

The Price of Hate: Household Finance and Non-Pecuniary Preferences*

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Abstract

Airbnb hosts in college towns increase their listing prices more than hotels on home football games against rival teams. As a result of setting listing prices too high, rental income is approximately 30% lower. The overestimation of demand and the possibility of damage cannot explain the inverse relation between listing prices and rental incomes on games against rival teams. Instead, financial constraints are associated with hosts setting smaller listing price increases and earning higher rental incomes on rival games.

Keywords: Non-Pecuniary Preference, Household Finance, Sharing Economy

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I Introduction

The “sharing economy” allows households to monetize their assets. Whether its their house (Airbnb.com), car (GetAround.com) or spare cash (Prosper.com), participation in the sharing economy is increasing rapidly.¹ Our study involves Airbnb, one of the largest firms in the sharing economy with over 44 million current users in the United States and a valuation exceeding \$30 billion. Airbnb, which provides a marketplace for rental accommodation, enables households to monetize the real estate assets that comprises more than 70% of their portfolio.² Case, Quigley, and Shiller (2013) highlight real estate’s importance to household finance (Keys, Pope, and Pope (2016)) by documenting that real estate prices impact consumption more than stock prices.³

However, success in the sharing economy and Airbnb in particular requires households to make an important financial decision: how to set listing prices? One might think households set listing prices on Airbnb to maximize rental income. After all, households list their property on Airbnb for precisely the purpose of generating rental income. Nevertheless, there is ample evidence that households exhibit peculiar preferences (e.g., Hirshleifer (2001), Campbell (2006)).

Airbnb listing prices in college towns on home football games provide an ideal laboratory to study the impact of non-pecuniary preferences on household financial decisions for several reasons. First, college football rivalries evoke strong emotions that result in a mutual disdain between rival fans. Cikara, Botvinick, Fiske (2011) find that “us versus them” behavior spreads beyond competitors to fans. Therefore, a non-pecuniary preference against rival fans

¹According to a 2015 Consumer Intelligence Series report by Pricewaterhouse Coopers, the international sharing economy is on track to reach \$335 billion by 2025.

<https://www.pwc.com/us/en/industry/entertainment-media/publications/consumer-intelligence-series/assets/pwc-cis-sharing-economy.pdf>

²Nearly six times the amount allocated to financial assets such as stocks, bonds, and mutual funds according to the Federal Reserve’s 2016 Survey of Consumer Finances.

³Barron, Kung, Proserpio (2018), Horn and Merante (2017), Sheppard and Udell (2018) find that Airbnb usage exerts upward pressure on housing prices, with financial intermediaries such as Loftium financing home purchases in exchange for a portion of the subsequent Airbnb rental income.

may be embedded into Airbnb listing prices. Second, governance mechanisms and regulatory oversight constrain hotels from incorporating non-pecuniary preferences into hotel prices. Therefore, we can compare the price-setting behavior of households on Airbnb to benchmark hotel prices that reflect demand. Third, we can observe the same household’s listing price and rental income on home games against rival teams and non-rival teams. Therefore, our empirical design enables us to hold the household fixed and vary their non-pecuniary preference toward the visiting team.

Our data consist of 1,320 “entire units” on Airbnb in 26 college towns encompassing 236 games during the 2014 and 2015 football seasons. Entire units resemble hotel rooms, and provide self-contained accommodation that physically separates hosts and guests. Thus, rental transactions for entire units typically do not involve any interaction or reciprocity between hosts and guests. Furthermore, over 60% of the total rental income earned by Airbnb hosts during the football season occurs on six home-game weekends (Friday and Saturday nights). We create a rival indicator variable that equals one on home games against a “rival” visiting team. Appendix A summarizes the college football rivalries in our study.⁴ This list of rivals is obtained from the sports media (e.g., ESPN and Sports Illustrated) and include well-known examples such as Florida-Florida State, Notre Dame-USC, Ohio State-Michigan, and Alabama-LSU.

After controlling for unit-level heterogeneity and demand using hotel prices, we find that Airbnb hosts set higher listing prices on games against rival teams.⁵ Nearly two thirds of units have higher listing prices on games against rivals, with an average increase of 22%. As listing prices reflect demand, we find a positive unconditional relation between listing prices and rental incomes for individual units. More important, we find that the interaction between unit-level listing prices and the rival indicator variable exerts a negative impact on

⁴Our list of rivals parallels the within-conference rivals obtained from Sports Illustrated in Quintanar, Deck, Reyes, and Sarangi (2015). However, their list excludes independent teams such as Notre Dame that are not members of any conference.

⁵Unit fixed effects account for variation in the quality and average listing price of individual units.

rental incomes. Consequently, the high listing prices set by households on games against rivals reduce rental income. This inverse relation between listing price increases and rental incomes on games against rivals is confirmed by robustness tests that orthogonalize listing price increases to game and team characteristics that proxy for demand.

As an illustration, Florida State had home games in Tallahassee against Notre Dame and the University of Florida during the 2014 college football season. For the home game against the fifth ranked team, Notre Dame, Airbnb units in Tallahassee were listed for an average listing price of \$201. Each unit was booked for this game, resulting in an average rental income of \$201. However, five weeks later, on the home game against the unranked but rival University of Florida team, the average listing price in Tallahassee was increased to \$267 but an average rental income of only \$67 materialized.⁶ Across the full sample, for every dollar in rental income earned by Airbnb hosts on games against highly ranked non-rival teams, only \$0.71 is earned on games against rivals. For comparison, hotels obtain \$0.96 in revenue on games against rivals relative to their revenue on games against highly ranked non-rival teams.

Figure 1 illustrates the listing price differences for Airbnb units relative to hotel room prices on games against rivals. This figure also illustrates that hotel prices increase more than Airbnb listing prices on homecoming, which corresponds to a large influx of home team fans (Alumni). Therefore, Airbnb hosts do not systematically increase their listing prices more than hotel prices on home games. Instead, Airbnb hosts target rival fans with high listing prices.⁷

A further analysis reveals that the financial constraints of hosts influence listing prices and consequently rental incomes. We divide the zip codes within each college town into areas where residents are financially unconstrained and financially constrained. Higher list-

⁶Individual Airbnb hosts can experience a larger loss than the average loss on rival games since each unit's occupancy is binary and zero rental income is the consequence of setting too high a listing price.

⁷Although hosts without a booking may be more likely to attend a home game, this higher likelihood cannot explain the inverse relation between listing prices and rental incomes that is unique to rival games.

ing prices on games against rivals are concentrated among financially unconstrained hosts. Indeed, financially unconstrained hosts and financially constrained hosts earn similar rental incomes; averaging \$189 and \$187 per night, respectively, on games against highly ranked non-rival visiting teams. However, on games against rivals, the average rental income of financially unconstrained hosts declines by over 20% to \$149, while the average for financially constrained hosts is nearly unchanged at \$183. This evidence indicates that financial constraints reduce the impact of non-pecuniary preferences on household financial decisions. Intuitively, animosity toward rival affiliations is a luxury that financially constrained hosts cannot afford to incorporate into their listing prices.

In contrast to entire units, shared units on Airbnb have common facilities (bathroom, kitchen, etc) and are suitable for visiting fans of the home team such as Alumni. Thus, self-selection in the real estate market (Longhofer and Peters (2005)) enables Airbnb hosts to infer whether prospective guests are fans of the rival team or home team based on their choice of an entire unit or shared unit, respectively. We find that hosts of shared units do not increase their listing prices on games against rivals. This finding is consistent with rival visiting fans avoiding shared units in favor of entire units to avoid interacting with the local population.

