Consumer Forwards:
Concept and Empirical Analysis of a Market for Sports Tickets

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Abstract

Tickets to sports events like the NCAA basketball tournament are currently sold well in advance. Fans who wait to purchase a ticket *after* knowing which teams will play are often disappointed because the tickets are sold out by then. Recently, some firms have offered fans the opportunity to purchase forwards on tickets *before* this uncertainty is resolved. Each purchased forward is linked to a team – if that team makes it, the fan must buy the ticket; otherwise, the forward expires. Such forwards protect fans from uncertainty and provide the firm with assured revenues. We analyze data from a company that offers forwards in a sports ticket market. We study how fans mitigate risk by buying forwards in this volatile setting. Accounting for fan heterogeneity, we estimate different models to capture fan purchase and resale behaviors. We examine how insights related to financial portfolio management apply to consumer forward markets. This is the first paper to empirically analyze the forward concept in marketing. Our findings lay a foundation for future work on consumer forwards.

Keywords: forward pricing, pricing under uncertainty, event tickets, Final Four tickets, consumer forwards.

Introduction

In financial markets, a forward is a product that confers upon the buyer the right and obligation to buy an asset at some future time for a price agreed on today. Forward contracts – as opposed to "spot" market transactions that are based on the prevailing price – are frequently employed to manage risk in financial and commodities markets (including those for currencies, grain, electricity, precious metals, and oil). Many forward contracts simply specify the prices and quantities related to a future transaction. Flexible forward contracts, however, can specify boundaries outside of which each party can walk away from, or delay, the proposed transaction. For example, a buyer may enter a forward contract in which she agrees to buy an underlying asset – say, a single-family home – a year from now at a predetermined price from a seller. The contract could further specify that both parties are obliged to complete the transaction provided the average price per square foot for comparable real estate in the area at the time of the purchase transaction – measured according to a predetermined method – is within a range specified in the contract. Such a flexible forward protects the buyer from sharp price hikes and the seller from steep price drops. Likewise, a flexible forward could allow a utility to decide how a pre-contracted amount of power to be delivered to an industrial consumer can be temporally staggered across a specified time period subject to demand and supply conditions (Bjorgan et al. 2000).

Consumers face significant risks related to the value of purchased assets in many product and service markets not directly related to financial products. These risks can impede market efficiency. For example, a few years ago there was significant uncertainty about which new technology – Blu-Ray or HD DVD – would win the standards war and replace conventional DVDs (Flaherty 2004). As the standards war raged, many consumers decided to postpone purchase until the dust settled and a victor emerged. According to a technology analyst "…consumers had held off

investing in the latest recorders and players because they did not know which format would emerge dominant" (Kageyama 2008). Rather than having consumers wait on the sidelines, enterprising firms could have encouraged the purchase of either a HD DVD or a Blu-Ray player bundled with the purchase of a flexible forward. For example, the HD DVD (Blu-Ray) purchaser could be sold a forward that spelled out a contract to purchase a Blu-Ray (HD DVD) player at 60% of the prevailing market price on a future date if Blu-Ray (HD DVD) instead emerged as the standard. The concept of the forward in now catching on in consumer markets, with firms like firstdibz.com offering forwards for consumer products that are popular and hard to obtain (e.g., the next Nintendo, Sony or Microsoft gaming console).

Despite the utility of the flexible forward (forward, henceforth) as a pricing and risk mitigation mechanism and its popularity in financial and commodities markets, there is little existing research on this concept in the marketing arena. To our knowledge, this is the first paper in the marketing literature that formally develops the concept of forward pricing and demonstrates how it can work in consumer markets that are characterized by consumption-related uncertainty. We study the factors that affect purchase and resale decisions relating to consumer forwards in a sports setting. Sports markets have considerable uncertainty in terms of the teams that will advance past the early elimination rounds, making it an ideal setting for the introduction of consumer forwards.

We analyze data on transactions within a marketplace for forwards on Final Four tickets for the 2006 NCAA Division 1 Men's Basketball tournament. In this elimination-style tournament, early predictions about the teams that will advance to the Final Four are often incorrect. Fans hesitate to buy tournament tickets upfront because their favorite team – the one they would like to see playing in the final game – may simply not make it to that stage. The data we analyze capture

both the purchases of forwards and the (possible) resale of those forwards before the uncertainty about the teams participating in the Final Four tournament is resolved. Applying a discrete choice model in a panel data setting to model consumer behavior, we demarcate the key drivers of forward buy and sell decisions across different fan segments. Our analysis yields descriptive insights into how nascent markets for consumer forwards operate, and normative insights into how they can be designed and managed.

There are three primary contributions of our research. First, we introduce and analyze the concept of a consumer forward. Whereas forwards are commonly encountered in financial and commodity markets, there is no research that formally examines how the concept can be adapted and applied to product and service markets with numerous, heterogeneous consumers. Our work begins to fill that gap. Consumer forwards can benefit both the demand and supply sides of the market. In the sports market setting, a forward allows consumers to make a modest upfront investment to "conditionally reserve" a seat at the tournament, subject to their favorite team making it to that stage. In this case, fans are not left scrambling to get a costly ticket at the last minute once they know their favorite team is playing. On the supply side, a forward ticket allows the firm to "conditionally sell" the same seat multiple times over to fans of different teams, knowing that only the one fan whose team makes it to the Final Four will ultimately pay the exercise price and occupy the seat during the game because all other forwards on the seat expire.

Second, little is known about decision-making in consumer forwards markets. We shed light on the key drivers of forward purchase and resale behavior. We consider a number of variables to explain observed behaviors, some of which are derived from finance and behavioral research. For example, a sports team's performance is similar in some respects to a stock's "run," a concept that has been extensively researched in the finance literature. Thus, we examine whether and how fans

react to a string of positive or negative performances by their favorite teams, the timing of that string of performances, and the implications of their reactions in ultimately (a) holding a forward ticket for their favorite team that makes it to the Final Four, or (b) selling off a forward ticket before their favorite team is eliminated en route to the final weekend. A central difference here is that consumers typically have differentiated preferences across offered products and services, whereas investors in financial markets primarily focus on creating a portfolio of stocks with a projected risk versus return profile. Likewise, investors can control risk by holding some "guaranteed" assets such as treasury bills to reduce portfolio volatility. In contrast, there are no sure shot teams in sports markets. [1] Correspondingly, our findings shed light on how consumer behavior in a sports forward ticket market is influenced by some of its unique features, and provide substantive insights into how consumers employ available information to evaluate the prospects of their favorite teams.

Third, our findings provide some normative insights into how consumers in the market for forwards should behave to maximize their chances of being able to attend the Final Four. For example, we examine whether consumers over- or under-react to certain types of information, and how they can moderate their reactions to maximize their likelihood of success. Overall, our findings can inform the design of markets for consumer forwards as well as the crafting of policies related to the provision of consumer information in these markets.

<div align="center">**The Market For Final Four Forward Tickets**</div>

Each year, college teams compete to reach the Final Four stage of the NCAA basketball tournament. The NCAA basketball tournament that we study – popularly labeled as "March Madness" – begins each year with 64 teams that are divided into 4 groups of 16 teams each. Teams play within each group in a "sudden death" (or knockout) format. Successful teams must progress

through the "Sweet Sixteen" and "Elite Eight" stages to arrive at the "Final Four" games. The two winners of the Final Four round play in the National Championship game.

The Forward Concept

Tickets to all tournament games are sold by the National Collegiate Athletic Association (NCAA) - hereafter 'the league' - well in advance of the games, when the teams that will actually play are unknown. Fans hesitate to purchase tickets to the Final Four tournament because their favorite teams are often eliminated before that stage. Worse yet, in the heated rivalry of college basketball, ticket holders may have to endure the pain of seeing a despised rival play in the Final Four. On the other hand, fans who decide to wait for the uncertainty to be resolved before purchasing tickets can be disappointed because tickets near game time are scarce. These fans may miss the big game or possibly resort to buying tickets at inflated prices from resellers (e.g., scalpers) who obtained tickets in advance. Importantly, the league does not benefit from the high prices charged by resellers. Not surprisingly, our field research indicates that neither fans nor the league are satisfied with this situation.

