previous season) for the team and the player. In this way, we use a variant of Goldfarb et al. (2009), who argue that brand equity is that value *over and above* the impact of search attributes.

3.1. Athlete Brands

In professional team sports such as football, basketball, baseball, and soccer, although the team's performance depends primarily on the entire team, spectators often attend live games or watch televised games because they are attracted by the superstar players. For example, it is well-known that David Beckham in soccer and Michael Jordan in the NBA have drawn massive audiences to their teams. This phenomenon is empirically demonstrated by Hausman and Leonard (1997), who find that NBA superstars such as Michael Jordan, Larry Bird, Shaquille O'Neal, and Charles Barkley have a large impact on TV ratings and game attendance. As a

result, teams compete for the service of the best athletes by offering attractive compensation packages worth millions of dollars every year. Superstar athletes also receive income through endorsement deals. For example, in 2003 LeBron James signed a seven-year endorsement contract with Nike worth \$90 million. Such deals further underscore the value of athlete brands.

Why do superstar athletes have such high brand equities? From the behavior perspective, McCracken (1989) proposes that the brand value could stem from the cultural meanings with which these celebrity athletes are endowed. Such cultural meanings may include status, class, gender, and age as well as personality and lifestyles. Athlete brands are valuable because these cultural meanings can be passed from the celebrity athletes to consumers through services provided (e.g., games) and products endorsed. From the economic perspective, Rosen (1981) argues that such superstar effects arise because of joint consumption technology and imperfect substitution of consumers' preferences. The joint consumption technology indicates that a large number of people can consume the "celebrity" service together, thus implying great economies of scale for superstars. The imperfect substitution means that quantity cannot substitute for quality; that is, the value of watching a superstar player is higher than the value of watching several mediocre players. As a consequence of joint consumption technology and imperfect substitution, in equilibrium only a small number of athletes can enjoy star status and high brand equities.⁸

We define a player's brand equity by the votes he receives in all-star balloting over and above his performance during the season. Therefore, a player who receives a large number of votes relative to his performance statistics will have a high level of brand equity. In this way, in examining player-team matches, we can assess the brand spillovers between players and teams separately from the value of the player's performance to the team.

3.2. Team Brands

We define a team's brand equity as its revenue over and above the team's performance in the previous season. To gain some insight on the factors related to a team's brand equity, in Table 1 we regress team

Table 1 Understanding of Team Revenue (Sample Size: 289)

Independent variables	Coefficient	Standard error
Number of high brand equity players	3.92*	1.68
—Elected all-star starters		
Number of medium brand equity players	2.03	1.16
—Guards and forwards ranked 3–5		
—Centers ranked 2 and 3		
Number of low brand equity players	0.22	1.00
—Guards and forwards ranked 6–10		
—Centers ranked 4–5		
Log(city's population)	36.85**	2.48
Team's winning percentage	37.07**	6.74
Year	5.48**	0.26
Constant	–11,109.32**	512.29
R ²	0.74	

*Significant at the 5% level; **significant at the 1% level.

brand equity (measured by revenue from paid attendance and broadcasting rights) on the host city's population, year, winning percentage, and athlete brand equity (defined by all-star status). Because of endogeneity concerns and omitted variables bias, we do not assert that this regression implies a causal relationship between team revenue and athlete all-star status. In addition, we recognize that a team's strength could be more or less than the quantity of players it has of different types. At this stage, we merely look for interesting correlations. The data used in this analysis are from the 1994–1995 season to the 2003–2004 season, excluding the 1998–1999 season in which no all-star game was held because of the 1998 lockout.

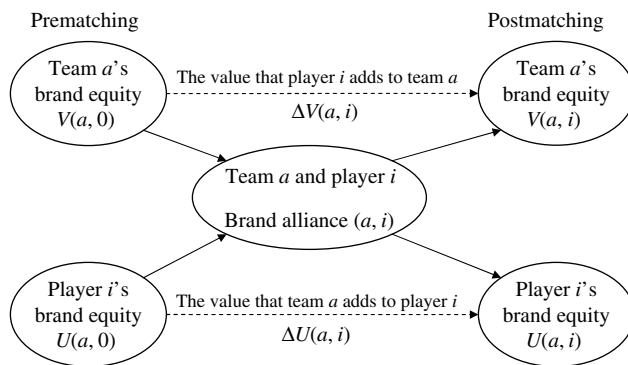
As shown in Table 1, the coefficients for the city's population and for the number of high brand equity players are each positive and significant, whereas the number of medium brand equity players is positive but insignificant. These positive correlations are perhaps not surprising. All else being equal, a large market provides a greater fan base, higher game revenues, and more TV viewers. As we define them, high brand equity players are selected by fan voting, which likely reflects overall popularity. Therefore, the medium brand equity players receive fewer votes and may not have the same significant impact on team revenues beyond their contribution to the team's performance. Of course, the direction of causality may be reversed: high-revenue teams can afford to pay the players with the highest brand equities. Either way, this regression analysis shows that a superstar player's brand equity is positively correlated with a team's brand equity as defined by revenue. The same is not true (at least to the same extent) for players with only medium brand equity.

3.3. Team–Athlete Brand Alliances

In many ways, team–athlete brand alliances are similar to component branding alliances as in Venkatesh

⁸ Given the high stakes involved, athletes manage their brands proactively. Athletes carefully select the right teams to join and the right endorsements to sign in order to enhance their brand value. For example, after Yao Ming was drafted and before he arrived in the NBA, "Team Yao" was assembled with a group of international consultants to create a detailed marketing plan to manage his brand. The team negotiated deals with the Houston Rockets and carefully selected sponsorship deals with companies like Reebok and China's Unicom (Duffy 2004).

Figure 1 The Conceptual Framework on Brand Alliance



and Mahajan's (1997) study of consumer preferences for Compaq computers and Intel processors. In team-athlete alliances, an athlete, as a component of the team, cannot be sold and consumed independently of team services. When a team and a player form a brand alliance, their brand equities change, as shown in Figure 1. For the team, the change in its brand equity is defined as the value that the player adds to the team's brand equity. In our analysis, we try to control for player performance and examine how a player's popularity influences his value to the team. High brand equity players attract fans beyond their direct impact on a team's performance by increasing the team brand's awareness and enhancing the team brand's positive image. As we saw in Table 1, a team's revenue is positively related to the number of all-star starters on the team.