We find no evidence that higher listing prices on games against rivals is compensation for higher expected property damage. The influence of financial constraints on listing prices is difficult to reconcile with hosts expecting greater damage on games against rivals. While financial constraints can reduce the impact of non-pecuniary preferences on listing prices, financial constraints are unlikely to influence host expectations regarding damage. Airbnb hosts are not more likely to block their unit from being rented on games against rivals compared to other home games. Furthermore, the probability that units booked on games against rivals subsequently become unavailable for rent is not higher compared to units booked on games against non-rivals. This result suggests that providing accommodation to rival fans is not associated a higher likelihood of damage that prevents the unit from being

rented. Airbnb also insures hosts for a million dollars in property damage.⁸

Our study documents the considerable influence that non-pecuniary preferences exert on household financial decisions. While non-pecuniary preferences have been found to affect the returns to wine, art, stamps, and socially responsible investments (Dimson, Rousseau, Spaenjers (2015), Dimson and Spaenjers (2011), Hong and Kacperczyk (2015), and Mandel (2009)), the advantage of studying real estate is this asset’s importance to household finance and the sharing economy. Although preferences such as risk aversion explain deviations between utility maximization and wealth maximization, our results highlight the extent to which households compromise wealth due to *trivial* non-pecuniary preferences. Furthermore, our results suggest that financial constraints weaken the influence of non-pecuniary preferences on household financial decisions. Our results also identify a geographic component to non-pecuniary preferences since rival college affiliations arise from personal experience in a college town. Thus, our findings are consistent with those in Kaustia and Knupfer (2008) and Choi, Laibson, Madrian, and Metrick (2009) that find households overweight personal experience when making financial decisions.

In terms of economic significance, the inability to obtain a booking on Saturday night due to increased listing prices on home games against rivals creates an average rental loss of \$325.06 or 33.9% of the unit’s monthly mortgage payment. Similarly, the failure to obtain a booking for both Friday and Saturday night results in a \$662.37 loss, or 68.8% of the unit’s monthly mortgage payment. The magnitude of this dollar-denominated loss parallels Agarwal, Ben-David, and Yao (2017)’s finding that poor mortgage decisions cost households an average of \$700 per refinancing. However, in our setting, the failure to obtain a booking on home games against rivals represents a *recurring* loss.

More broadly, our study contributes to both the household finance literature and the growing literature on the sharing economy that includes the studies of peer-to-peer online

⁸The website www.airbnb.com/guarantee provides details of the insurance provided by Airbnb to its hosts.

lending markets by Duarte, Siegel, and Young (2012) and Iyer, Khwaja, Luttmer, and Shue (2015). Compared to lenders setting interest rates, Airbnb hosts have more discretion when setting listing prices due to the uniqueness of their rental unit. Our results indicate that household financial decisions manifest taste-based price discrimination against specific affiliations that is more subtle than discrimination against a specific race or gender (Ge, Knittel, MacKenzie, and Zoepf (2016), Bertrand and Mullainathan (2004), King and Mieszkowski (1973)). Consequently, taste-based price discrimination may be more difficult to identify and eradicate in the sharing economy. Moreover, the importance of non-pecuniary preferences to household financial decisions is unlikely to be limited to college affiliations. Instead, our results motivate further research on the economic implications of non-pecuniary preferences involving political affiliations.

The remainder of the paper begins with a description of our data in Section II. Section III then provides our main empirical results, while Section IV offers results conditional on financial constraints. Robustness tests are reported in Section V, with our conclusion in Section VI.

II Data

Our analysis uses Airbnb information obtained from AIRDNA (www.airdna.co), which specializes in collecting and processing Airbnb data. Using the Airbnb platform, a guest can book accommodation at the listing prices specified by the host on specific dates. Our sample of Airbnb units are located in college towns during the 2014 and 2015 college football seasons. In this sample, Airbnb bookings are concentrated on home football games and typically involve two nights of accommodation. The start of the sample period ensures an adequate supply of Airbnb units in each college town, while the end of the sample period predates listing price recommendations on Airbnb. Thus, our results are not influenced by pricing algorithms that subsequently became available to hosts.

Variation in listing prices during the football season is dramatic for Airbnb units located in college towns since home games represent large anticipated demand increases for accommodations. We examine units whose listing price changes at least once during the football season to ensure the Airbnb hosts in our sample are active. Requiring at least one price change during the football season removes inactive hosts whose listing prices fail to account for the difference between home games versus away games. As inactive hosts set high listing prices that result in a low occupancy rate, their removal ensures our later results regarding an inverse unit-level relation between listing prices and rental incomes is not driven by inactive hosts. Initially, we focus on entire units that resemble large hotel rooms with self-contained facilities. Entire units are appropriate for visitors who prefer being physically separate from fans of the home team. A later empirical test examines shared units on Airbnb.

We examine the top 30 ranked college football programs for the 2014 and 2015 football seasons. In alphabetical order, these teams include: Arizona State University, University of Alabama, University of Arkansas, Auburn University, University of California-Los Angeles, Clemson University, University of Florida, Florida State University, University of Georgia, University of Iowa, University of Kentucky, Louisiana State University, University of Michigan, Michigan State University, Mississippi State University, University of Nebraska, University of Notre Dame, Ohio State University, University of Oklahoma, University of Oregon, Oregon State University, Stanford University, University of Southern California, University of South Carolina, Texas Christian University, University of Tennessee, University of Texas, Texas Tech University, University of Utah, and University of Wisconsin.

To further identify pairs of rivals, we require at least 50 prior games between the two teams. If a team does not have at least one home game against a rival, the team's entire season is eliminated from the sample. Our final sample consists for 236 unique home games, of which 42 games are against a rival. Appendix A contains a complete list of rivals. We identify two determinants of a college football rivalry: rival teams have played each other for many years and have a won-loss record near parity. As the first game between rivals often occurred

before long-distance travel was made convenient by interstate highways and aviation, rivals are often located in the same state or contiguous states. However, our empirical results are robust to controlling for the distance between college football stadiums.⁹ This robustness is consistent with many visiting fans not residing in the opposing team’s college town after graduation.

We limit our main analysis to college towns with fewer than 1,000 entire unit listings on Airbnb per football season to exclude home games in urban areas such as Los Angeles (teams excluded: USC, UCLA, Stanford, and Texas). We also restrict our sample of Airbnb listings to units located within 15 miles from the stadium.

A unit-level Airbnb Listing Premium is calculated as the listing price on a specific game minus the unit’s average listing price across all home games. Our results are similar using the average listing price for games against non-rival visiting teams or if the Airbnb Listing Premium is computed as a percentage deviation rather than a dollar-denominated deviation. For example, robustness tests exclude specific games (homecoming for example) from the average listing price. These exclusions offer greater flexibility than controlling for each unit’s average listing price with unit fixed effects. Our study also utilizes average hotel prices, occupancy rates, and income from STR, formerly known as Smith Travel Research, within a 15 mile radius of each college football stadium. A college town-level Hotel Premium is then computed as the average hotel price on a specific game minus the average hotel price across all home games.