To combat this problem, some firms (e.g., yoonew.com, ticketoption.com, firstdibz.com) have recently introduced consumer forwards to help fans manage both the (ex ante) risk of buying a ticket upfront for what turns out to be the "wrong" game and the (ex post) risk of finding that tickets are sold out for a game they do want to attend. Buying a forward on a team for the Final Four confers upon the fan the right and the obligation to purchase a ticket for the game if that team makes it to the final game. If that team does not make it through to the Final Four, the forward simply expires.

Specifically, if a consumer is interested in attending a game in which her favorite team is playing, she purchases the team's forward ticket (at the firm's website) by paying a forward price

(as shown in Figure 1). Fans can buy forwards for multiple teams across athletic conferences.

Consumers have access to the firm's proprietary market in which they can resell their forwards – or

buy additional forwards from other fans – at any time after they purchase the forward but before the

uncertainty about the teams playing in the Final Four is resolved. Reflecting supply and demand

conditions, forward ticket prices vary by team and over time. If a fan's favorite team for which she

holds a forward ticket advances past the preliminary rounds and all the way to the Final Four, she

then is obliged to pay an additional exercise price (set by the league) to buy the ticket. The exercise

price is the same as the face value of the ticket. This face value which is determined by the NCAA

can vary from year to year, but has ranged between $140-$160 for the past few years. The exercise

price is set in advance and fans are aware of this price when they purchase the forward. If the

specific team for which the forward ticket was purchased does not make it to the final weekend, the

fan loses the forward price (i.e., the forward expires). The firm obtains revenue from its initial sale

of forwards as well as a percentage of the value of transactions between the consumers in its

marketplace (i.e., a buyer and seller fee of 5%). The revenues from the exercise of forwards in the

form of actual tickets all accrue to the league.

[insert Figure 1 about here]

Data

Our data come from a company that is a pioneer in offering forward tickets for many sports

markets. This firm shared its data on all initial forward purchase and resale transactions that

occurred within its proprietary marketplace for tickets to the NCAA Division 1 Men's Final Four

Basketball games that were held in Indianapolis during April 2006. The transactions begin with the

firm offering forwards in April 2005. Each consumer was allowed to purchase a maximum of eight

forwards per team. Forwards could be resold to other fans within the marketplace at any time before

the Final Four games in April 2006. Forward tickets were initially sold by the firm at $5 per seat. Resale prices ranged from $5 to $800 per forward depending on the team and the time that the forward was resold. Consumers who wish to sell a forward post their minimum selling price on the firm's online marketplace. This available forward is then matched up with a potential buyer whose maximum willingness to pay is higher than this minimum selling price. If a match can be made any point in time, the transaction is executed.

Each participating consumer has a unique identification code, allowing us to track each individual's purchase and resale behavior (should resale occur). The data are organized at the transaction-level, including: (a) the team the buyer bought, (b) the number of forward tickets purchased, (c) the price of the forwards, and (d) the day and time of purchase. If the forward was subsequently sold, we have information about: (a) the team that was sold, (b) the timing of the sale and (c) the identity of the seller and the buyer. Forwards can be resold to other consumers, but not to the firm. Overall, our dataset comprises 581 unique buyers who engaged in 3315 transactions across 83 unique teams.

Types of Consumers in a Sports Forward Ticket Market

Following Sainam et al. (2010), consumers participating in our forwards market include: (1) fans who bought and possibly sold forwards on only one team (called "team-based fans to capture their allegiance to a single team), and (2) fans who bought and possibly sold forwards on multiple teams (called "game-based' fans to capture their interest in attending the Final Four regardless of the teams playing). In addition, we identified several individuals that seemed to have abnormal reselling activity. As in markets for entertainment and sports event tickets, professional ticket resellers also exist in online forwards markets. Aiming to profit from buying low and selling high, these resellers

have little interest in watching the game itself. Because resellers only want to acquire tickets for which they can make a profit by later selling, we exclude them from our analyses.

We employ two methods to identify resellers. First, we link resale behavior to team performance. True fans will hold on to a forward when their team is performing well. In contrast, a reseller would have an incentive to sell a forward for a team doing well to take advantage of the prevailing high price. Accordingly, we classify buyers as resellers when they resell a team forward when that team is performing well, i.e., when the team rank is worse in the week of resale than in the previous week. Second, we consider the resale price transactions. For our data, the average cumulative resale revenue across sellers (which could include the resale of multiple tickets on any given transaction) is $1500. However, most sellers have transactions far less than this amount. In the second method we classify those sellers whose transactions netted them any amount over this average resale revenue as resellers. This reflects the notion that resellers are more focused on, and competent at, executing resale transactions as opposed to holding on to a forward hoping to attend the big game. We note that there is a strong overlap for the resellers identified by these two rules. Here, buyers who never resold a forward are automatically classified as fans.

After eliminating resellers, we have data on 529 unique buyers (fans) who engaged in a total of 1955 transactions across 83 unique teams.[2] There are 221 game-based fans in our data. Most game-based fans bought forwards for 2 to 5 unique teams; very few bought forwards for more than 10 teams. A frequency plot of the number of unique teams bought by fans is displayed in Figure 2. Only 20% of the transactions undertaken by fans relate to teams that eventually made it to the Final Four. The fact that 80% of the transactions involved teams that never made the Final Four highlights the relevance of understanding fan behavior in this market.

[insert Figure 2 about here]

Model: Theoretical Arguments and Measures

Dependent Variables

Consistent with standard economic theory, we assume that fans attempt to maximize their utility (Jehle and Reny 2003). In this setting, maximizing utility is a function of attending the desired game. The utility of not attending a game is normalized to zero. A forward expires if the team that is associated with it does not make it to the tournament. Therefore it becomes important for the fans to first buy forwards on the 'right' teams (or, alternatively, to not buy forwards on the 'wrong' teams). Further, even if the team makes it to the tournament, unless the fan retains a forward on that team, she cannot attend the game. That is, the fan cannot attend the Final Four if she resells all her forwards on teams that make it to the final game. To summarize, the fan can derive positive utility from attending the game if she (a) has purchased the "right" team's forward(s) and (b) has not resold the purchased forward(s) on the winning team(s). The fan's decision process is described in Figure 3.

[insert Figure 3 about here]

As stated above, because fans derive positive utility from their purchase and resale decisions, we estimate two models – one for the purchase decision and the other for the resale decision. A purchase decision can be classified as being 'good' if the transaction relates to a team that eventually made it to the Final Four, or 'bad' if it relates to a team that did not.[3] Because the fan derives positive utility if she *does not* resell a winning team's forward we classify a transaction in the resale model as being 'good' if the fan resold a forward on a team that eventually did *not* make it to the Final Four. Given that we know which teams eventually made it to the Final Four, we can study optimal fan behavior in this setting.

The dependent variables, for the purchase (P_{it}) and resale models (R_{it}), are created from this classification of whether or not the team that was purchased eventually made it to the Final Four. For the purchase (resale) model, the dependent variable is set at one if the fan bought (sold) a forward on a team that eventually made (did not make) it to the Final Four, and zero otherwise.

Measures (Independent Variables)

Conceptual framework. Multiple variables can influence a fan's purchase and resale behaviors in a forwards market. We develop and group these variables drawing on the finance literature, where scholars have examined the forces that influence investor behavior in stock markets (e.g., Lewellen et al. 1977).

First, there are elements outside the influence of the individual fan and the team, such as the price of the forward, which could affect the fan's purchase decision. We group these elements, which are essentially in the nature of controls, under **market-level variables**. Second, fans can interpret the temporal pattern of a team's past and current performance as signals of future performance. If a team performs well over several weeks, fans may believe that buying that team's forward is a good investment that offers a fair likelihood of attending the Final Four game. Drawing from research on sports betting and from the literature in finance, we motivate a second group of variables – **team performance variables**. Finally, the finance literature has examined how individual investors' risk tolerance can affect the composition and management of their asset portfolio. For example, the diversification of the asset portfolio though the inclusion of dissimilar assets can reduce risk (Markowitz 1991). To examine how attempts to mitigate risk can influence the purchase and sale of forwards, we complement our existing data by constructing a set of **risk reduction variables.** We now describe how variables within these groupings can influence fan

behavior in the forwards market. Some of the variables can influence both purchase and resale behaviors, while others may be relevant in the context of one of these behaviors.