For the player, the change in his brand equity is defined as the value that the team adds to the player's brand equity through their match. This value can be interpreted as the player's other sources of income beyond current salary, such as endorsement deals and future income potential. When matched with the right team, an athlete can increase his popularity in several ways, such as reaching a larger market and generating more media exposure.

Next, we structurally model how a team and a player form their partnership choices and then estimate the impact of a team–player brand alliance on both brand equities.

4. The Two-Sided Matching Model

Since professional sports introduced the free agent system, a player has been able to choose his team when he becomes a free agent. Similarly, a team chooses which players to offer contracts. Therefore, a two-sided matching model is appropriate to jointly study the choices of players and teams. To identify the matching model, we assume no relevant asymmetric information across agents. In other words, each agent in the market knows the relevant information

about all other agents.⁹ The observed partner choices will be equilibrium outcomes derived from the two-sided matching model based on those added values. Because teams and players choose their best possible matches, observed outcomes can be used to estimate the value that a player brand adds to the team brand, and vice versa. After estimating these values, we can analyze how these values vary across players and teams, one of this paper's objectives.

4.1. Local Production Maximization

In this subsection, we define the equilibrium concept used to solve the two-sided matching problem. We use the local production maximization condition developed by Fox (2008) to define equilibrium. Following Fox, we use the economic language of “production” but simply mean the joint value of the team–player match. Fox's definition accommodates matching models with unobserved endogenous transfers. Accommodating unobserved transfers is important in this context because although we observe annual salaries and contract length,¹⁰ many features of the contracts are unobserved (such as options, incentives, no-trade clauses, etc.).¹¹ In addition, this equilibrium concept can allow for local (i.e., nonglobal) complementarities, which cannot be solved by an assortative matching model. This equilibrium concept is closely related to pairwise stability in cooperative game theory. A match is stable if no coalition of agents prefers to deviate and form a new match. Pairwise stability means that no pair of agents is willing to exchange and form new matches. Similarly, the local production maximization condition means that the total production of any two observed matches should exceed the total production from an exchange of partners. Otherwise, the alternative matches could be formed without disturbing any other matches to make all the agents better off. In what follows, we derive the local production maximization condition based on single-agent best responses under price-taking behavior (Fox 2008).

⁹ With millions of dollars involved in almost every contract, teams and players will try their best to obtain as much information as possible when signing a contract. Thus, given the data we use in our analysis, we feel it is reasonable to assume symmetric information across all the agents.

¹⁰ Contract length can be an important decision for both players and teams. In our model, the endogenous transfer could be in any format (salaries, incentives, no-trade clause, options, contract length) as long as teams and players value contract length in the same way. However, if players or teams value money or other incentives differently, then contract length may affect our results.

¹¹ Furthermore, no appropriate empirical framework exists for including the value of the transfers (i.e., the salaries) in matching analysis. This might be an interesting extension of our work (it might allow separate identification of team and player benefits to matches), but we need to wait until the methods are developed.

Suppose the matching outcomes are team a with player i and team b with player j .¹² Let t be the transfer (salary) from a team to a player, the function $\Delta V(a, i)$ be the value that player i adds to team a 's brand equity through their brand alliance, and $\Delta U(a, i)$ be the value that team a adds to player i 's brand value through their brand alliance such as increased popularity or endorsement deals. Then, the payoff functions for the team (denoted by π^T) and player (denoted by π^P) can be defined as

$$\pi^T(a, i) = \Delta V(a, i) - t_{ai}, \quad (1)$$

$$\pi^P(a, i) = t_{ai} + \Delta U(a, i). \quad (2)$$

Assume that \tilde{t}_{aj} is the transfer (salary) from team a to player j to make player j indifferent between teams a and b .¹³ We then derive the following equation for player j :

$$\tilde{t}_{aj} + \Delta U(a, j) = t_{bj} + \Delta U(b, j). \quad (3)$$

Given that team a matches with player i instead of player j , team a 's payoff from matching with player i exceeds the payoff from matching with player j . We assume that the salaries of players i and j do not influence other players' salaries because most players are under contract and their salaries are fixed. Therefore, the following inequality is derived:

$$\pi^T(a, i) \geq \pi^T(a, j) \Rightarrow \Delta V(a, i) - t_{ai} \geq \Delta V(a, j) - \tilde{t}_{aj}. \quad (4)$$

Substituting \tilde{t}_{aj} of Equation (3) into inequality (4),

$$\Delta V(a, i) - t_{ai} \geq \Delta V(a, j) - [t_{bj} + \Delta U(b, j) - \Delta U(a, j)]. \quad (5)$$

Similarly, the following inequality is derived from team b matching with player j instead of player i :

$$\Delta V(b, j) - t_{bj} \geq \Delta V(b, i) - [t_{ai} + \Delta U(a, i) - \Delta U(b, i)]. \quad (6)$$

Combining these two inequalities (5) and (6) and rearranging terms, we get

$$\begin{aligned} & [\Delta V(a, i) + \Delta U(a, i)] + [\Delta V(b, j) + \Delta U(b, j)] \\ & \geq [\Delta V(a, j) + \Delta U(a, j)] + [\Delta V(b, i) + \Delta U(b, i)]. \end{aligned} \quad (7)$$

¹² A complete matching outcome would also indicate all players matched at all positions for each team. Our equilibrium concept assumes that all those other assignments are given and do not change simultaneously. For the reason of expositional simplicity, in the rest of this paper we do not include the notation for a team's matching outcomes at other positions.

¹³ The NBA imposes salary caps for the teams. A team's remaining salary cap may impose constraints on the team's contract offers and signings. We do not have information about teams' remaining team salary caps. However, the team salary caps in the NBA are soft caps with many exceptions, and we therefore assume that the impact on the matching outcomes is minimal.