III Empirical Results

Motivated by the illustrative model in Appendix B, our empirical tests examine unit-level listing prices, occupancy rates, and rental incomes. Table 1 reports the average number of

⁹To clarify, there is little variation in stadium attendance across home games, although the composition of home team versus visiting team fans may vary if, for example, lower ranked visiting teams have fewer fans in attendance.

units listed, listing price, rental income, listing premium, and occupancy rate on different home games for entire units listed on Airbnb. For comparison, the average price, revenue, hotel premium, and occupancy rate of hotels are also reported. The average Airbnb listing price of \$277.06 is highest on games against rival visiting teams, which corresponds to the highest Airbnb listing premium of \$28.77 but the lowest occupancy rate of 65.03%. On rival games, unreported results indicate that 63% of Airbnb hosts increase their listing price by an average of 22%. As a consequence, games against rivals fail to generate the highest average rental income due to the lower occupancy rate.

In contrast to Airbnb units, hotel prices are not the highest on games against rivals. Instead, hotel price increases are largest for games against top-ranked visiting teams (both incoming rankings and pre-season rankings), whereas Airbnb hosts only marginally increase their listing price for games against top-ranked visiting teams. The occupancy rate of Airbnb units and hotels are both highest for games against top-ranked visiting teams, suggesting that these games are associated with the highest demand for accommodation.

Table 1 also indicates that the supply of entire units listed on Airbnb is stable across different home games. Consequently, lower rental income on games against rivals cannot be attributed to an increased supply of Airbnb units. Moreover, the occupancy rate of hotel rooms is consistently below 100%, especially on games against rivals. Therefore, Airbnb listing prices are not set in an environment where hotel rooms are scarce or unavailable. Instead, hotel room and Airbnb units are substitutes.¹⁰

A. Listing Prices

While ex-post sporting outcomes (Edmans, Garcia, and Norli (2007)) and weather (Hirshleifer and Shumway (2003)) can affect the sentiment and mood of market participants,

¹⁰Unreported results examine a subset of Airbnb units that accommodate between one and four adults, which is comparable to a standard hotel room. As few Airbnb units accommodate more than four adults, our results are similar for this “matched” subset.

respectively, the ex-ante listing prices set by hosts before the game capture non-pecuniary preferences. Specifically, the high average listing premium on games against rivals in Table 1 motivates an analysis of listing premiums using the following panel regression

$$\text{Airbnb Listing Premium}_{i,t} = \beta_1 \text{Rival}_{i,t} + \gamma X_t + \epsilon_{i,t}, \quad (1)$$

with unit fixed effects that control for the each unit’s quality, including its location (distance to the stadium). The control variables that define X are proxies for demand. These proxies include an indicator variable for games during prime time, which equals one if the game occurs after 5pm local time, and an indicator variable for homecoming games. Games during prime time and homecoming games are both associated with higher than average demand. The rank of the home team and the visiting team before the game are also included, along with an indicator variable for whether the opponent was highly ranked before the football season. Games involving higher ranked teams are also associated with higher than average demand. Most important, Hotel Premium proxies for demand on each home game, while the number of entire units listed on Airbnb accounts for the supply of Airbnb accommodation. A full list of variable definitions is contained in Appendix C. Standard errors in equation (1) are clustered at the team level.

To clarify, a unit’s Airbnb Listing Premium varies across different home games. While the inclusion of unit fixed effects also converts listing prices into a similar premium, a later empirical analysis has rental income as the dependent variable. This specification requires us to condition on the Airbnb Listing Premium in order to examine the unit-level relation between rental incomes and listing price increases on different home games. Therefore, we examine the Airbnb Listing Premium in equation (1) instead of listing prices.

The β_1 coefficient for Rival in equation (1) determines whether games against rivals are associated with a larger listing premium after controlling for a multitude of demand proxies. The positive β_1 coefficients in Panel A of Table 2 indicate that Airbnb hosts significantly

increase their listing prices on games against rivals. For example, the 24.756 coefficient (t -statistic of 5.982) in the last specification indicates that listing prices are nearly \$25 higher on games against rivals compared to the average home game.

The results in Panel A indicate that Airbnb listing prices co-move with hotel prices. This finding is consistent with hotel rooms and entire units on Airbnb being substitutes. The negative coefficients for the Prime Time Game indicator variable are at odds with the positive coefficients in Panel B for hotels. Intuitively, prime time games are important, although the interpretation of this indicator function's coefficient is complicated by its correlation with team rankings and the Hotel Premium. Indeed, the Hotel Premium is higher on prime time games according to our next analysis.

Hotel prices are unlikely to be influenced by non-pecuniary preferences regarding team affiliations due to governance mechanisms that ensure their pricing maximizes income. Therefore, with hotel prices providing a proxy for demand, we repeat the estimation of equation (1) using Hotel Premium as the dependent variable. To clarify, hotel prices refer to transaction prices. An alternative demand benchmark based on hotel listing prices from Orbitz was also used to construct the Hotel Premium and produced identical findings. Therefore, hotel listing prices and hotel transaction prices provide similar proxies for demand.

Panel B of Table 2 reports that hotel prices are consistently higher on homecoming games but not on games against rivals since the coefficient for the Rival indicator variable is usually only marginally significant. Thus, games against rivals are not necessarily associated with a greater demand for accommodations. In contrast to games against rivals, homecoming is clearly stated on every college football schedule for hotels to condition on when setting prices.

A positive coefficient for the Prime Time Game indicator variable signifies that hotels increase prices on important home games. As the rank variable is larger for lower quality teams, a negative coefficient for Opponent's Rank signifies smaller price increases on games against lower quality opponents. Conversely, a positive coefficient for the Pre-Season Top 25

Opponent indicator variable signifies that highly-ranked opposing teams increase prices. This increase can be attributed to the greater willingness of fans to travel with a highly-ranked team, which increases the demand for accommodations.

B. Occupancy Rates

Our next specification has an indicator variable that equals one if a unit is booked and zero otherwise as the dependent variable

$$\begin{aligned} \text{Booking}_{i,t} = & \beta_1 \text{Airbnb Listing Premium}_{i,t} + \beta_2 \text{Rival}_{i,t} \\ & + \beta_3 \text{Airbnb Listing Premium}_{i,t} \times \text{Rival}_{i,t} + \gamma X_t + \epsilon_{i,t}. \end{aligned} \quad (2)$$

This specification supplements equation (1) with an additional independent variable defined as the interaction between the Airbnb Listing Premium and the Rival indicator variable. While a positive β_1 coefficient is consistent with higher listing prices reflecting greater demand for accommodations, a negative β_3 coefficient signifies that a high listing premium on games against a rival team lowers the likelihood a unit is booked. Consistent with the illustrative model in Appendix B, Table 3 reports negative β_3 coefficients that indicate listing price increases on games against rivals reduce the likelihood of a booking.

A negative β_2 coefficient for the Rival indicator variable would indicate that hosts discriminate against rival fans by rejecting their attempted booking. However, the non-negative β_2 coefficients are inconsistent with this form of discrimination. Indeed, as 95.5% of hosts activate Airbnb’s Instant Book feature, guests can obtain immediate confirmation of their booking without host intervention. Furthermore, guests are not required to state any college or team affiliation on their Airbnb profile.¹¹

¹¹Edelman, Luca, and Svirsky (2017) create fake guest Airbnb accounts and find that hosts are more likely to reject prospective guests who are minorities. However, their empirical design does not examine the price mechanism that is the basis of our study.

With regards to the control variables, the positive coefficients for Hotel Premium and Hotel Occupancy indicate that the occupancy of Airbnb hosts increases with the demand for hotel accommodations. Thus, Airbnb units and hotel rooms have a common response to increases in demand. In unreported results, hotel occupancy rates do not produce a negative β_2 coefficient nor a negative β_3 coefficient.