Market-level (Control) Variables. (1) Price paid per forward *(PRICE)*: Empirical studies have consistently established the important role of price in driving consumer purchase decisions (Kenesei et al. 2003). In fact, when potential budget constraints are in play, price can influence purchase decisions independent of the expected value associated with the purchased offering. In our context, price can influence both whether or not a forward is purchased, and the number of forwards purchased at a given point in time. From a theoretical perspective, though, our goal is to understand the key drivers of forward purchase and resale, over and above the effect of price. Therefore, we include the price of the forward as a control variable.

(2) Week that the forward was bought/sold *(WB, WS)*: We code the purchase dates into 19 weeks of the regular basketball season; this is the time span across which the forward market operates. *WB* (*WS*) represents the group of 19 time dummies related to the week the forward was bought (sold). These variables control for any temporal fluctuations in the forward purchase and resale transactions.

(3) Day of the week *(DB, DS)*: Numerous empirical studies over multiple decades have documented the presence of calendar anomalies in financial markets. A well-established anomaly is the "day of the week effect," which demonstrates that the average stock return on Monday is significantly lower than the average return over the other (trading) days of the week (Berument and Kiymaz 2001). To control for such potential anomalies in the context of sports forward trading, we code seven 'day of the week' dummies (*DB*) to represent the day the forward was purchased (*DB*) or sold (*DS*).[4]

Team performance variables. (1) Team rank at purchase week *(P_RANK, R_ RANK)*: Rankings serve as easily accessible, if imperfect, predictors of future performance. Research across domains has demonstrated that consumers are sensitive to information on the relative superiority of offerings. Consumers often make decisions based on rankings and ratings, especially when they lack sufficient expertise to evaluate and/or predict performance, or when such evaluation and prediction calls for intensive effort. For example, researchers have demonstrated that individuals and markets respond to ranking and rating information related to stocks (Stickel 1985), hospitals (Pope 2009), movies (Basuroy et al. 2003), and products (Park 2007). Emerging research on virtual stock markets also suggests that pooled estimates of future performance can serve as robust predictors of such performance (e.g., Foutz and Jank 2010).

In our context, the variable that comes closest the capturing the future performance of a basketball team is its national ranking. This ranking is partially based on how well the team has played in the past against other teams of various ranks, but can also incorporate more subjective factors that attempt to capture, for example, the strength of team's talent and its ability to perform well under pressure. Since 1993, National Association of Basketball Coaches has published a weekly ranking that reflects the performance and perceived potential of college basketball teams across the regular season. This ranking is sponsored by ESPN and USA Today and is commonly referred to as the *USA Today Coaches Poll*.[5] A key strength of this measure is that it is based on the pooled inputs of numerous experts – this reduces idiosyncratic errors in perception and evaluation of team performance and potential. To examine the influence of rankings on forward purchase and resale decisions, we include this information in the estimation by coding the Top 50 team ranks at the week of purchase *(P_RANK)* and at the week of resale *(R_RANK)* as proxies for team performance.

(2) Change in team rank: If performance in the recent past is a good signal of future performance, then purchasing or selling an asset based on its recent performance should yield a significant economic return. Such a "momentum effect" has been frequently discussed in the finance literature, where multiple studies have revealed that over a period ranging from three to 12 months, past winners continue to perform well, and past losers continue to exhibit below par performance (Hong et al. 2000). On even smaller time scales, momentum traders could implement quick buy and sell decisions to exploit short-term price swings in the market. The case for momentum trading in financial markets has been frequently debated because, in an efficient market, all market information is immediately reflected in the stock price. Therefore, researchers have sought to explain the potential for profitable momentum-based trading by arguing that financial markets exhibit either sustained overreactions to news about fundamentals (e.g., DeLong et al. 1990), or sustained under-reactions to such news (e.g., Daniel et al. 1998).

In sports markets, in contrast, a team's past (positive) performance could result from genuine improvements in the team's skills, inter-player coordination, confidence, or some combination of these attributes. Some of these improvements could be sustained over time, leading to a higher probability of the team making it to the Final Four match. On the other hand, a good performance may sometimes result from the opposing team having an off day, or a flash of skillful execution that may not reflect enduring improvement. In basketball, for example, it is frequently believed that a player who has scored two shots in a row is more likely to score the third shot. Basketball players themselves suggest that it was important for players on a team to pass the ball to someone who had just made multiple successful shots in a row because they are perceived to have a higher probability of getting the next shot in (Gilovich et al. 1985). This belief about the "hot hand"

endures despite statistical evidence indicating that the probability of success associated with a given shot does not significantly increase just because the player has made the previous shot(s).

The issue of interest here is whether relying on a short term change in team ranking (say, from the week before purchase, t-1, to the week of purchase, t) can help fans make the right decisions related to either purchasing or reselling a forward. To examine this issue, we first create two rank change variables: the first captures the change in rank between week t-1 and t (indicating a momentum effect) whereas the second captures the change in rank between week t-2 and t-1 (a lagged momentum effect). If the change is positive it implies the team has performed better in the recent past. Next, we divide the change in rank variable by the average rank of the team to yield our variables of interest *(P_RANKCH1, P_RANKCH2)*. Whereas simply capturing the change in rank gives us just the directionality of the ranking, dividing by the average rank accounts for the fact that a rank change matters more for a higher ranked team. For example, a change in a couple of ranks for a top-ranked team matters more than, say, for the 40th ranked team.[6] We repeat the process to find the change in rank between weeks t-1 and t-2 of resale and divide these by the average rank to create the two variables of interest: *R_RANKCH1* and *R_RANKCH2*.

(3) Long-term performance *(LONGRUN)*: Investing in an asset that yields relatively stable returns over the long run can beat investing in more volatile assets that can occasionally yield a strong return. This viewpoint anchors the concept of blue chip investing, whereby investors focus on stocks on well-established companies that exhibit stable earnings, consistently pay out dividends, and carry a low level of liabilities.

Likewise, a consistently winning or consistently losing performance by a team over the last few games can indicate that the team is steadily growing in strength or is falling apart, respectively. On the other hand, short-term performance can be driven by chance, or by the players failing to

come together as a team, or by consistently unfavorable game conditions. Given that even a good team can have bad days, the average performance of the team over the long run – the dominance of wins over losses, or vice-versa – can possibly serve as a better indicator of the quality and prospects of the team. To capture long term performance, we code *LONGRUN* as equal to one if the team cumulatively has more wins than losses at the time that the fan purchases the team's forward.

Variables related to risk-reduction strategies. (1) Buyer resale at time t (RESELL): The situation where the fan rarely, or never, resells purchased team forwards would parallel a "buy and hold" strategy in the stock market. This strategy is built on the assumptions that (a) investments in the stock market and in particular, in blue chip stocks, will yield a positive and significant rate of return in the long run and (b) short term timing of market trades is, on average, unprofitable. However, short-term movements in price can often trigger the sale of an asset. For example, early exercise of stock options by employees is a pervasive phenomenon, and a key driver of early exercise is the market-to-strike ratio (Huddart and Lang 1996). More generally, as information is revealed over time, the holders of an asset continuously monitor the balance of benefits between holding the asset and selling it.

In our setting fans have access to a market where they can resell any team forward they possess to another fan until the time that the team is eliminated. We seek to understand whether the presence of a resale market reduces fans' purchase-related risk. A fan could buy a risky forward based on the belief that he or she can always turn around and resell the forward as team performance-related information is revealed, but before the team is eliminated. For this fan, trading in and out of forwards can represent an appropriate responsiveness to the changing likelihood of the teams making it to the Final Four tournament. In fact, there is a stronger reason for proactive, short term trading in forward tickets than in stocks or financial options because the set of teams that

remain in the tournament is continuously being pruned. This is not the case with the stock market where multiple stocks, even within the same industry, could rise over time.

To identify the effect of resale behavior, we code a *RESELL* variable that captures the cumulative number of forwards a fan has resold at a certain point in time. If a fan never resold any of her forwards during the course of the season the value of this variable is set at zero throughout. For a game-based fan operating with a limited budget, the resale of a forward could generate the revenue that can be invested in a more promising forward. Therefore, such resale could enhance the likelihood of a fan ultimately holding a ticket for the Final Four games.

(2) Portfolio Variables: Portfolio diversification in financial markets can substantially reduce a trader's risk if the correlation among the securities is low (Markowitz, 1991). If, however, this correlation is high, the returns on them will move up (or down) in unison – therefore, such a portfolio does not reduce risk.