The sum of payoffs to team a and player i from their match is the total value that the brand alliance generates to the two individual brands (team a and player i). We define this value as the production value of the brand alliance as follows:

$$f(a, i) = \Delta V(a, i) + \Delta U(a, i). \quad (8)$$

We define production values for other matches similarly. Then, inequality (7) becomes

$$f(a, i) + f(b, j) \geq f(a, j) + f(b, i). \quad (9)$$

The above inequality means that the sum of production values from two observed matches is greater than the sum of production values if they exchange partners. This defines our solution concept: the local production maximization condition. This condition says the observed matches are socially optimal for a market with two players and two teams. However, it is important to note that the local production maximization condition derived from such a model of single-agent best response under price-taking behavior is a necessary (but not sufficient) condition for the equilibrium. A more robust condition is a core stability concept in which no coalitions of agents deviate from the equilibrium. However, the computational cost of computing core stability is much higher than the benefit for estimation (Fox 2008). Therefore, in our context, the local production maximization condition is a useful equilibrium concept.

4.2. Maximum Score Function

From the local production maximization conditions, we derive a system of inequalities that defines the interaction between a team's and a player's brand equities. We apply maximum score estimation (Manski 1975) and find production functions that maximize the total number of inequalities that satisfy Equation (9). Therefore, the objective function can be written as

$$\begin{aligned} \max_f Q_H(f) = \frac{1}{H} \sum_{h \in H} \left\{ \sum_{\{a, b, i, j\} \in A_h} 1[f(a, i) + f(b, j) \right. \\ \left. \geq f(a, j) + f(b, i)] \right\}. \end{aligned} \quad (10)$$

H is the number of observed markets and A_h is a realized quartet $\{a, b, i, j\}$ in the observed market h . $1[\cdot]$ is the indicator function that is equal to 1 when the inequality in the bracket is true. The maximum score estimator will be any function f that maximizes the score function $Q_H(f)$. It is a consistent semiparametric estimator that makes no assumptions about the distribution of the error terms.

The maximum score estimator does not suffer from the “curse of dimensionality” involved with integrating over multivariate distributions. In particular, standard maximum likelihood and method-of-moment estimators require a nested computation of an equilibrium for every realization of error terms. These complex equilibrium computations are nested within an integral over the unobserved error terms in the market, which should be of a dimension equal to the number of potential matches in the market. In our analysis, this would mean calculating integrals of several hundred dimensions. Maximum score estimation eliminates the need to calculate this multidimensional integral. Maximum score estimation has the further advantage of allowing situations with multiple equilibria because equilibrium selection rules do not enter the objective function. Using the maximum score has two costs: it can be less efficient than many other estimation techniques, and the precision of the estimates can only be estimated using a subsampling procedure. Following Fox (2008), we believe the numerous benefits of this method outweigh these costs.

4.3. Market Definition and Production Function Specification

In this subsection, we first define a market and then specify the production function. In each off season, some free agent players enter the market. Meanwhile, teams have vacancies that are filled by free agent players. Naturally, each off season can be defined as one market. To account for the fact that players play different positions, we separate markets for guards, forwards, and centers. A market, therefore, contains all players who play the same position and become free agents in the same off season and all teams who need players in that position in the off season.¹⁴

The production function in these markets models the total value of the player–team match. The production function f consists of three parts: the fixed effects of the team’s characteristics, the fixed effects of the player’s characteristics, and the interaction between the team’s characteristics and the player’s characteristics. The following equation shows the specification of the production function:

$$f(a, i) = \alpha \times X_a + \beta \times [X_a \times Y_i] + \gamma \times Y_i + \epsilon_{ai}. \quad (11)$$

In Equation (11), X_a are independent variables measuring team a ’s brand equity and performance, and Y_i are independent variables measuring player i ’s brand equity, performance, and age. All the variables for

both a team and a player are from the season preceding the off-season market. Team vector X_a includes one continuous variable and three dummy variables to measure the team’s brand equity. The continuous variable is the team’s performance measured by the team’s winning percentage. The dummy variables are categorized from teams’ yearly revenues from attendance and broadcasting. We denote the first dummy variable as *high*, which equals one if a team’s revenue ranks in the league’s top eight. The second dummy variable, denoted as *medium*, equals one if a team’s revenue ranks between 9th and 16th. The third dummy variable, denoted as *low*, equals one if a team’s revenue ranks worse than 16th. Thus, 8 teams are types *high* and *medium* each year whereas team type *low* contains 11 teams before the 1996–1997 season, 13 teams between the 1996–1997 and 2003–2004 seasons, and 14 teams since the 2004–2005 season.

Player vector Y_i includes two continuous variables (player performance and age) and four dummy variables based on players’ brand equity. The continuous variable *player performance* is defined in §2 as the sum of a player’s average per-game statistics such as points, rebounds, and assists. The other continuous variable is age, ranging from 21 to 41. To make the results easier to interpret, we rescale both player performance and age to range from zero to one. We measure player brand equity using a series of dummy variables based on ranking in all-star voting. We define a *high* brand equity player as an all-star starter (i.e., ranked at the top in all-star voting) for the all-star game in the preceding season. A *medium* brand equity player was ranked highly in all-star voting but did not come first. Since two guards and forwards are elected all-star starters per conference, for these positions, *medium* brand equity players are ranked third through fifth. For centers, with only one elected starter per conference, *medium* brand equity players are ranked second and third. *Low* brand equity players are defined as guards and forwards who were ranked sixth through tenth in all-star voting and centers who were ranked fourth and fifth in voting. All other players are grouped in the *very low* brand equity category.

Thus, we use the team’s revenue in the previous season as its prematch brand equity and the player’s votes received in the previous season’s all-star balloting as his prematch brand equity. Instead of using continuous variables such as the actual team revenue and the number of all-star votes, we construct the dummy variables to allow for richer results. With the continuous variables, we can identify whether a team’s brand equity globally substitutes or complements a player’s brand equity. However, the match between a high brand equity player and a medium brand equity team could (and does) generate the

¹⁴ Although it is computationally feasible to ignore positions and consider the free agent signings as part of one large market, we believe the position-specific markets better reflect the reality of the NBA.

highest match value even though the team revenue globally complements to player all-star votes. In other words, the production functions may exhibit local (rather than global) complementarity, which can be accommodated with discrete variables.