Equation (2) conditions on the rival indicator function and the Airbnb Listing Premium that also conditions on the rival indicator function according to equation (1). To address this nested dependency, we orthogonalize the Airbnb Listing Premium with respect to the demand proxies in X to create an Orthogonal Airbnb Listing Premium variable that captures listing price fluctuations unrelated to demand.¹² Consistent with Figure 1, the average Orthogonal Airbnb Listing Premium is positive on home games against rivals and negative on home games against non-rival visiting teams. We then modify equation (2) by estimating the following panel regression

$$\text{Booking}_{i,t} = \beta_1 \text{Orthogonal Airbnb Listing Premium}_{i,t} + \epsilon_{i,t}. \quad (3)$$

with unit fixed effects separately for home games against rival visiting teams and non-rival visiting teams. Unreported results confirm that the β_1 coefficient is negative (positive) on home games against rival (non-rival) teams. Specifically, these coefficients are -0.049 (t -statistic of -2.70) and 0.033 (t -statistic of 4.40), respectively. Therefore, consistent with hosts having a non-pecuniary preference against fans of a rival team, listing price increases unrelated to demand are associated with a lower occupancy on home games against rival visiting teams but a higher occupancy on home games against non-rival visiting teams.

The next analysis of rental income provides additional evidence that the listing prices set by households are confounded by non-pecuniary preferences regarding team affiliations.

¹²The Orthogonal Airbnb Listing Premium variable is created using the *ORTHOG* command in STATA.

C. Rental Incomes

Conditional on a unit being booked on a specific date, the unit’s rental income equals its respective listing price on the date. Without obtaining a booking, the unit’s rental income equals zero. Our next analysis examines the impact of unit-level listing premiums on rental incomes using the following panel regression

$$\begin{aligned} \text{Rental Income}_{i,t} = & \beta_1 \text{Airbnb Listing Premium}_{i,t} + \beta_2 \text{Rival}_{i,t} \\ & + \beta_3 \text{Airbnb Listing Premium}_{i,t} \times \text{Rival}_{i,t} + \gamma X_t + \epsilon_{i,t}, \end{aligned} \quad (4)$$

with unit fixed effects. A negative β_3 coefficient for the interaction variable (Airbnb Listing Premium \times Rival) signifies that listing price increases on games against rivals are inversely related to rental income. Appendix B illustrates a rental income reduction due to a non-pecuniary preference being embedded into a unit’s listing price.¹³

The positive β_1 coefficients in Table 4 are consistent with hosts earning higher rental incomes by setting higher listing prices. This finding captures the relation between higher listing prices and greater demand. According to Table 4, the β_1 coefficient equals 0.752 (t -statistic of 14.342) in the specification with all control variables. However, the insignificant β_2 coefficients and negative β_3 coefficients in Table 4 indicate that hosts increase listing prices on games against rivals to levels that lower their respective rental incomes. In the specification with all control variables, the β_3 coefficient equals -0.284 (t -statistic of -2.248). This reduction in rental income indicates that preferences regarding team affiliations confound the listing prices set by households, and consequently reduces household income. The inverse relation between listing prices and rental incomes captured by the β_3 coefficient is unlikely to be explained by inexperience or a lack of information regarding demand on rival games. Indeed,

¹³According to the illustrative model in Appendix B, a host’s rental income is a quadratic function of their unit’s listing price. Unreported results confirm that our empirical results are robust to the inclusion of both squared and cubed listing premiums that capture non-linearities in rental income.

Airbnb hosts have months to lower their listing price and have access to both the availability as well as the listing price of other Airbnb units.

The economic significance of our results are comparable to those of Agarwal, Ben-David, and Yao (2017). These authors find that poor mortgage decisions cost households approximately \$700 per financing. Failure to secure a guest booking on a game against a rival due to a high listing price translates into a similar dollar-denominated loss (over three nights). However, this recurring loss would typically occur each year, while a mortgage refinancing is less frequent. Furthermore, our results may underestimate the economic importance of college football rivalries in the total population since “superfans” are unlikely to rent their units on home games.¹⁴

Airbnb’s blocking feature essentially sets an infinite listing price in Appendix B. Although setting a high listing price on games against rivals parallels blocking, setting a high listing price offers the low probability of obtaining the satisfaction from price-gouging a rival fan in the event of a booking. This satisfaction cannot be obtained if the host simply blocks their unit on games against rivals to prevent it from being booked. In unreported results, blocking is infrequent and is not more prevalent on games against rivals.

The positive coefficients for the Homecoming and Pre-Season Top 25 Opponent indicator variables are consistent with greater demand for accommodations on these games, hence higher rental income. In unreported results, we replace the Rival indicator variable in the interaction term with the Opponent’s Rank (before the game), Pre-Season Top 25 Opponent indicator variable, and Prime Time Game indicator variable. The coefficients for these alternative interaction terms are insignificant, suggesting that the response of Airbnb hosts to rivals is unique.

Recall that the Orthogonal Airbnb Listing Premium in equation (3) captures listing price

¹⁴Across all Airbnb hosts with entire units, unreported results indicate that 11.75% block their unit from being rented on every home game. These “superfans” may attend each home game, although their units do not have listing prices on home games to analyze.

increases on games against rivals that are unrelated to demand. As a robustness test, we use the Orthogonal Airbnb Listing Premium variable in the following panel regression

$$\begin{aligned} \text{Rental Income}_{i,t} = & \beta_1 \text{Orthogonal Airbnb Listing Premium}_{i,t} + \beta_2 \text{Rival}_{i,t} \\ & + \beta_3 \text{Orthogonal Airbnb Listing Premium}_{i,t} \times \text{Rival}_{i,t} + \epsilon_{i,t}, \quad (5) \end{aligned}$$

with unit fixed effects. Unreported results from equation (5) parallel those reported in Table 4 as the above estimation yields a positive β_1 coefficient, insignificant β_2 coefficient, and a negative β_3 coefficient. In particular, the β_3 coefficient for the interaction term is -19.297 (t -statistics of -2.82). Consistent with hosts having a non-pecuniary preference against rival fans, the negative β_3 coefficient in equation (5) indicates that listing price increases on games against rival visiting teams lower rental incomes.

IV Financial Constraints

Financial constraints can explain heterogeneity across the financial decisions of households (Campbell, 2006). To examine the impact of financial constraints, we collect the average credit utilization score of individual zip codes from Experian. The credit utilization score divides outstanding credit card debt by the total available credit, with the availability of credit reflecting household income. Zip codes where the average credit utilization score is above a college town’s median credit utilization score are classified as having financially constrained hosts, while zip codes where the average credit utilization score is below this median are classified as having financially unconstrained hosts.¹⁵

A household’s credit utilization score is determined by its credit card debt, not mortgage debt. Thus, financial constraints are not necessarily higher for households who utilize the tax

¹⁵Results are similar if the median credit utilization score across all zip codes is used to distinguish financially constrained hosts from financially unconstrained hosts.

deductibility of mortgage interest. Indeed, the average credit utilization score in a zip code is independent of the average mortgage payment. Zip-code level credit utilization scores range from 15 to 37 percent, with right skewness indicating that residents in several zip codes have significantly less available credit.

Equation (1) and equation (4) are re-estimated separately for financially constrained and financially unconstrained hosts. According to Panel A and Panel B of Table 5, financially unconstrained hosts have larger listing premiums on games against rivals than financially constrained hosts. In particular, according to equation (1), the β_1 coefficient for financially unconstrained hosts is 31.992 (t -statistic of 4.000) compared to 20.087 (t -statistic of 4.180) for financially constrained hosts. This difference is significant at the 5% level. Thus, financially unconstrained hosts set listing price that are 60% larger than financially constrained hosts on games against rivals.