In the context of men's college basketball, a fan could potentially eliminate the risk of not having a ticket for the Final Four by buying a forward on every team in the conference. This is an expensive proposition, though, because the forward purchased on every team that does not make it to the Final Four ultimately expires. However, fans could reduce the risk by owning a portfolio of forwards on multiple teams. In constructing this portfolio, the fan may seek to accommodate a variety of playing styles and personal team preferences. Most conferences consist of teams from the same geographic area, and these teams generally recruit from the same areas. Therefore, the diversity of talent among teams from the same conferences tends to be low (Whenham 2009). Further, even fans are unlikely to have a strong preference for two historical rivals with the same conference. Rather, they may prefer to watch a favorite team from their home conference circuit and a high profile team from a different conference play in the Final Four. This could lead to a

diversification of the portfolio of held forwards across multiple conferences. To capture the diversification in a fan's portfolio (portfolio depth) we create two variables: (a) the number of unique team's forwards a fan purchases *(UNIQTEAM)* and (b) resells *(R_UNIQTEAM)*. Further, to capture the effect of portfolio breadth we code for the number of unique teams in unique conferences held by a fan at any given point in time *(UNIQTEAMCONF)*. This last variable allows us to examine whether diversifying one's portfolio with dissimilar components is effective in this market. Note that these variables are only applicable to game-based fans because team-based fans, by definition, only buy forwards on a single team.

(3) Bought after team won in rivalry game *(BEAT RIVAL)*: Many basketball teams have storied rivalries. Given that most teams will not eliminate themselves from post conference contention in non-conference games, these rivalries tend to be focused within the same conference (Whenham 2009). In fact, many of these rivalries tend to occur between neighboring universities (USC versus UCLA), or universities located in adjacent states (Texas versus Oklahoma).

These heated rivalries draw in huge crowds. For example, the Duke-UNC basketball rivalry is ranked among the top 100 "must-see live" sporting events for fans (Tuchman 2009). The market for forwards on teams that feature in high profile rivalries is active – this liquidity makes it easier to both buy and resell forwards. In financial markets, stocks with higher liquidity offer lower risk and are considered preferred investments (Shen 2000) – the same effect may hold in the market for sports team forwards. Furthermore, a win over an established rival can be a more informative signal about the innate capability of the team. Each team is expected to bring its best game to a matchup with such a rival, and a win in such a match may signal the resilience of the team, and its ability to prevail over some determined opposition in the future. This signal, and the boost in motivation from the win, arguably bode well for the prospects of the team in other, less celebrated matchups.

To capture this argument, we code high-intensity rivalries (e.g., USC-UCLA) and identify whether a team won against its archrival.[7] The *BEAT RIVAL* variable is set to 1 if a fan buys a forward on a team within two days of its victory over an archrival.

(4) Expert Predictions *(EXPPICK):* Relying on expert opinions can reduce consumers' cognitive effort and uncertainty when perceived risk associated with a purchase decision is high (Dowling and Staelin 1994). Consumers are particularly sensitive to the opinions of others when attribute information is not highly informative or difficult to ascertain (West and Broniarczyk 1998). These conditions hold in sports markets, wherein a team's likelihood of making it to an advanced stage of the tournament may be a function of not just historical performance, but also of the outcome of the recruiting season that is reflected in the innate ability of the individual team-members, the quality of team play in the first few games, and, at late stages of the tournaments, even the likely match-up of competitors in the schedule (Leitner et al. 2010). In such conditions reliance on expert forecasts can lighten the burden of personal responsibility associated with consequential decisions.

Expert judgments in sports settings can forecast sports tournament outcomes more accurately than backward-looking ratings that predicate future performance solely based on past performance (Leitner et al. 2010). Against this backdrop, fans who purchase forwards may allow their decisions to be influenced by expert predictions about specific teams that will ultimately make it to the Final Four games in a particular year. Much like populating a portfolio with stocks from reputed firms can help mitigate risk (Stein and DeMuth 2008), relying on expert predictions can possibly increase the likelihood of buying a forward on the "right" team.

For the purposes of this study, we used the NCAA midseason expert predictions of the Top 5 teams during the 2005-2006 season. These predictions reflect experts' combined assessments of

the rankings of the teams – which ostensibly reflect the perceived likelihood of the teams playing in

the final stages of the tournament.[8] Capturing whether transactions involve the Top 5 teams allows

us to examine the implications of relying on expert opinions in the forwards market.

(5) Forward purchase after that team beat a highly ranked team *(QUALITY WIN)*: Fans draw

inferences about the quality of a team not just based on its record of wins, but also on the quality of

teams against which those wins were achieved. In fact, under some proposed ranking systems,

beating a winless team is more harmful than not playing such a team as all (Keener 1993). In

contrast, a highly ranked team sets a benchmark for high quality performance, and beating such an

opponent can signal that a team is potentially capable of beating other, strong opponents in the

league. Beating a top-ranked team can also enhance the team's confidence and increase fan

presence and morale at the games, both of which can result in higher quality and invigorated play.

We set the variable *QLTY WIN* equal to 1 if the fan bought the forward of a team that beat a highly

ranked team – one that was ranked within the Top 5 – at the time of purchase.

Models

General Estimation Approach

All fans in our sample have purchased at least one forward (i.e., our analysis is conditional

on fan i having purchased a forward at time t). Panel logit models are used to estimate the effects of

our explanatory variables because the dependent variable is binary (Cameron and Trivedi 2009).

The individual-effects logit model is $\Pr(y_{it}=1) = \Lambda(\alpha_i + \beta\, \mathbf{x}_{it} + \gamma\, z_i)$ where y_{it} is our dependent

variable (that takes on the values of 0 or 1) and $\Lambda(w)=e^w/(1+e^w)$. Here, x_{it} are all the variables that

vary over individuals and time, z_i are the variables that describe the individuals but do not vary over

time, and α_i captures all the unobserved differences between fans that are stable over time and not

otherwise accounted for by z_i.

There are two main approaches for estimating this model. One approach considers the α_i to

be fixed effects, i.e., each fan has a separate α_i that captures unobserved individual differences. In

our situation including dummy variables for each individual will lead to the incidental parameter

problem in which the coefficient estimates will not be consistent (Lancaster 2000). Alternatively,

estimation of this fixed effect logit model can be accomplished using a conditional maximum

likelihood estimator where all time-invariant individual effects α_i are conditioned out of the model

based on the total number of outcomes equal to one for a given individual over time (Cameron and

Trivedi 2009). While this approach allows the individual specific effects to be correlated with the

independent variables (and thus is less likely to be biased), a conditional fixed effects model has

some important restrictions. In particular, fans that have $y_{it}=1$ (or 0) for all *t* are eliminated from the

estimation sample due to the conditioning, and time-invariant variables z_i (including the constant)

cannot be estimated. In our setting, this would mean that information on 108 game-based fans (i.e.,

48% of all our game-based fans) and all team-based fans (since these individuals only purchase

forwards on a single team) is not available for estimation purposes.

The other main estimation approach is to consider a random effects model. Unlike a fixed

effects approach that considers the α_i to be nuisance parameters that can be eliminated from the

estimation, a random effects approach specifically includes the distribution of individual effects, α_i

$\sim N(0,\sigma_\alpha^2)$. This model assumes that the individual specific effects are uncorrelated with the

independent variables. Here, the parameters β, γ and σ_α are obtained using maximum likelihood

estimation (after α_i is integrated out of the joint density function; Cameron and Trivedi 2009).

Importantly, this approach allows us to estimate the "average" effects of our explanatory across the

population of fans and thus to apply our results beyond the specific individuals in our sample. Random effects estimation is more efficient than fixed effects because random effects models use the variation across, as well as within, individuals.

Typically, a Hausman test is used to select among these approaches (Greene 2000). However, because this test is based on asymptotic arguments, practical applications in finite samples often (as in our case) lead to an indeterminate outcome (e.g., the covariance matrix is not positive definite). Thus, we employ an alternative statistical test based on a "hybrid" model suggested by Allison (2005). In this approach, the time-varying predictors are decomposed into two parts representing within- and between-person effects (Neuhaus and Kalbfleisch 1998). Both of these components are then used in a subsequent logit model (here, the within-person component will be the same as the fixed effects estimates). A test of whether the within-person estimated coefficients are the same as the between-person coefficients performs the same function as a Hausman test (here, the null hypothesis is that the Random Effects model is appropriate).