4.4. Identification

In this two-sided matching model, the matching outcomes used in the estimation are qualitative. Therefore, as in a discrete choice model, any positive monotonic transformation of the production function will produce the same value for the objective function in the maximum score estimation. Drawing on Manski (1975, 1988), Matzkin (1993) discusses non-parametric identification of these types of models and notes that a sufficient condition for point identification is the inclusion of a continuous interaction variable in the independent variables. Therefore, we include a continuous interaction variable, *player performance* \times *team performance*, to ensure the identification of the parameters in the production function. We normalize the coefficient for this continuous variable to be ± 1 . Because the objective function is a step function, there may exist multiple optima for the same maximum score. In each of these optima, however, the ordinal ranking of the parameter estimates is the same. This implies that the maximum score estimator shows the rank ordering of the production function rather than its cardinal value. This identification limitation is not surprising given the qualitative nature of the matching data. Even with this limitation, we are still able to understand the qualitative drivers of matching.

From inequality (9), coefficients for the team and player fixed terms in the production function f cannot be identified by the matching outcomes alone because the fixed terms will cancel out in the local maximization condition. Therefore, we can estimate only the interaction terms between a team and a player, and rewrite f as

$$f(a, i) = \beta \times [X_a \times Y_i] + \epsilon_{ai}. \quad (12)$$

Similarly, the agent-specific nest fixed effects cannot be identified. For example, if both teams a and b are in the *high* type nest and both players i and j are *high* players, then the nest fixed effects cancel out in the local production maximization condition. To study why player i matches with team a and player j matches with team b , we need some independent variables that vary within nests, for example, player age. This is fine for our purposes as our primary interest focuses on the cross-nest interactions. In particular, players vary in their popularity, performance, and age, whereas teams differ in their winning percentages and revenues. Our main interest is the interaction of player and team brand equity as measured by player popularity and team revenues.

4.5. Estimation Procedure

In this section, we describe the estimation procedure. The algorithm is as follows:

Step 1. Define markets. All players who play the same position and sign a contract during the same off season are grouped into one market.

Step 2. Construct the independent variables. In each market, the independent variables (defined in §4.3— X_a for each team and Y_i for each player) are constructed from the data set.

Step 3. Construct exchange pairs. Within each market, a pair is formed by any two players who sign with different teams. A pair consists of two players and two teams. We denote the pair with team a matching with player i and team b matching with player j as (ai, bj) . Variations of independent variables on these two players and two teams allow us to identify coefficients for those independent variables.

Step 4. Construct the interaction variables. We divide the interaction variables into two parts for each pair: the original observed matches and the counterfactual pair after exchanging partners. These interaction variables for the pair (ai, bj) are denoted as $[(X_a \times Y_i, X_b \times Y_j); (X_a \times Y_j, X_b \times Y_i)]$. Specifically, we use *player_performance* \times *team_performance*, *age* \times *team_performance*, [*high, medium, low, very low player brand equity*] \times [*high, medium, low team brand equity*]. As mentioned in §4.4, we normalize the coefficient of the first interaction variable to be ± 1 . We do this by comparing the maximum scores for both $+1$ and -1 and choose the sign with the larger maximum score. In our estimation, it is positive.

Step 5. Set the initial values for the parameters β in the production function f .

Step 6. Compute the production functions according to the specification in Equation (12): f_{original} is for the original pair and f_{counter} is for its counterfactual pair.

Step 7. Calculate the value of the objective function for the maximum score estimator according to Equation (10).

Step 8. Apply the differential evolution method to search the global optimum for those parameters. Because the objective function of the maximum score estimator is a step function, there are many local optima. Therefore, we apply a global optimization routine, the differential evolution method (Storn and Price 1997), to estimate the parameters β .

Step 9. Calculate confidence intervals. Maximum score estimation does not assume a distribution for the error terms; therefore, we use subsampling techniques to calculate the confidence intervals for the estimators. Specifically, we follow the procedure proposed in Santiago and Fox's (2008) toolkit for matching maximum score estimation. First, from the whole data containing n ($=199$) contracts, we randomly generate 200 subsamples, each containing

$(n - 1)$ distinct contracts. Second, we repeatedly apply the above estimation procedure to each of the 200 subsamples and obtain 200 sets of parameter estimates. Finally, for each parameter, we use these 200 estimates as its empirical distribution from which we calculate its confidence interval.

5. Estimation Results and Interpretation

Next, we show how the total value of a team–player alliance varies across team and player brand equities. Table 2 includes the parameter estimates and their 95% confidence intervals.

The first line of Table 2 shows a positive coefficient for the interaction between team performance and player performance. Thus, a player with better performance is more likely to match with a team with better performance. The second line shows a positive coefficient for the interaction between age and team performance, which means that experienced (older) players tend to play for those teams with better performance. These results suggest positive assortative matching based on both performance and age.

Our main interest in this paper is on the role of brand equity in matches. The coefficients for the interactions between player brand equity and team brand equity measure the total value generated by a team–player alliance after controlling for the effects of the interaction between player and team performance and of the interaction between age and team performance. The parameter estimates in Table 2 have the same interpretation as brand fixed effects in logit

and probit models. In particular, we need to interpret the values relative to the base (the outside option in the logit and probit models), which is normalized to zero. In our model estimation, the base is the matching value between a very low brand equity player and a low brand equity team. With 4 player types and 3 team types, we estimate 11 dummy variables for each type of team–player match relative to the very low player–low team base. For example, “6.07” in Table 2 indicates the highest matching value because it is positive and larger than all other matching values.

For high brand equity players, the results in Table 2 indicate that the brand alliance value is highest when matching with a medium brand equity team (rather than with a high brand equity team).¹⁵ The model gives two possible explanations for this result. First, the marginal value of adding a high brand equity player may be higher for a medium brand equity team than for a high brand equity team. For example, the medium brand equity team may be able to fill empty seats in the stadium by adding a high brand equity player while the high brand equity team always sells out, or the demand for team merchandise may be more elastic to the brand equity of the players for medium brand equity teams. Alternatively, the marginal value to a high brand equity player of joining a medium brand equity team may be higher than that of his joining a high brand equity team. For example, the medium brand equity team may give the high brand equity player an opportunity to demonstrate a distinct brand identity from the team, leading to more personal endorsement deals. Although we suspect that the first explanation is more likely, the results do not separately distinguish between one or the other or both of the explanations holding. The above discussion is suggestive of an S-shaped curve for the marginal value of a superstar.