In terms of rental income, Panel C of Table 5 indicates that among financially unconstrained hosts, the β_3 coefficient in equation (4) for the interaction between the Airbnb Listing Premium and the Rival indicator variable equals -0.502 (t -statistic of -3.256). This coefficient is significantly more negative than its counterpart in Table 4 for the entire sample. In contrast, according to Panel D of Table 5, the β_3 coefficient is insignificant among financially constrained hosts. Thus, the listing prices of financially constrained households do not appear to be affected by non-pecuniary preferences against rival fans.

The following in-sample averages summarize the economic implications of financial constraints. The average rental income of financially unconstrained hosts is similar to financially constrained hosts on games against highly ranked non-rival teams; \$189.42 compared to \$187.23, respectively. Thus, financial constraints do not affect the average rental income of Airbnb hosts on games against non-rival teams. However, on games against rival teams, the average rental income of financially unconstrained hosts declines by over 20% to \$149.24, while the average rental income of financially constrained hosts is almost unchanged at \$182.56.

Although the exact location of Airbnb hosts is unknown, our analysis assumes that hosts have a credit utilization score that parallels the average score near their Airbnb listing. In support of this assumption, we define professional hosts as those with more than one property listed on Airbnb. Of the 155 professional hosts in our sample, 133 have Airbnb listings in areas with the same financial constraint classification. Furthermore, professional hosts typically manage properties in the same zip code since these hosts have an average of 2.85 units in 1.34 zip codes. This geographic concentration is consistent with the need for hosts to actively manage their short-term rentals. In unreported results, the inverse relation between listing prices and rental incomes strengthens after removing 317 observations where the financial constraints of professional hosts are ambiguous since the misidentification of financial constraints weakens their relation with listing prices and rental incomes.

Overall, financial constraints appear to reduce the impact of non-pecuniary preferences on household financial decisions. This evidence is difficult to reconcile with the over-estimation of demand since this alternative explanation requires financially unconstrained hosts, whose low credit card balances are presumably a signal of financial sophistication, to be less sophisticated at setting listing prices.

In unreported results, constrained hosts have a higher average occupancy rate, which is consistent with financially constrained hosts having a greater need for rental income. However, the average rating assigned by guests to constrained hosts is not significantly different from the average rating assigned to unconstrained hosts. As the majority of guest ratings are favorable, accommodating rival fans once or twice a year is unlikely to significantly lower a host's average rating.¹⁶ Consequently, the high listing premium on games against rivals is not compensation for the risk of receiving a poor review. Moreover, if rival fans did systematically assign lower ratings to their host, this risk would apply to all hosts in the college town. Therefore, the risk of being assigned a low rating by rival fans cannot explain

¹⁶Constrained hosts have marginally more guest reviews than unconstrained hosts, which is consistent with constrained hosts having a higher occupancy rate.

variation in the listing premium across unconstrained hosts and constrained hosts.

As a robustness test, we confirm that higher income zip codes have less financially constrained residents on average.¹⁷ Moreover, after estimating equation (4) separately for high income and low income hosts within each college town, this unreported robustness test finds a negative β_3 coefficient for high income hosts and an insignificant β_3 coefficient for low income hosts. Therefore, the inverse relation between listing prices and rental incomes that identifies a non-pecuniary preference against rival fans is limited to high income hosts. Intuitively, in support of the results in Table 5 that condition on financial constraints, animosity toward rival affiliations is a luxury that low income hosts cannot afford to incorporate into their listing prices.

V Robustness Tests

Several robustness tests provided additional support for our conclusion that the lower rental incomes of Airbnb hosts on games against rivals is due to non-pecuniary preferences regarding college football team affiliations that are manifested in listing prices.

A. Residual Listing Premium

To ensure our results are not driven by demand, we construct a unit-level Residual Listing premium by regressing the original Airbnb Listing Premium on the Hotel Premium of each college town. This Residual Listing Premium is defined by the residual from this regression and captures listing price increases on games against rivals that are due to non-pecuniary host preferences. Equation (1) and equation (4) are then re-estimated using the Residual Listing Premium.

¹⁷In contrast to income and credit utilization, mortgage payments exhibit less variability across the zip codes in a college town.

The results in Table 6 parallel our earlier results as the β_3 coefficient for the interaction between the Airbnb Listing Premium and the Rival indicator variable is negative for financially unconstrained hosts and insignificant for financially constrained hosts. Therefore, after controlling for demand using hotel prices, the results in Table 6 confirm that financial constraints reduce the impact of non-pecuniary preferences.

B. Homecoming

While our analysis focuses on a non-pecuniary preference against rival fans, homecoming coincides with an influx of home team fans. Typically, homecoming games are associated with a friendly atmosphere and an expected victory for the home team. Although homecoming games are associated with higher hotel prices in Panel B of Table 2, listing prices on Airbnb are not higher on homecoming games after controlling for hotel prices (Hotel Premium) in Panel A of Table 2. This evidence suggests that Airbnb hosts do not exhibit a non-pecuniary preference against visitors on homecoming games.

We test for an inverse unit-level relation between listing prices and rental incomes on homecoming games by re-estimating equation (4) after replacing the Rival indicator variable with the indicator variable for Homecoming. Table 7 reports insignificant β_3 coefficients for the interaction variable defined as Airbnb Listing Premium \times Homecoming. Therefore, we find no evidence that Airbnb hosts set listing prices on homecoming that are too high, which suggests that Airbnb hosts do not systematically overestimate demand.

C. Shared Units

Taste-based discrimination (Becker, 1957) can explain why Airbnb hosts accept lower rental incomes on games against rivals. Longhofer and Peters (2005) connect taste-based discrimination with self-selection in the real estate market. Motivated by this self-selection, we extend our study to examine shared units on Airbnb.

The physical separation from the local population offered by entire units is important for visiting fans of the rival team but not for visiting fans of the home team such as Alumni. Thus, while visiting fans of the rival team are expected to avoid shared units in favor of entire units, shared units are suitable for visiting fans of the home team. Consequently, although hosts cannot discriminate against guests by denying their bookings due to the Instant Book feature, the affiliation of guests can be inferred through their choice of either entire units or shared units. Thus, the Airbnb Listing Premium can differ between the two types of accommodation on rival games since listing prices for shared units are unlikely to manifest non-pecuniary preferences against rival affiliations.

To examine the difference between entire units and shared units on Airbnb, we re-estimate equation (1) for the subset of shared units. Table 8 reports that rival games are not associated with higher listing prices for shared units, which is consistent with shared units appealing to fans of the home team rather than fans of the rival team. In unreported results, shared units are as likely to have a financially constrained host as a financially unconstrained host. Thus, the results in Table 8 are not driven by the financial constraints of hosts.

D. Professional Hosts

Every host on Airbnb is assigned a unique host identification number that is linked with each of their property listings. We classify an Airbnb host as a professional if they have multiple properties listed on Airbnb. Professionals comprise 13.7% of the hosts and manage 25.5% of the listings in our sample. Intuitively, professional hosts may have stronger incentives to maximize their rental income if they have forgone labor income or acquired debt to become professional hosts.