Purchase Models

As stated earlier we estimate different purchase and resale models for the two types of fans because their objectives relating to forward purchase and resale can differ. Further we introduce the three groups of independent variables (control variables, team performance and risk reduction variables) sequentially into the model to examine their incremental effects for each fan type. The first model includes only the control variables, the second adds the team performance variables, and the third model includes, in addition, the variables related to fans' risk reduction strategies. Therefore we estimate twelve separate models in all and discuss only the four best-fitting models. Equations (1) and (2) below represent the purchase models for team- and game-based fans.

Purchase model – Game-based fans. This is the most general model that includes all three groups of independent variables, and the motivations for every variable previously discussed apply here. Accordingly, this model can formalized as:

$$
\begin{aligned}
P_{it}^{GB} = \alpha_1^{GB} &+ \beta_1 DB_i + \beta_2 WB_i + \beta_3 PRICE_{it} + \beta_4 P\_RANK_i + \beta_5 P\_RANKCH1_i \\
&+ \beta_6 P\_RANKCH2_i + \beta_7 LONGRUN_{it} + \beta_8 RESELL_{it} + \beta_9 BEAT\,RIVAL_{it} \qquad (1) \\
&+ \beta_{10} QLTY\ WIN_{it} + \beta_{11} EXPPICK_{it} + \beta_{12} PDEPTH_{it} + \beta_{13} PBREADTH_{it} + u_i^{GB} + \zeta_{1it}
\end{aligned}
$$

Here, the Hausman-like test (Allison 2005) supports the use of a Fixed Effects estimation approach (the null hypothesis that a Random Effects approach is appropriate is rejected; χ^2=13.81, p<0.02)[9].

Purchase model – Team-based fans. A team-based fan is interested in viewing games that feature just one team. Therefore, the variables related to the number of unique teams purchased and the number of unique conferences purchased do not apply here. Accordingly, the most general model that includes all three groups of independent variables can formalized as:

$$
\begin{aligned}
P_{it}^{TB} = \alpha_1^{TB} &+ \beta_{14} DB_i + \beta_{15} WB_i + \beta_{16} PRICE_{it} + \beta_{17} P\_RANK_i + \beta_{18} P\_RANKCH1_i \\
&+ \beta_{19} P\_RANKCH2_i + \beta_{20} LONGRUN_{it} + \beta_{21} RESELL_{it} + \beta_{22} BEAT\,RIVAL_{it} \qquad (2) \\
&+ \beta_{23} QLTY\ WIN_{it} + \beta_{24} EXPPICK_{it} + u_i^{TB} + \zeta_{2it}
\end{aligned}
$$

As noted above, a conditional Fixed Effects model is inappropriate for team-based fans because they only purchase forwards for a single team. Thus, we use a Random Effects estimation approach.

Resale Models

Next, consider the forward resale model. Here, the dependent variable, R_{it}, represents the likelihood that the fan sells the "correct" forward, i.e., the forward on a team that does not ultimately make it to the Final Four. Given that the resale of a forward is dependent on the purchase of that forward, it appears logical to estimate a sample selection model of resale to capture these

two interlinked behaviors. However, a selection model is not appropriate in our situation.

Theoretically, to justify a selection model we require some variance in the dependent variable at the

second stage. When the "correct" team's forward is purchased in Stage 1 in our data, the fan only

has two choices going forward – sell that forward or hold it (until either the forward expires because

the team exits the tournament or attend the game if the team makes it to the Final Four (see Figure

3). The fans' behavior in the latter case, when they do not resell the forward, is unknown. Because

there is no variance in the dependent variable of the resale model in Stage 2 we estimate

independent purchase and resale models.

Resale model – Game -based fans. The following variables from the purchase model for

game-based fans were dropped from the resale model because they only pertain to a purchase

decision: buyer resell and purchases made after a win against a high profile rival or a top ranked

team. On account of loss-averse thinking related to endowment effects, consumers who hold an

asset and are evaluating selling it tend to be more sensitive to the shock of recent, bad news rather

than the long run performance – the latter is easily rationalized by the consumer (Sen and Block

2009). We therefore capture the relevant team performance by including the team rank at the week

of resale and the corresponding rank change variables. Accordingly, this model can formalized as:

$$
\begin{aligned}
R_{it}^{GB} = \alpha_2^{GB} &+ \beta_{25}DS_i + \beta_{26}WS_i + \beta_{27}PRICE_{it} + \beta_{28}R\_RANK_i + \beta_{29}R\_RANKCH1_i \\
&+ \beta_{30}R\_RANKCH2_i + \beta_{31}EXPPICK_{it} + \beta_{32}R\_PDEPTH_{it} + v_i^{GB} + \zeta_{3it}
\end{aligned}
\tag{3}
$$

Here, the Hausman-like test (Allison 2005) supports the use of a Random-Effects estimation

approach (the null hypothesis that a Random Effects approach is appropriate is accepted; $\chi^2=1.75$,

$p>0.63$). Further, we find that σ_α is not significantly different from zero ($\chi^2=0.09$, $p>0.38$),

indicating that a pooled logit model (with standard errors corrected for correlated observations) is

preferred.

Resale model – Team -based fans. The variables in the resale model for team-based fans mirror those in the resale model for game-based fans, except for the exclusion of the variable that measures the presence of unique teams in the portfolio. By definition, team-based fans focus on just one team. Accordingly, this model can formalized as:

$$
\begin{aligned}
R_{it}^{TB} = \alpha_2^{TB} &+ \beta_{33}DS_i + \beta_{34}WS_i + \beta_{35}PRICE_{it} + \beta_{36}R\_RANK_i + \beta_{37}R\_RANKCH1_i \\
&+ \beta_{38}R\_RANKCH2_i + \beta_{39}EXPPICK_{it} + v_i^{TB} + \zeta_{4it}
\end{aligned}
\tag{4}
$$

As previously noted, a conditional Fixed Effects model is inappropriate for team-based fans because individuals only resell forwards for one team. Thus, we use a Random Effects estimation approach. Again, we find that σ_α is not significantly different from zero (χ^2=0.27, p>0.30), indicating that a pooled logit model (with standard errors corrected for correlated observations) can be used.

Findings and Discussion

Table 1 provides the descriptive statistics and correlations for our variables across the purchase and resale models. Tables 2 and 3 present the maximum likelihood estimates of the random effects logit purchase model for game-based fans and team-based fans, respectively. These estimates will differ from the beta coefficients in a corresponding OLS regression because the grouping variable (buyer) is treated as a random or fixed effect depending upon the fan type.

[insert Tables 1, 2, and 3 about here]

The three columns in Table 2 represent the parameter estimates for the model with the three groupings of independent variables (model 1 indicates a model with controls only, model 2 is the controls + team performance variables model whereas model 3 indicates a model with all variables, i.e., controls + team performance + risk reduction variables), respectively. The fit statistics in Table 2 indicate that the most general model (model 3) fits the data best. We focus our discussions on this model.

In terms of specific findings, first, buying a forward on a team that beats a top ranked team at that point in time helps the game-based fan increase the likelihood of picking the right team – one that makes it to the Final Four. Such a win can either signal the innate quality of the team, or serve as a morale-booster for the team and its supporters, or both. In any case, such a win serves as a significant signal of the team's future prospects. The next risk reduction strategy – buying a forward on a team that beats a prominent rival – also helps the game-based fan. Winning a game that features a high-profile competitive pairing signals an increased likelihood of the team's long-term tournament prospects. On average, expert picks help game-based fans choose the right teams. Specifically, game-based fans engaged in numerous transactions related to the Florida Gators – and that team was picked by experts for the 2006 season.

Purchasing forwards on multiple teams spread across conferences helps game-based fans increase the likelihood of ending up with a team that makes it to the Final Four. Most post-season elimination games are held between teams from the same conferences. In men's college basketball, over the last decade no two teams from the same conference have ever competed in the final championship game. Therefore, it is useful for game-based fans to diversify their portfolio of forward tickets to include unique teams from unique conferences.