Although high brand equity players matching with medium brand equity teams generate the most value, they will not necessarily be common. When considering two matches, the total value from two matches—one match between a high brand equity player and a high brand equity team and another match between a medium brand equity player and a medium brand equity team—edges out the total value from two alternative matches—one match between the high brand equity players and a medium brand equity team and another match between a medium brand equity player and a high brand equity team. This is how, after including the effects of the interaction between player performance and team performance and the interaction between age and team

Table 2 Results of the Two-Sided Matching Model by All-Star Rank

	Team performance		
(1) Player performance	1		
(2) Age	4.69 (4.64, 4.95)		
Player type*	Team type		
	High	Medium	Low
(3) High brand equity players	3.73	6.07	−12.97
—Elected all-star starters	(2.12, 6.02)	(4.69, 7.50)	(−21.96, −5.99)
(4) Medium brand equity players	−0.41	1.94	−0.60
—Centers ranked 2–3	(−1.41, 0.31)	(1.26, 2.86)	(−1.49, 0.06)
—Guards ranked 4–5			
—Forwards ranked 4–5			
(5) Low brand equity players	−1.31	1.05	−1.35
—Centers ranked 4–5	(−2.14, −0.48)	(0.37, 2.04)	(−2.21, −0.49)
—Guards ranked 6–10			
—Forwards ranked 6–10			
(6) Very low brand equity players	0.08	2.63	0†
—All other players in the data	(−0.89, 0.87)	(1.86, 3.60)	
Maximum score	67.09%		

*Based on ranking in all-star voting.

†Value is zero because it is the base.

¹⁵ The matching value between high brand equity players and low brand equity teams is very low, perhaps because low brand equity teams may have a negative impact on the brand equity of players.

performance, we still observe more high brand equity players matching with high brand equity teams in our data.

Table 2 shows that, for lower brand equity players, the matching values are highest when matching with a medium brand equity team. Their matching values are lower when matched with either a high brand equity team or with a lower brand equity team. One possible reason for this result is that medium brand equity teams' markets are not as saturated as high brand equity teams' markets. Still, unlike low brand equity teams, medium brand equity teams possess some brand value that can spill over to their players. Thus, matching with medium brand equity teams is unlikely to negatively affect players' personal brand equity, but it can still generate substantial positive spillovers to the teams.

The matching values in Table 2 clearly show that matching between players and teams are not assortative. The most valuable matches are between brands of different relative strengths. More broadly, this suggests that top brands are not necessarily better off by matching with other top brands. The total value generated may be higher if top brands match with middle-level brands as long as middle brands can compensate the top brands appropriately.

6. The Impact of Maximum Individual Salary Policy

So far, our analysis has assumed that a team can offer any salary it is willing to pay. However, as described in §3, the 1998 CBA imposed a maximum individual salary for players. As a result, a team cannot give any player more than the maximum salary. In this section, we first show that parameters on performance (calculated in §5) do a reasonably good job of predicting matches both before and after 1998. In contrast, parameters on brand equity only do a good job predicting matches before 1998. They predict the post-1998 out-of-sample matches poorly. We interpret this as suggesting that the 1998 CBA had a particularly large influence on matches driven by brand equity spillovers. We end this section with a simple theoretical model showing how a maximum salary restriction can change matching outcomes.

6.1. Counterfactual Simulation for the Post-1998 Period

To understand the impact of the maximum salary restriction on outcomes, we simulate matches both before and after the 1998 CBA. We use three different simulations to better understand the effect of the maximum salary restriction on brand equity spillovers in contrast to performance complementarities. These are (1) simulated matching based on all

estimated parameters from §5, (2) simulated matching assuming there are no brand equity spillovers, and (3) simulated matching assuming there are no performance and age reasons for matching. This separation gives insight into how the maximum salary restriction affects matching because of performance separately from how it affects matching because of brand equity spillovers.

The simulation process contains the following steps.

Step 1. Define simulated markets. First, those players who played the same position and sign a contract in the same year in the post-1998 period are grouped into one market. Second, select the one with the highest performance score from those players who sign with the same teams within each market defined above. Third, choose the top M players based on the performance score from the selected ones.

Step 2. Calculate the payoff matrix. Within each simulated market, calculate the total payoff for all the possible matches between a player and a team using the estimates from the pre-1998 period: $f(a, i) = \hat{\beta} \times X_a \times Y_i + \varepsilon_{ai}$, where ε_{ai} is a random draw from $N(0, 1)$. Thus, the payoff matrix is an M by M matrix. When calculating the counterfactual matching based on only some of the parameters, we effectively set the coefficients of the others to zero and draw ε_{ai} from $N(0, 1/\sqrt{2})$.

Step 3. Simulate the counterfactual matching outcomes using the linear programming. Construct the matching problem using the payoff matrix calculated above and solve it by the linear programming (Shapley and Shubik 1971) for each simulated market.

When we define the simulated markets, we select only one player from each team to make our markets one-to-one matching. We select a set of M contracts in each market to make sure that it is solvable by the linear programming. Limiting to only M contracts in each market is not expected to have a significant effect on the matching outcomes across player brand equity types because the eliminated contracts are associated with low performance players. We ran simulations with $M = 8$ and $M = 9$ and found little difference between them. Here, we present the results for $M = 9$. The random error in the production function is a match-specific error. After repeating Steps 2 and 3 100 times, we obtain the counterfactual results by computing the average of these 100 simulated outcomes.

We simulate the matching outcomes for both the pre-1998 and post-1998 periods. We use the pre-1998 period to assess the fitness-of-simulation process and the separate ability of performance and brand equity parameters to predict outcomes. We then compare the counterfactual with actual matching outcomes in the post-1998 period and examine how the maximum

individual salary changed the matching outcomes. We summarize the simulated as well as the observed matching outcomes for both the pre- and post-1998 period in Table 3. We measure the goodness of fit of counterfactual simulations by the mean squared errors (MSEs) over the possible matching outcomes, defined as follows:

$$\text{MSE} = \frac{1}{12} \left(\sum (\text{actual matching percentage} - \text{simulated matching percentage})^2 \right),$$

where 12 is the number of possible matching types. MSE is a simple and direct measure for goodness of fit. The smaller the MSE, the better the goodness of fit.