In unreported results, professional hosts are as likely to be financially constrained as financially unconstrained, and 94.2% adopt the Instant Book feature. We divide our sample of entire Airbnb units into four categories according to the following host characteristics; finan-

cially unconstrained non-professional hosts, financially constrained non-professional hosts, financially unconstrained professional hosts, and financially constrained professional hosts before re-estimating equation (4) within each subset.

According to Table 9, the inverse relation between unit-level listing premiums and rental incomes is limited to non-professional financially unconstrained hosts. Specifically, the β_3 coefficient for the Airbnb Listing Premium \times Rival interaction is negative for this subset of hosts that manage 40% of the entire Airbnb units in our sample. This result is consistent with professional hosts excluding their non-pecuniary preferences from their financial decisions.

E. Stadium Incidents

To ensure our classification of rival teams captures the mutual disdain between rival fans, we compile data on disorderly conduct violations and ejections (incidents) occurring at the stadium.¹⁸ Stadium incidents are available for a subset of colleges, typically state-funded institutions, that provide these statistics. We then estimate a team fixed effects model where the dependent variable is the number stadium incidents, and control for game characteristics such as the opponent's rank, home team's rank, homecoming, and whether the game began at 5pm or later (Prime Time Game).

In Table 10, our main variable of interest, Rival, has a positive coefficient of 16.489 (t -statistic of 2.808) in the full specification. Thus, consistent with the mutual disdain between rival fans, there are more stadium incidents on games against rivals. In contrast, homecoming games, which are typically associated with a friendly opponent, have fewer stadium incidents as indicated by Homecoming's negative coefficient of -5.376 (t -statistic of -2.126).

The Prime Time Game indicator variable has positive coefficients that are consistent with more important college football games eliciting stronger fan emotions. Similarly, higher

¹⁸Rees and Schnepel (2009) report increased crime surrounding the location of college football games, while Card and Dahl (2011) link unexpected losses in the National Football League to increased domestic violence.

ranked opponents lead to more stadium incidents as the Pre-Season Top 25 Opponent indicator variable has positive coefficients while the coefficients for Opponent's Rank are negative. These coefficients are consistent with fans of higher ranked teams being more willing to travel with the visiting team, which increases the likelihood of conflict between opposing fans at the stadium.

F. Expected Damage

Although Table 10 indicates that several game characteristics influence the number of stadium incidents, Table 2 reports that their respective price impacts are inconsistent with higher expected damage. For example, Panel B of Table 2 indicates that homecoming games are associated with higher hotel prices, while Table 10 indicates that homecoming games are associated with fewer stadium incidents. Similarly, a higher ranked opponent is associated with more stadium incidents but is not associated with higher Airbnb listing prices. Therefore, incidents at the stadium where opposing fans interact do not imply higher expected damage for Airbnb units and hotel rooms that physically separate visitors from the local population.

Furthermore, the inverse relation between unit-level listing premiums and rental incomes cannot be attributed to a higher cost of providing accommodations to rival fans. Besides the insurance provided by Airbnb to hosts, unreported results confirm that Airbnb hosts do not increase their required damage deposits on games against rivals. Furthermore, hotel rooms are also susceptible to damage but hotel prices do not increase significantly on rival games. In addition to retaining the credit card information of guests, Airbnb hosts rate guests. This rating provides a further incentive for guests to act responsibly. Moreover, variation in listing prices attributable to financial constraints is unlikely to explain the likelihood that a unit is damaged. Finally, Airbnb allows hosts to block their unit from being booked on specific dates. In unreported results, units booked on rival games are not more likely to be blocked

during the following week. Consequently, we do not find evidence that units booked by rival fans are more likely to require repairs.

VI Conclusion

We study the impact of non-pecuniary preferences on household financial decisions and find that non-pecuniary preferences against fans of a rival college team lead Airbnb host to set listing prices that are too high. Specifically, listing price increases on games against rival teams lower the rental incomes of Airbnb hosts. This inverse relation between listing price increases and rental income is concentrated among financially unconstrained hosts. Thus, financial constraints reduce the impact of non-pecuniary preferences on household financial decisions.

While our results are specific to a certain laboratory setting, namely rental accommodations in college towns, they highlight an important issue in the rapidly expanding sharing economy. Price-setting by households may differ substantially from price-setting by corporations. Specifically, we find that the listing prices set by Airbnb hosts are altered by trivial non-pecuniary preferences regarding guest affiliations. Our results also identify the importance of professional management in “rationalizing” the sharing economy as the pricing decisions of professional Airbnb hosts, some of which are rental management companies, are less affected by non-pecuniary preferences.

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Figure 1: Difference in Listing Premium: Airbnb - Hotels

This figure illustrates the difference in the listing premium between Airbnb units and hotel rooms. The Airbnb listing premium is computed at the unit level as the listing price on a specific game, such as homecoming, minus the unit's average listing price across all home games in the same season. The hotel listing premium is computed at the college level as the average hotel price on a specific game minus the average hotel price across all home games in the same season.

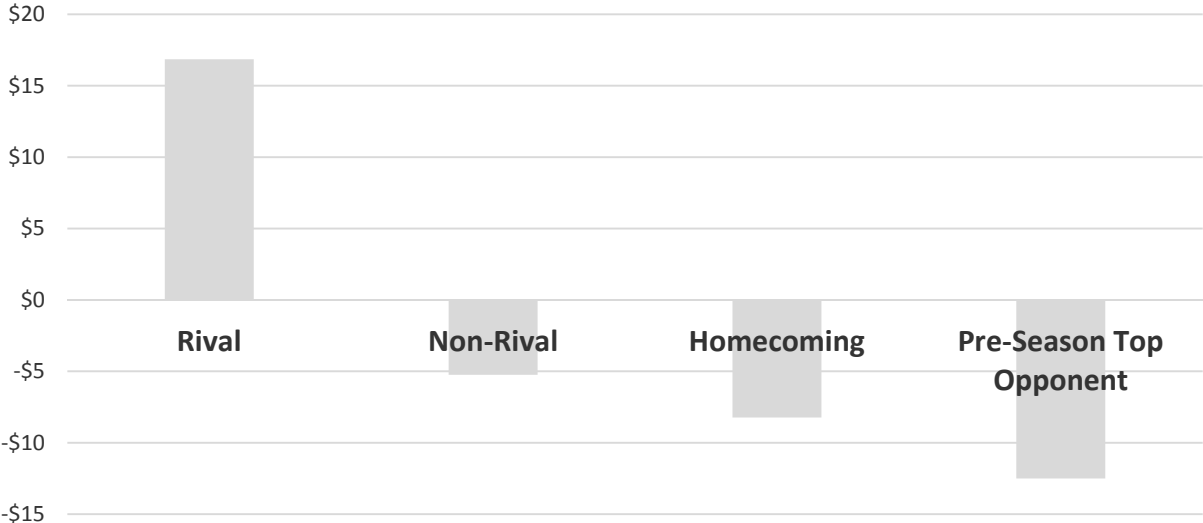


Table 1: Summary Statistics

This table reports the average number of units in each college town listed on Airbnb as well as the average listing price, rental income, Airbnb listing premium, and occupancy rate on games against rival and non-rival teams. Airbnb Listing Premium is computed at the unit level as the listing price on a specific game minus the average listing price for all home games during the season. For comparison, the average price, revenue, hotel premium, and occupancy rate of hotels is also reported. Hotel Premium is computed at the city level as the average hotel price minus the average hotel price for all home games during the season. The Airbnb sample consists of entire units located in college towns whose listing price changes at least once during the football season. The average listing price, rental income, listing premium, and occupancy rate are also reported for hotels within a fifteen mile radius of the football stadium. Rival teams are identified in Appendix A. Pre-Season Top 25 opponents are teams classified as a top 25 football program at the start of the season by the Associated Press Poll. Incoming Top 25 Opponents are teams among the top 25 teams before the game. Homecoming refers to games on homecoming weekend.