In the context of the control variables, the week in which the forward is bought has a significant effect. Game-based fans benefit from buying later in the season. This makes intuitive sense – more information is revealed later in the season as teams are steadily eliminated and fewer prospects are left in contention late in the season. The counteracting risks related to waiting, though, are that the market for teams left in the competition may be less liquid closer to the date of the tournament, and that the prices paid for forwards, on average, would be higher closer to the tournament.

Next, consider the purchase model for team-based fans. As seen in Table 3, the second model (which is significant and has the lowest log likelihood value) is the best fitting model for team-based fans. The only variable that affects team-based fans' purchase is the rank of the team at the week of purchase. Buying a team's forward when the team is highly ranked – corresponding to a low absolute rank value – at the week of purchase, helps team-based fans. This makes intuitive sense – team-based fans by definition already know which team's forward to buy; the only remaining decision in their case is when to buy it. Further, given that the hopes of team-based fans are contingent on the performance of just one team, a diversification approach that serves game-based fans well cannot be employed by team-based fans. This demonstrates the challenge faced by team-based fans compared to game-based fans in a forwards market.

[insert Tables 4 and 5 about here]

Following that, we estimate resale models for the game- and team-based fans. First, consider the estimates of the logit resale model for game-based fans (see Table 4). The most general model (model 3) fits the data the best in this case as well. In the context of resale, two of the three team performance variables are significant. The two variables demonstrate the effect of change in team's performance on its resale. If the team's performance is improving (two weeks before resale or a week before resale) the likelihood that the fan makes the correct decision in selling that team's forward is lower. Recall that reselling the right team in the resale model involves reselling a team that will *not* ultimately make it to the final games. In contrast, the team's (absolute) rank *at* the week of resale does not have a significant effect on the likelihood of its resale being a correct choice. This highlights the importance of momentum, or performance trajectory, as a predictor of the team's success or failure as opposed to its (absolute) current rank. Converse to its effects in the purchase model heeding expert picks hurts the fans' chances of reselling the right teams. This

makes intuitive sense – expert recommended teams ended up making it to the final game; therefore they should not be sold.

In terms of the control variables, selling early in the week helps. This may be because most games are played later in the week (after Wednesday). If teams lose, their value decreases; in the extreme case if a team is eliminated from the tournament the corresponding forward becomes worthless instantaneously.

The other significant control variable is price. If fans paid a higher purchase price for the forward then it improves their chances of reselling the right forward. Recall that reselling the right forward implies reselling a forward on a team that *did not* make it to the final game. Therefore price serves as an imperfect signal of team quality in this setting. This finding is surprising because one would expect that, based on standard "invisible hand" arguments, the market would correctly price forwards based on the prospects of the team entering the Final Four. There is a demand side explanation that fits here. The primary source of demand for a team forward would come from the geographical area where the parent university if located, and to a lesser extent, from geographically dispersed supporters. High profile teams located in relatively affluent geographical areas (e.g., Duke) are likely to see a higher level of primary demand and a higher willingness-to-pay for forwards compared to talented and promising teams that are located in relatively low income areas. Therefore fans with a high income would be willing to put down money to buy the forward on their favorite team but as the realization about the team's real potential sinks in, these fans would do well to resell the forwards.

In Table 5 we see that model 3 is the best fitting resale model for team-based fans. Again, team performance variables are crucial to the team-based fan's success in reselling the right forward. Interestingly, unlike the game-based fans, team-based fans need to pay attention to both

the absolute rank at the time of resale and the lag momentum effects. This could be because team-based fans already know which team to purchase forwards on (unlike game-based fans) and should therefore be more sensitive to the performance of the team. For the same reason that selling an expert pick hurts game-based fans, it hurts team-based fans also – these are good teams and the fan would be better off holding onto them.

Taken together, the four models yield a better understanding of the factors that fans must pay attention to when purchasing or reselling a team forward. Such an understanding can help fans maximize the likelihood of either holding a forward on a team that ultimately makes it to the Final Four or reselling a forward of a team that ultimately does not make it to the Final Four.

Conclusion

This paper sheds light on fans' decision-making in the market for forward tickets. Accounting for fan heterogeneity, we identify different fan types and different strategies for fans and understand their purchase and resale behaviors in a volatile sports market setting. For each fan type we study forward purchase and resale decisions. We shed light on the key drivers of forward purchase and resale behavior across these fan segments using a number of independent variables – some of which were created based on insights from other functional fields, including finance, where individuals make decisions in environments with uncertainty. We classify the explanatory variables into (a) risk-reduction variables, (b) team-related variables, and (c) controls. We examine the drivers of forward purchase and resale behaviors to understand how fans navigate a market that is characterized by considerable consumption-related uncertainty.

Overall, the purchase and resale models yield some interesting insights. It is clear that risk reduction strategies are the most helpful variables to game-based fans seeking to make the right

purchases. This intuitively makes sense because game-based fans buy multiple teams' forwards and are seeking to minimize their portfolio risks. Among the risk reduction strategies heeding expert picks, buying unique teams across conferences and buying teams that beat their rivals are the most significant predictors of fan success. Consistent with the portfolio diversification theory in financial markets, we see that it is a good strategy for fans to buy forwards of unique teams across unique conferences. This finding verifies the result that diversifying one's portfolio of dissimilar components is an effective risk management strategy not just in financial markets but in consumer markets as well. Next, buying a team that beats its rival or a top-ranked team increases fans' likelihood of buying the right team. These two measures serve as reliable signals for team quality. For team-based fans the team rank at the week of purchase is a sufficient predictor of a good purchase. The effect of the team performance variables in the purchase and resale models indicate that it is just as important to buy a team that is performing well as it is to sell a team that is not performing well.

In this paper we take the first steps in studying how consumer forwards perform in a ticket market with numerous, heterogeneous consumers, and the key drivers of consumer decision-making in this market. We examine how the consumer's utility maximization and risk minimization objectives translate into observed behaviors in the marketplace for sports forwards and the effectiveness of those behaviors in ultimately achieving those objectives. A natural question that arises at this stage is: Can the concept of the consumer forward be more generally applied? We propose that the general principle of forward-based pricing advanced in this paper can be applied, with appropriate adjustments, across multiple product and service markets. For example, forward contracts can be implemented in the following situations:

➢ Consider a popular ski resort that has a limited number of rooms in its onsite ski-lodge. Skiers who try and book late may be turned away – however, skiers would be particularly be interested in booking a room if there is ample snow on the ground. The ski-lodge also faces a revenue-risk here. If skiers waited for a favorable snow forecast but the weather was ultimately predicted to be dry, the rooms would go empty. In such a situation, the ski-lodge could implement forward pricing for the rooms. Skiers would be allowed to purchase a forward on the room reservation, with the reservation becoming active and non-refundable if there were, for example, at least 6 inches of (natural) snow on the ski slopes. This example differs from the sports ticket-pricing example in an important way. The basketball fans in our model were horizontally differentiated in terms of their preferences for the teams – in the case of the ski resort, skiers would predominantly prefer more snow to less. However, some skiers would be "satisfied" with a thinner snow cover than others. Interestingly, this also presents an opportunity for price discrimination for the forward, where a more expensive forward could be conditionally linked to heavier snow cover.

➢ Consider an airline that flies to a popular theme park destination such as Orlando in Florida or Anaheim in California. The quality of a theme park holiday depends significantly on the weather – a rainy day could ruin a family's holiday. The airline could sell forward tickets that would convert to tickets or expire, say, four days before the date of the flight as a function of the forecasted weather. The contract would detail the conditions for conversion (or expiration) based on the projected likelihood of showers by a recognized weather authority and other climatic variables. The interesting opportunity here is that, if the forwards are not converted, the corresponding seats could be released to the general public, including business travelers who are less sensitive to the weather.

➤ Consider the battle of the standards between the HD-DVD and Blu-Ray formats for digital video content. As noted at the outset of the paper, consumers held off on the purchase of either technology because they were unwilling to undertake the risk of investing in a technology that ultimately did not emerge as a standard. This constricted the cash flow and profits of firms and kept superior formats out of the marketplace. In this situation, to reduce the risk faced by consumers and to improve the cash flow of the firm, a forward could be bundled with the purchase of either technology. The forward could be structured differently from the examples discussed above; it could take the form of a rebate that is paid to the consumer at a future date if the technology that the consumer has adopted does not clearly emerge as the standard by that date. The consumer could choose to apply this rebate to shift to the (now) standard technology.