In the pre-1998 period, the simulated matching outcomes are very close to the actual matching outcomes. This shows that the simulation works very well in the pre-1998 period. Although this is not surprising because the parameters are estimated from these data, it provides support for comparing simulated with actual outcomes in the post-1998 data. The simulations on pre-1998 data also show that the model assuming that matches are entirely based on brand equity spillovers also predicts the underlying data reasonably accurately. The model that simulates matches assuming no brand equity spillovers does a relatively poor job matching the actual data.

The simulations for the post-1998 period do a much worse job fitting the data. Because this is an out-of-sample prediction, this is not entirely surprising. By separately simulating matches based entirely on brand equity spillovers from matches that assume no brand equity spillovers, we can assess the reasons why the post-1998 simulation fits the data poorly. We find that the performance and age parameters do nearly as well predicting outcomes in the post-1998 data as in the pre-1998 data. In contrast, the brand equity parameters do much worse in the post-1998 data. A possible explanation for this discrepancy is that salary caps affect matches because they impact incentives to form brand alliances. Although good performance is equally valuable across teams, spillovers from player brands vary by team brand strength. Next, we provide a simple theory that shows that matches may change under a maximum salary restriction. The theory shows that matches can change if the total surplus from a brand alliance cannot be realized because of the restriction on transfers from teams to players.

6.2. Theoretical Analysis

To illustrate the potential impact of maximum individual salary constraint on the optimal matching outcomes, let us consider a pair of matches (ai, bj) with

two teams $\{a, b\}$ and two players $\{i, j\}$.¹⁶ If neither of the two players' salaries (or their potential salaries with the other team) is binding, then the local production maximization condition remains the same after the maximum individual salary constraint is imposed. If both players' salaries are binding, these two players are most likely to be the same type of players. In this paper, we cannot identify the within-group-specific parameters under a local production maximization model, and therefore, we will leave this case to future research. Here, we focus on two situations: in one situation, the player's salary from the observed matching team is binding, and in the other situation, the player's salary from the alternative team is binding. In both situations, only one player's salary is binding with one team. We will examine these two situations separately.

Without loss of generality, we assume player i 's salary or potential salary is binding. To better distinguish the two players, we call player i the high brand equity player and player j the other player. In the first situation, player i 's salary from team a (observed matching team) is binding; in the second situation, player i 's salary offered by team b (the alternative team) is binding.

Situation 1. High Brand Equity Player i 's Salary from the Observed Match Is Binding ($t_{ai} = \bar{t}$). In this situation, because player i 's salary from team b is not binding, team b could offer more money to attract player i . However, team b chooses not to do so because it can get more profit from player j . Therefore, this situation is similar to the one without the maximum salary restriction. The maximum individual salary constraint does not alter the local maximization condition. (Please refer to the appendix for more details.) That is,

$$f(a, i) + f(b, j) \geq f(b, i) + f(a, j),$$

where

$$\begin{aligned} f(a, i) &= \Delta V(a, i) + \Delta U(a, i), \\ f(b, j) &= \Delta V(b, j) + \Delta U(b, j); \\ f(a, j) &= \Delta V(a, j) + \Delta U(a, j), \\ f(b, i) &= \Delta V(b, i) + \Delta U(b, i). \end{aligned}$$

¹⁶ This analysis of a two-player and two-team market, although not equivalent to a full equilibrium analysis for a market consisting of many players and many teams, sheds useful insight on the impact of a maximum individual salary on matches and on the benefits to different teams and players. In a larger market, chain reactions might happen because of the maximum individual salary. For example, the change of one pair of matches might cause the change of other matches. This question is beyond this paper's reach and is left to future research.

Table 3 Brand Equity Predicts Matches Well Pre-1998 But Not Post-1998

Player brand equity	Team brand equity	Pre-1998				Post-1998—Simulations based on pre-1998 estimates			
		Actual matching	Simulated matching	Simulation assuming no brand equity spillovers	Simulation based only on brand equity spillovers	Actual matching	Simulated matching	Simulation assuming no brand equity spillovers	Simulation based only on brand equity spillovers
High	High (%)	71.43	58.71	38.86	53.71	53.33	56.60	31.60	59.07
	Medium (%)	28.57	41.29	29.00	46.29	13.33	43.40	27.27	40.93
	Low (%)	0.00	0.00	32.14	0.00	33.33	0.00	41.13	0.00
Medium	High (%)	30.77	32.85	29.54	30.15	25.00	32.88	32.50	36.50
	Medium (%)	30.77	28.62	35.69	29.08	62.50	32.88	30.25	22.75
	Low (%)	38.46	38.54	34.77	40.77	12.50	40.75	37.25	40.75
Low	High (%)	25.00	24.50	28.00	23.67	29.63	26.19	30.19	24.00
	Medium (%)	25.00	27.75	32.17	24.08	25.93	24.74	30.89	23.52
	Low (%)	50.00	47.75	39.83	52.25	44.44	49.07	38.93	52.48
Very low	High (%)	29.73	30.65	32.54	31.73	27.10	26.93	29.45	26.86
	Medium (%)	28.38	27.11	26.31	27.15	28.04	26.82	27.24	27.75
	Low (%)	41.89	42.24	41.15	41.12	44.86	46.25	43.31	45.39
Mean squared error ^a			0.0029	0.0193	0.0054		0.0317	0.0208	0.0377

Note. Values shown are percentage of players in the player brand equity category that match with teams in that category.

^aMSE defined by the data in this table: $MSE = (\sum(\text{actual matching percentage} - \text{simulated matching percentage})^2)/12$.

Shapley and Shubik (1971) have demonstrated that there exist many price solutions for such a unique optimal assignment of a matching game. In this situation, the maximum individual salary constraint does not alter the matching outcomes. It merely shifts some profit from the player to the team.

Situation 2. High Brand Equity Player i 's Salary from the Potential Match (Team b) Is Binding ($\tilde{t}_{bi} = \bar{t}$). There are two possible scenarios in this situation. In one scenario, in spite of the restricted pay that high brand equity player i can receive from team b , it is still better for team b to match with the other player j . As a result, the same equilibrium condition holds with or without the maximum individual salary constraint. As in the first situation, the maximum individual salary constraint does not alter the matching outcome and the policy merely reallocates the profit from the player side to the team side.