Airbnb	Number of Units	Listing Price	Rental Income	Airbnb Listing Premium	Occupancy Rate
Rival	31	\$277.06	\$176.36	\$28.77	65.03%
Pre-Season Top 25 Opponent (Non-Rival)	33	\$259.57	\$185.05	\$7.06	68.01%
Incoming Top 25 Opponent (Non-Rival)	32	\$260.55	\$198.35	\$8.87	69.15%
Homecoming (Non-Rival)	31	\$247.13	\$144.54	\$2.90	65.06%

Hotel	Price	Revenue	Hotel Premium	Occupancy Rate
Rival	\$160.17	\$138.20	\$13.51	83.72%
Pre-Season Top 25 Opponent (Non-Rival)	\$172.59	\$154.97	\$19.56	88.61%
Incoming Top 25 Opponent (Non-Rival)	\$162.73	\$146.06	\$16.18	88.48%
Homecoming (Non-Rival)	\$149.68	\$131.87	\$5.77	87.09%

Panel B: Determinants of the Hotel Premium

	Hotel Premium								
Rival	16.016*** (3.140)	10.381* (2.054)	10.739* (2.038)	7.190 (1.456)	7.663* (1.737)	9.432* (2.032)	9.474* (2.044)	9.987* (2.000)	9.819* (1.981)
Opponent's Rank		-0.572*** (-4.336)	-0.588*** (-4.201)	-0.156 (-1.079)	-0.171 (-1.273)	-0.165 (-1.250)	-0.165 (-1.249)	-0.167 (-1.257)	-0.176 (-1.297)
Home Team's Rank			0.120 (0.733)	0.099 (0.676)	0.113 (0.789)	0.104 (0.755)	0.104 (0.750)	0.099 (0.710)	0.091 (0.656)
Pre-Season Top 25 Opponent				25.833*** (5.026)	22.599*** (4.499)	23.417*** (4.959)	23.378*** (4.953)	23.491*** (5.011)	23.243*** (4.828)
Prime Time Game					11.928*** (3.605)	11.970*** (3.784)	12.034*** (3.640)	11.587*** (3.264)	11.601*** (3.261)
Homecoming						12.828*** (3.556)	12.840*** (3.535)	12.913*** (3.564)	12.812*** (3.588)
Number of Hotel Rooms							-33.167 (-0.185)	-29.124 (-0.161)	-79.022 (-0.357)
Distance								0.935 (0.523)	0.898 (0.505)
Number of Units									2.687 (0.729)
Observations	236	236	236	236	236	236	236	236	236
R-squared	0.054	0.169	0.172	0.267	0.305	0.334	0.334	0.335	0.336

Table 6: Residual Listing Premiums

This table reports the coefficients from the unit fixed effects panel regression where the rental income of Airbnb units is the dependent variable. Residual Listing Premium is computed by regressing the Airbnb Listing Premium onto the Hotel Premium. Airbnb Listing Premium is computed at the unit level as the listing price on a specific game minus the average listing price for all home games during the season. Hotel Premium is computed at the city level as the average hotel price on a specific minus the average hotel price for all home games during the season. A low credit utilization score corresponds with financially unconstrained hosts in Panel A, while a high credit utilization score corresponds with financially constrained hosts in Panel B. Rival is an indicator variable that equals one if the home game is against a rival opponent, and zero otherwise. Opponent's Rank is the incoming rank of the opponent prior to the start of the game, and equals 50 if the team is unranked. Home Team's Rank is the rank of the home team prior to the start of the game, and equals 50 if the team is unranked. Prime Time Game is an indicator variable equal to one if the game occurs at 5pm or later, and zero otherwise. Pre-Season Top 25 Opponent is an indicator variable equal to one if the incoming opponent was ranked a top 25 team on the Associated Press Poll at the start of the season, and zero otherwise. Homecoming is an indicator variable equal to one if the game takes place on the homecoming weekend, and zero otherwise. Distance refers to the number of miles separating the location of the home team and the visiting team. *t*-statistics are reported in parentheses. Standard errors are clustered at the team level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Residual Listing Premium and Rental Incomes of Financially Unconstrained Airbnb Hosts

	Airbnb Listing Premium	Financially Unconstrained Hosts				
		Airbnb Rental Income				
Hotel Premium	0.914*** (3.170)					
Residual Listing Premium		0.576*** (3.737)	0.569*** (5.084)	0.569*** (5.142)	0.569*** (5.150)	0.586*** (5.191)
Rival		29.544 (1.606)	21.537 (1.614)	25.904* (2.026)	27.031* (1.924)	27.246* (2.035)
Residual Listing Premium×Rival		-0.357*** (-3.319)	-0.330*** (-3.128)	-0.321*** (-3.021)	-0.321*** (-3.014)	-0.336** (-2.700)
Opponent's Rank			-1.479* (-2.048)	-1.433* (-1.779)	-1.439* (-1.858)	-1.332** (-2.279)
Home Team's Rank			-0.530* (-2.000)	-0.584* (-1.764)	-0.583* (-1.786)	-0.367 (-0.873)
Pre-Season Top 25 Opponent			44.508 (1.630)	47.470** (2.118)	47.659** (2.284)	28.211 (1.367)
Prime Time Game			28.470* (2.069)	28.376** (2.748)	28.274** (2.584)	6.050 (0.775)
Number of Units			34.848*** (4.145)	32.799*** (3.805)	32.647*** (3.870)	30.468*** (3.827)
Homecoming				30.510** (2.150)	30.278** (2.410)	-7.270 (-0.741)
Distance					1.257 (0.113)	-2.157 (-0.283)
Hotel Occupancy						3.236*** (3.098)
Observations	2,854	2,854	2,854	2,854	2,854	2,854
R-squared	0.071	0.085	0.156	0.162	0.162	0.194
Number of Unique Units	572	572	572	572	572	572

Panel B: Residual Listing Premium and Rental Incomes of Financially Constrained Airbnb Hosts

	Financially Constrained Hosts					
	Airbnb Listing Premium	Airbnb Rental Income				
Hotel Premium	0.808*** (4.085)					
Residual Listing Premium		0.763*** (6.421)	0.749*** (8.242)	0.751*** (8.513)	0.752*** (8.629)	0.769*** (9.913)
Rival		38.339* (1.927)	22.767 (1.670)	30.163** (2.474)	37.964*** (2.983)	36.578** (2.556)
Residual Listing Premium×Rival		0.107 (0.514)	0.163 (0.914)	0.164 (0.915)	0.163 (0.916)	0.159 (0.957)
Opponent's Rank			-0.265 (-0.436)	-0.278 (-0.407)	-0.369 (-0.573)	-0.399 (-0.800)
Home Team's Rank			-0.625 (-1.638)	-0.715 (-1.648)	-0.703 (-1.696)	-0.489 (-0.998)
Pre-Season Top 25 Opponent			61.264** (2.428)	64.555*** (3.362)	64.067*** (3.618)	44.190** (2.389)
Prime Time Game			40.566** (2.357)	42.731*** (3.064)	40.234** (2.740)	17.845 (1.222)
Number of Units			34.224** (2.529)	31.588* (2.066)	31.747** (2.390)	31.291*** (2.955)
Homecoming				44.407** (2.694)	42.949** (2.874)	5.507 (0.549)
Distance					9.814 (0.964)	6.509 (0.826)
Hotel Occupancy						3.189*** (4.253)
Observations	2,639	2,639	2,639	2,639	2,639	2,639
R-squared	0.049	0.209	0.264	0.273	0.275	0.303
Number of Unique Units	536	536	536	536	536	536