➤ Consider hotel reservations made in connection with a Super Bowl match or with the finals of high profile events at the Olympic Games. Fans in these contexts have horizontally differentiated preferences across teams, and a fan's value for a hotel room is correlated with the projected likelihood of the team making it to the final event. This situation is amenable to the sale of forwards on hotel room reservations – these forwards would be linked to specific teams. Further, the fortunes of the teams and their perceived likelihood of playing in the Super Bowl will vary across the season. Similar to the case of the sports forward tickets, hotels could therefore sell forwards on their rooms, and in parallel, facilitate a marketplace where those forwards could be mutually traded by fans.

As with any new pricing mechanism, the contractual details that govern the market for forwards must be carefully crafted. In particular, the conversion conditions should be clearly demarcated and

be based on information provided by neutral parties to avoid any perceived and real bias that may favor either the buyer or the seller.

More generally, the concept of the forward can be applied in any market where there is some combination of heterogeneity in consumer preferences – either in the vertical or horizontal sense – and some uncertainty about the outcomes of interest. The application of the forward in these markets can benefit both the buyer and the seller. Forwards can help the seller leverage constrained capacity across consumers with heterogeneous preferences by allowing scarce assets (e.g., a seat at a game) to be "sold" multiple times to distinct consumers. Forwards also help reduce the risk faced by the seller by guaranteeing revenues from forward sales before uncertainty is resolved. Specifically, they can help the seller avert the situation encountered in conventional selling where consumers may withhold purchasing a ticket or reservation in the face of uncertainty, but then do not make a purchase anyway because the event is finally revealed to be of low quality (e.g., a matchup between relatively unknown teams). On the other hand, forwards also allow the consumer to lock in the opportunity to potentially participate in an event of high value at a relatively low cost without requiring a heavy investment that may go waste if the event ultimately turns out to be of low value to the consumer.

Future research. This is the first paper to analyze the concept of consumer forwards, and many important issues remain to be researched in this context. From an experimental perspective, researchers could examine the reactions of consumers to specific configurations of forwards under varying degrees and kinds of uncertainty. From an empirical perspective, researchers could examine consumer behavior in other emerging markets for consumer forwards. From an analytical perspective, researchers could model competition between conventional sellers and forward sellers. We hope this paper catalyzes research in this new research domain.

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Footnotes

[1] To highlight the magnitude of uncertainty in this setting, in the last 10 years, of the 40 teams that made it through to the men's Final Four tournament only eight teams had made it there more than once. The teams are: Connecticut, Duke, Florida, Maryland, Michigan State, North Carolina, Kansas, and UCLA.

[2] This implies that the average "true" fan engaged in 3.7 transactions, whereas the average reseller had 26.2 transactions. This again strongly suggests that our approach worked well in terms of identifying frequent traders who were in the market for commercial reasons rather than for their love of the game or team.

[3] Teams that made it to the 2006 NCAA Basketball Final Four were the Louisiana State Tigers, the UCLA Bruins, the Florida Gators, and the George Mason Patriots.

[4] Most of the games relevant to this study occur on weekdays, rather than on weekends.

[5] The data for the top 50 ranked teams (rank 1= best) through the length of the regular season were collected from http://www.warrennolan.com.

[6] In the financial sector, market responses to changes in the Value Line Investor Survey follow a similar pattern. The Survey ranked 1700 common stocks into 5 groups based on the projected financial performance over the next 12 months. The market reacts most positively when a stock was moved up from group 2 to group 1 (representing the most promising stocks) than when stocks were moved up by one ranking to any of the other 4 groups (Stickel 1985). Stated differently, both the magnitude of the upward movement and the absolute value of the initial and final rankings can influence market perceptions and reactions.

[7] We compiled a list of sources of top college basketball rivalries from the following websites: nbcsports.msnbc.com, collegesports.com and sports.espn.go.com.

[8] Each year, team rankings are sought from 31 head coaches at Division I institutions. The picks are ranked based on the total number of points each team garners in the Coaches' Poll. The top five expert picks for 2006 were Connecticut, Duke, Memphis, Florida, and Texas. The *EXPPICK* variable was dummy-coded to capture transactions involving any of these teams.

[9] We note that the same conclusions to be discussed in the next section are obtained from a Random Effects model.

Table 1: Descriptive Information and Correlations

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Day of the week	4.06	2.26	1.00																	
2. Day of the week sold	4.70	1.90	0.14	1.00																
3. Week bought	13.6	6.80	0.25	0.23	1.00															
4. Week resold	16.1	5.05	0.20	0.20	0.62	1.00														
5. Price paid per forward	98.8	115	0.00	0.11	0.26	0.13	1.00													
6. Team rank at purchase week	11.6	20.2	0.01	-0.14	-0.32	-0.15	-0.29	1.00												
7. Team rank at week of resale	6.93	16.0	-0.09	-0.19	-0.35	-0.23	-0.15	0.36	1.00											
8. Rank change at purchase wk 1	0.03	0.25	-0.02	-0.00	0.00	0.01	-0.10	0.01	-0.02	1.00										
9. Rank change at purchase wk 2	0.02	0.27	0.04	-0.03	-0.01	0.02	0.01	-0.02	-0.03	-0.40	1.00									
10. Rank change at resale wk 1	0.25	0.63	0.04	0.07	0.01	0.15	-0.12	0.11	-0.20	0.03	0.00	1.00								
11. Rank change at resale wk 2	0.66	0.85	0.30	0.23	0.50	0.42	-0.00	-0.23	-0.31	-0.03	0.01	-0.35	1.00							
12. Longrun	0.69	0.71	0.10	0.13	0.40	0.57	0.10	-0.09	-0.15	0.00	-0.03	0.03	0.30	1.00						
13. Did buyer resell	4.57	5.50	0.10	0.03	0.14	0.17	0.03	-0.03	-0.10	0.07	-0.04	0.00	0.13	0.23	1.00					
14. Beat rival	0.19	0.39	0.05	0.07	0.09	0.14	0.00	0.01	-0.00	0.02	-0.04	0.00	0.10	0.24	0.06	1.00				
15. Quality Win	0.03	0.19	-0.01	-0.05	-0.00	0.02	0.04	-0.02	0.00	-0.01	0.01	-0.02	-0.00	0.08	0.02	0.33	1.00			
16. Expert picks	0.01	0.11	-0.00	0.01	-0.15	-0.01	0.04	-0.03	-0.04	0.07	0.08	-0.02	-0.02	-0.02	0.03	-0.02	-0.00	1.00		
17. Tot. num. unique teams bought	8.65	8.51	0.16	0.05	0.31	0.20	0.06	-0.02	-0.06	0.03	-0.05	-0.00	0.19	0.14	0.05	0.09	0.00	-0.06	1.00	
18. Tot. num. unique teams sold	3.75	4.71	0.12	0.02	0.25	0.13	0.02	0.00	-0.01	0.05	-0.08	0.00	0.10	0.09	0.05	0.06	0.03	-0.07	0.83	1.00

Table 2: Purchase Model for Game-Based Fans
(standard errors in parentheses)

Variables	Model 1	Model 2	Model 3
Team Performance			
Team rank		-0.01 (0.01)	**-0.01 (0.01)**
Momentum		0.14 (0.42)	**0.01 (0.44)**
Lag momentum		-0.07 (0.40)	**-0.18 (0.43)**
Longrun		0.02 (0.13)	**-0.05 (0.14)**
Risk Reduction			
Resale activity			**0.01 (0.01)**
Portfolio depth			**-0.16* (0.07)**
Portfolio breadth			**0.38* (0.12)**
Beat rival			**0.48* (0.19)**
Expert pick			**2.25* (1.16)**
Quality win			**0.72* (0.38)**
Controls			
Price paid	-0.00* (0.00)	-0.00* (0.00)	**-0.00* (0.00)**
Day dummies	yes	yes	**yes**
Week dummies	yes	yes	**yes**
Model Fit			
Log Likelihood	-417.44	-416.43	**-400.50**
Chi-square (df)	144.05* (22)	146.05* (26)	**177.93* (32)**

*significant at 0.05 level or better

Table 3: Purchase Model for Team-Based Fans
(standard errors in parentheses)