In another scenario, it is also possible that team b 's profit from high brand equity player i is higher than its profit from other player j , but team b cannot offer a higher salary to attract the high brand equity player because of the maximum individual salary constraint. In this scenario, optimal matching is altered by the maximum individual salary constraint. We derive the following theorem to show the condition where optimal matching is altered (for details, see the appendix).

THEOREM 1. Suppose high brand equity player i can obtain more spillovers from team a than from team b ; that is, $\Delta U(a, i) > \Delta U(b, i)$. When the maximum individual salary \bar{t} is sufficiently low such that $\Delta S(b, i, j) = [(\Delta V(b, i) - \bar{t}) - (\Delta V(b, j) - t_{bj})] > f(a, j) + f(b, i) -$

$[f(a, i) + f(b, j)]$, the observed matches (a_i, b_j) with the maximum individual salary constraint are different from the optimal matches (a_j, b_i) without the constraint.

Theorem 1 shows that under some conditions, the maximum individual salary constraint prevents the team who benefits more from the high brand equity player from signing that player. Even though the team has higher valuation (ΔV) for the player, the team cannot offer more money to compensate the player's loss of brand equity spillovers from the other team. In this scenario, the maximum individual salary constraint alters the matching outcomes and total alliance values.

7. Conclusions and Future Research

To our knowledge, this paper is the first to empirically study the spillover effect of brand alliances by analyzing the two-sided strategic choices of partners. Specifically, we analyze matching incentives through brand spillovers in a team–player alliance through a structural analysis of both partners' choices.¹⁷ We also analyze how these values vary across different types of players and teams. We find that top brands do not necessarily benefit most by matching with other top brands. Instead, if they match with slightly weaker brands, they generate the largest benefits from the

¹⁷ This methodology may yield insights in other contexts such as the actor–producer–director relationship in the entertainment industry, alliances between manufacturers and suppliers, channel alliances between manufacturers and retailers, the marriage market, and academic collaboration.

alliance. Furthermore, our simulations provide suggestive evidence that if one partner's brand gains more from an alliance than the other's, unrestricted compensation allows the matches with the highest total value to proceed. Overall, we find that brand equity spillovers affect partner choices nonmonotonically. Although our application focuses on brands in professional sports, we believe the insight may apply more broadly. Brand alliances between brands of different strengths may be the most valuable.

Appendix. Local Production Maximization with a Maximum Individual Salary Constraint

Consider a pair of matches (ai, bj) under the maximum individual salary constraint, where player i is a high brand equity player and player j is a lower brand equity player. There are two possible scenarios under the maximum individual salary constraint.

Situation 1. High Brand Equity Player i 's Salary from the Observed Match Is Binding ($t_{ai} = \bar{t}$)

The salary that makes player i indifferent to switching to team b is

$$\tilde{t}_{bi} = \bar{t} + \Delta U(a, i) - \Delta U(b, i). \quad (13)$$

Because the potential salary from team b is not binding, the salary in (13) should be smaller than the maximum individual salary \bar{t} . Thus, the condition $\Delta U(a, i) \leq \Delta U(b, i)$ holds. In other words, player i gets more brand spillovers from team b than from team a . Because player j 's salary is not binding for either team, the salary that makes player j indifferent to switching to team a is

$$\tilde{t}_{aj} = t_{bj} + \Delta U(b, j) - \Delta U(a, j). \quad (14)$$

Because team b 's offer to player i is not binding, team b could increase the offer to induce player i to switch. However, team b chooses not to do so because the team gets higher profit from its alternative player j . Thus, team b 's payoff from player j should be no smaller than that from player i with the maximum individual salary constraint. That is,

$$\Delta V(b, j) - t_{bj} \geq \Delta V(b, i) - \tilde{t}_{bi}. \quad (15)$$

Because player j 's offers from both teams are not binding, team a 's payoff from player i should be no smaller than that from player j . That is,

$$\Delta V(a, i) - \bar{t} \geq \Delta V(a, j) - \tilde{t}_{aj}. \quad (16)$$

Substituting Equation (13) into (15) and Equation (14) into (16), we derive the following two inequalities:

$$\Delta V(b, j) - t_{bj} \geq \Delta V(b, i) - \bar{t} - \Delta U(a, i) + \Delta U(b, i), \quad (17)$$

$$\Delta V(a, i) - \bar{t} \geq \Delta V(a, j) - t_{bj} + \Delta U(b, j) - \Delta U(a, j). \quad (18)$$

Summing these two inequalities together, we get

$$\begin{aligned} & \Delta V(b, j) - t_{bj} + \Delta V(a, i) - \bar{t} \\ & \geq \Delta V(b, i) - \bar{t} - \Delta U(a, i) + \Delta U(b, i) + \Delta V(a, j) - t_{bj} \\ & \quad + \Delta U(b, j) - \Delta U(a, j). \end{aligned}$$

Cancelling out the salaries and moving some items from the right to the left gives

$$\begin{aligned} & \Delta V(a, i) + \Delta U(a, i) + \Delta V(b, j) + \Delta U(b, j) \\ & \geq \Delta V(b, i) + \Delta U(b, i) + \Delta V(a, j) + \Delta U(b, j). \end{aligned} \quad (19)$$

We assume the same payoff function as without the constraint (i.e., pre-1998). That is,

$$f(a, i) = \Delta V(a, i) + \Delta U(a, i),$$

$$f(b, j) = \Delta V(b, j) + \Delta U(b, j);$$

$$f(a, j) = \Delta V(a, j) + \Delta U(a, j),$$

$$f(b, i) = \Delta V(b, i) + \Delta U(b, i).$$

The inequality (19) is the same as the one without maximum individual salary constraint:

$$f(a, i) + f(b, j) \geq f(b, i) + f(a, j).$$

Shapley and Shubik (1971) demonstrated that there are many price solutions for a unique optimal assignment in a matching game. Under this situation, the maximum individual salary constraint does not alter the matching outcomes or social welfare.

Situation 2. High Brand Equity Player i 's Salary from the Potential Match (Team b) Is Binding ($\tilde{t}_{bi} = \bar{t}$)

Knowing that team b 's offer to player i is binding, team a offers player i the following amount:

$$t_{ai} = \bar{t} + \Delta U(b, i) - \Delta U(a, i). \quad (20)$$

Player i 's salary from team a will be lower than the maximum salary. That is,

$$\Delta U(a, i) > \Delta U(b, i).$$

Thus, player i gets more brand spillovers from team a than from team b . Because player j 's salary is not binding for either team, player j 's salary to make him indifferent switching to team a is

$$\tilde{t}_{aj} = t_{bj} + \Delta U(b, j) - \Delta U(a, j). \quad (21)$$

Because we observe that team a matches with player i instead of player j , team a 's payoff from player i should be no smaller than that from player j . That is,

$$\Delta V(a, i) - t_{ai} \geq \Delta V(a, j) - \tilde{t}_{aj}. \quad (22)$$

Substituting Equations (20) and (21) to inequality (22),

$$\begin{aligned} & \Delta V(a, i) - \bar{t} - \Delta U(b, i) + \Delta U(a, i) \\ & \geq \Delta V(a, j) - t_{bj} - \Delta U(b, j) + \Delta U(a, j) \\ & \rightarrow \Delta V(a, i) + \Delta U(a, i) + \Delta U(b, j) - \bar{t} \\ & \geq \Delta V(a, j) + \Delta U(a, j) + \Delta U(b, i) - t_{bj}. \end{aligned} \quad (23)$$

Even though we observe team b matching with player j instead of player i , we still cannot infer that team b 's payoff from player j is weakly larger than that from player i because team b 's offer to player i is binding. There are two possible scenarios: In one scenario, team b wants to offer

just \bar{t} to player i because team b gets more profit from its alternative match player j . In another scenario, team b wants to offer a higher salary to player i to make him switch teams because team b gets more profit from player i than from player j . However, the maximum individual salary constraint prevents team b from doing so. We will discuss the two scenarios.

Case 1. Team b 's payoff from player j is no smaller than that from player i . That is,

$$\Delta V(b, j) - t_{bj} \geq \Delta V(b, i) - \bar{t}. \quad (24)$$

Summing (23) and (24) yields the same equilibrium condition as the one without maximum individual salary constraint. That is,

$$\begin{aligned} & \Delta V(a, i) + \Delta U(a, i) + \Delta V(b, j) + \Delta U(b, j) \\ & \geq \Delta V(b, i) + \Delta U(b, i) + \Delta V(a, j) + \Delta U(b, j) \\ & \rightarrow f(a, i) + f(b, j) \geq f(b, i) + f(a, j). \end{aligned}$$

Similar to Situation 1, the maximum individual salary constraint does not alter the matching outcome or social welfare in this case. It just reallocates the profit from players to teams.

Case 2. Team b 's payoff from player j is smaller than that from player i . That is,

$$\begin{aligned} & \Delta V(b, j) - t_{bj} < \Delta V(b, i) - \bar{t} \\ & \rightarrow \Delta V(b, i) - \bar{t} - [\Delta V(b, j) - t_{bj}] > 0. \end{aligned} \quad (25)$$

Adding $\Delta V(b, j) + \Delta V(b, i)$ into both sides of inequality (23),

$$\begin{aligned} & \Delta V(a, i) + \Delta U(a, i) + \Delta U(b, j) + \Delta V(b, j) + \Delta V(b, i) - \bar{t} \\ & \geq \Delta V(a, j) + \Delta U(a, j) + \Delta U(b, i) + \Delta V(b, j) + \Delta V(b, i) - t_{bj}. \end{aligned} \quad (26)$$

Using the same payoff function as pre-1998,

$$\begin{aligned} f(a, i) &= \Delta V(a, i) + \Delta U(a, i), \\ f(b, j) &= \Delta V(b, j) + \Delta U(b, j); \\ f(a, j) &= \Delta V(a, j) + \Delta U(a, j), \\ f(b, i) &= \Delta V(b, i) + \Delta U(b, i). \end{aligned}$$

Then, inequality (26) becomes the following:

$$\begin{aligned} & f(a, i) + f(b, j) + \Delta V(b, i) - \bar{t} \\ & \geq f(a, j) + f(b, i) + \Delta V(b, i) - t_{bj}. \end{aligned}$$

Moving some items in the left to the right of the above inequality, we get

$$\begin{aligned} & f(a, i) + f(b, j) + [(\Delta V(b, i) - \bar{t}) - (\Delta V(b, i) - t_{bj})] \\ & \geq f(a, j) + f(b, i). \end{aligned}$$

Denoting $\Delta S(b, i, j) = [(\Delta V(b, i) - \bar{t}) - (\Delta V(b, j) - t_{bj})]$, the above inequality becomes

$$f(a, i) + f(b, j) + \Delta S(b, i, j) \geq f(a, j) + f(b, i). \quad (27)$$

From inequality (25), we derive $\Delta S(b, i, j) > 0$. Therefore, inequality (27) does not imply that the total payoff from the observed two matches is weakly larger than that from the alternative matches, which is the local production maximization condition without the maximum individual salary constraint. When $\Delta S(b, i, j)$ is large enough, we may have $f(a, i) + f(b, j) < f(a, j) + f(b, i)$, in which we should observe matches (aj, bi) without the maximum individual salary constraint. Instead, we observe (ai, bj) with the maximum individual salary constraint. As the maximum individual salary \bar{t} becomes lower, the value of $\Delta S(b, i, j)$ becomes larger. Therefore, we can derive the following theorem:

THEOREM A.1. Suppose high brand equity player i can obtain more spillovers from team a than from team b ; that is, $\Delta U(a, i) > \Delta U(b, i)$. When the maximum individual salary \bar{t} is sufficiently low such that $\Delta S(b, i, j) = [(\Delta V(b, i) - \bar{t}) - (\Delta V(b, j) - t_{bj})] > f(a, j) + f(b, i) - [f(a, i) + f(b, j)]$, the observed matches (ai, bj) with the maximum individual salary constraint are different from the optimal matches (aj, bi) without the constraint.

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