Variables	Model 1	Model 2	Model 3
Team Performance			
Team rank		**-0.15* (0.04)**	-0.12* (0.05)
Momentum		**3.41 (3.02)**	4.00 (3.38)
Lag momentum		**-0.80 (3.11)**	-2.11 (3.48)
Longrun		**0.48 (1.09)**	0.31 (1.07)
Risk Reduction			
Resale activity			-0.11 (0.14)
Beat rival			0.09 (1.68)
Expert pick			-1.88 (2.40)
Quality win			3.15 (2.99)
Controls			
Price paid	0.00 (0.00)	**0.00 (0.00)**	0.00 (0.00)
Day dummies	yes	**yes**	yes
Week dummies	yes	**yes**	yes
Constant	-10.57* (1.51)	**-7.94* (1.77)**	-5.90* (1.87)
Model Fit			
Log Likelihood	-113.73	**-111.97**	-111.56
Chi-square (df)	40.51* (14)	**38.37* (18)**	22.27 (22)

*significant at 0.05 level or better

Table 4: Resale Model for Game-Based Fans
(robust standard errors in parentheses)

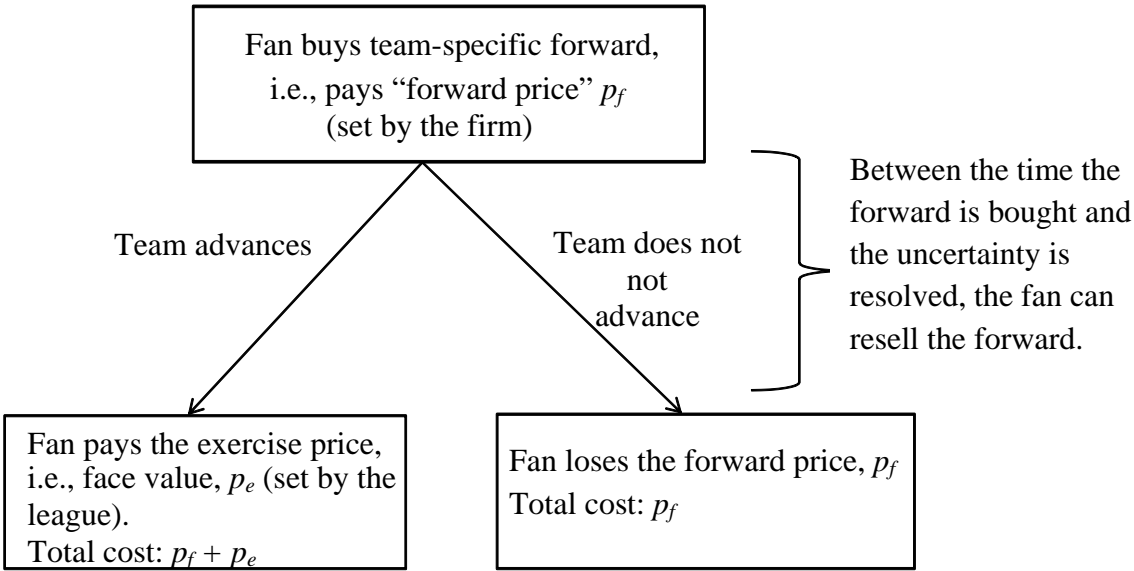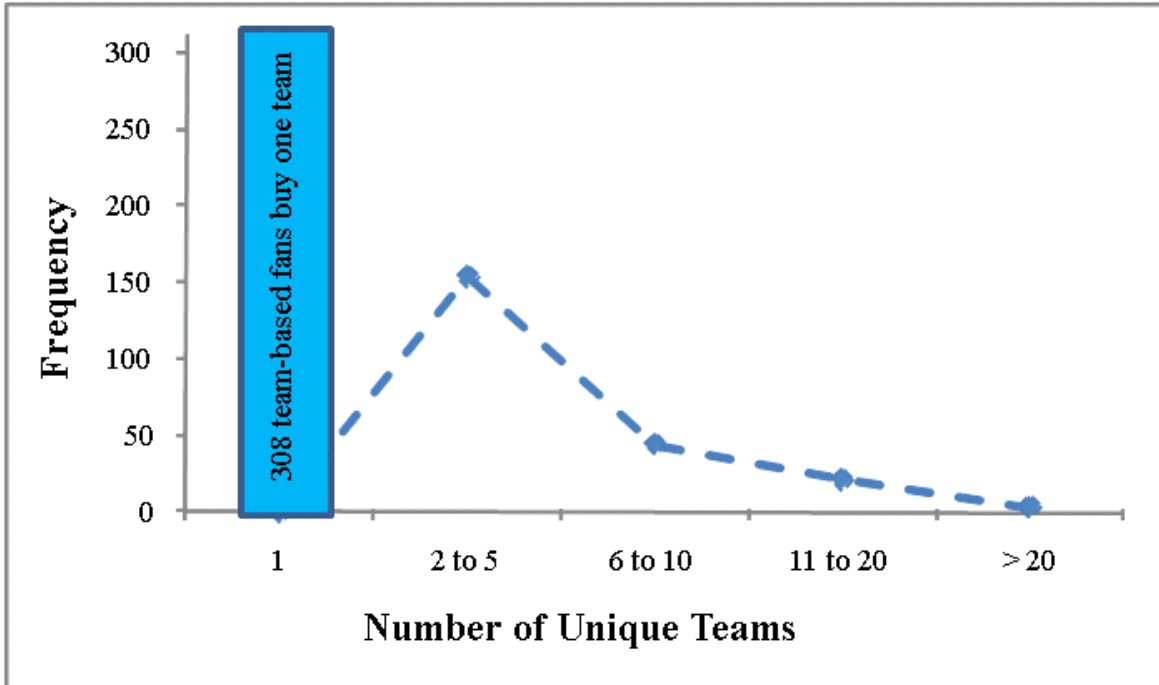| Variables	Model 1	Model 2	Model 3

<u>Team Performance</u>
  Team rank
  Momentum
  Lag momentum
		0.01 (0.02)
		-2.40* (0.62)
		-3.40* (0.65)
			0.01 (0.02)
			-2.53* (0.64)
			-3.58* (0.61)

<u>Risk Reduction</u>
  Portfolio depth
  Expert pick
			- 0.04 (0.05)
			-2.52* (1.23)

<u>Controls</u>
  Price paid
  Day dummies
  Week dummies
	0.01* (0.00)
	yes
	yes
		0.00* (0.00)
		yes
		yes
			0.00* (0.00)
			yes
			yes

Constant	-1.13* (0.28)	4.30* (1.18)	**4.77* (1.14)**

<u>Model Fit</u>
  Log pseudolikelihood
  Chi-square (df)
	-191.46
	76.71* (11)
		-158.82
		113.56* (14)
			-154.54
			114.58* (16)

*significant at 0.05 level or better

Table 5: Resale Model for Team-Based Fans
(robust standard errors in parentheses)

Variables	Model 1	Model 2	Model 3
Team Performance			
Team rank		-0.24 (0.13)	**-0.37* (0.11)**
Momentum		-3.93* (1.50)	**-4.43* (1.74)**
Lag momentum		-6.52* (2.22)	**-7.05* (1.66)**
Risk Reduction			
Expert pick			**-3.51* (1.51)**
Controls			
Price paid	0.02* (0.01)	0.04* (0.02)	**0.04* (0.01)**
Day dummies	yes	yes	**yes**
Week dummies	yes	yes	**yes**
Constant	-2.44* (0.94)	-1.94 (2.42)	**-1.62 (1.30)**
Model Fit			
Log pseudolikelihood	-21.49	-9.47	**-7.41**
Chi-square (df)	17.92* (6)	17.06* (9)	**22.05* (10)**

*significant at 0.05 level or better

Figure 1: Consumer Decision Sequence in a Sports Forward Market

Fan buys team-specific forward, i.e., pays "forward price" p_f (set by the firm)

Team advances

Team does not not advance

Between the time the forward is bought and the uncertainty is resolved, the fan can resell the forward.

Fan pays the exercise price, i.e., face value, p_e (set by the league).
Total cost: $p_f + p_e$

Fan loses the forward price, p_f
Total cost: p_f

Figure 2: Number of Unique Teams Bought By Fans

Figure 3: Possible Fan Decisions and Outcomes Before the Final Four is Determined