Table 9: Professional Hosts

This table reports the coefficients from the unit fixed effects panel regression where unit-level rental income is the dependent variable. The sample consists of entire units listed on Airbnb in college towns. Professional hosts have more than one active property listed on Airbnb. High credit utilization corresponds with financially constrained hosts, while low credit utilization corresponds with financially unconstrained hosts. Airbnb Listing Premium is computed at the unit level as the average listing price on a specific game minus the average listing price for all home games during the season. Rival is an indicator variable that equals one if the home game is against a rival opponent, and zero otherwise. Opponent's Rank is the incoming rank of the opponent prior to the start of the game, and equals 50 if the team is unranked. Home Team's Rank is the rank of the home team prior to the start of the game, and equals 50 if the team is unranked. Prime Time Game is an indicator variable equal to one if the game occurs at 5pm or later, and zero otherwise. Pre-Season Top 25 Opponent is an indicator variable equal to one if the incoming opponent was ranked a top 25 team on the Associated Press Poll at the start of the season, and zero otherwise. Homecoming is an indicator variable equal to one if the game takes place on the homecoming weekend, and zero otherwise. Hotel Premium is computed at the city level as the average hotel price on a specific game minus the average hotel price for all home games during the season. Distance refers to the number of miles separating the location of the home team and the visiting team. *t*-statistics are reported in parentheses. Standard errors are clustered at the team level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Airbnb Rental Incomes			
	Non-Professional Hosts		Professional Hosts	
	Unconstrained	Constrained	Unconstrained	Constrained
Airbnb Listing Premium	0.626*** (12.570)	0.747*** (9.138)	0.644** (2.577)	0.854*** (29.532)
Rival	1.227 (0.124)	-0.828 (-0.044)	-27.281 (-1.648)	4.763 (0.262)
Airbnb Listing Premium × Rival	-0.521** (-2.692)	0.046 (0.240)	-0.390 (-1.554)	0.045 (0.308)
Opponent's Rank	-1.032* (-1.884)	-0.328 (-0.595)	-0.764 (-1.238)	-0.177 (-0.370)
Home Team's Rank	-0.327 (-0.969)	-0.053 (-0.130)	-0.544 (-0.739)	-1.302*** (-3.293)
Prime Time Game	12.539 (1.261)	26.263* (2.038)	-4.979 (-0.452)	-4.801 (-0.341)
Pre-Season Top 25 Opponent	16.105 (1.284)	22.713* (1.781)	-9.798 (-1.013)	23.001* (2.023)
Homecoming	-2.579 (-0.275)	8.671 (0.925)	-28.743* (-1.861)	-1.704 (-0.077)
Hotel Premium	1.608*** (3.779)	1.343*** (2.978)	1.739*** (3.492)	1.388*** (3.455)
Number of Units	6.040 (0.733)	16.364 (0.933)	50.815* (1.757)	16.389 (1.093)
Distance	-5.542 (-0.947)	-4.797 (-0.625)	-16.580* (-2.014)	9.706 (1.486)
Constant	184.254*** (3.417)	100.099 (1.315)	50.243 (0.575)	62.998 (0.665)
Observations	2,154	1,941	700	698
R-squared	0.251	0.289	0.256	0.495
Number of Unique Units	426	395	146	141

Table 10: Stadium Incidents

This table reports the coefficients from a team fixed effects regression explaining the number of stadium incidents, defined as the sum of disorderly conduct violations at the stadium and stadium ejections on each home game. Rival is an indicator variable that equals one if the home game is against a rival opponent, and zero otherwise. Homecoming is an indicator variable equal to one if the game takes place on the homecoming weekend, and zero otherwise. Prime Time Game is an indicator variable equal to one if the game occurs at 5pm or later, and zero otherwise. Opponent's Rank is the incoming rank of the opponent prior to the start of the game, and equals 50 if the team is unranked. Home Team's Rank is the rank of the home team prior to the start of the game, and equals 50 if the team is unranked. Pre-Season Top 25 Opponent is an indicator variable equal to one if the incoming opponent was ranked a top 25 team on the Associated Press Poll at the start of the season, and zero otherwise. Distance refers to the number of miles separating the location of the home team and the visiting team. *t*-statistics are reported in parentheses. Standard errors are clustered at the team level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Stadium Incidents				
Rival	25.292*** (3.491)	24.009*** (3.422)	24.401*** (3.486)	17.824** (2.841)	16.489** (2.808)
Homecoming		-8.893** (-2.308)	-7.943** (-2.128)	-5.507** (-2.209)	-5.376** (-2.126)
Prime Time Game			21.746** (2.872)	17.967** (2.742)	16.182** (2.727)
Opponent's Rank				-0.682** (-2.851)	-0.479** (-2.406)
Home Team's Rank				-0.269 (-1.085)	-0.277 (-1.167)
Pre-Season Top 25 Opponent					12.108* (2.040)
Observations	214	214	214	214	214
R-squared	0.506	0.512	0.563	0.631	0.639
Number of Teams	19	19	19	19	19

Appendix A: List of Home Games Against Rivals

Home Team	Opponent	Year	Home Team	Opponent	Year
South Carolina	Georgia	2014	South Carolina	Clemson	2015
Georgia	Georgia Tech	2014	Clemson	Georgia Tech	2015
Florida State	Florida	2014	Georgia	South Carolina	2015
Florida	LSU	2014	Florida State	Miami	2015
Tennessee	Kentucky	2014	Florida	Florida State	2015
Kentucky	Vanderbilt	2014	Alabama	LSU	2015
Ohio State	Michigan	2014	Auburn	Alabama	2015
Iowa	Iowa State	2014	Tennessee	Vanderbilt	2015
Iowa	Wisconsin	2014	Mississippi State	LSU	2015
Wisconsin	Minnesota	2014	Mississippi State	Alabama	2015
Nebraska	Minnesota	2014	Kentucky	Tennessee	2015
LSU	Mississippi State	2014	Notre Dame	USC	2015
LSU	Alabama	2014	Michigan	Michigan State	2015
Arkansas	LSU	2014	Michigan	Ohio State	2015
Arkansas	Ole Miss	2014	Michigan St.	Indiana	2015
Oklahoma	Oklahoma State	2014	Iowa	Minnesota	2015
TCU	Texas Tech	2014	Wisconsin	Iowa	2015
Texas Tech	Texas	2014	LSU	Florida	2015
Oregon State	Oregon	2014	LSU	Arkansas	2015
Oregon	Washington	2014	Texas Tech	TCU	2015
			Utah	Colorado	2015
			ASU	Arizona	2015

Appendix B: Illustrative Model

Let P denote the listing price set by a household. In the absence of non-pecuniary preferences, the host sets the listing price to maximize

$$\text{Rental Income} = \text{Listing Price} \times \text{Probability}(\text{Occupancy} | \text{Listing Price}) . \quad (6)$$

This maximization is equivalent to setting a listing price that maximizes

$$P \times [1 - \alpha P] \quad (7)$$

provided Occupancy is determined by the function $\text{Probability}(\text{Occupancy} | \text{Listing Price}) = 1 - \alpha P$ where $\alpha > 0$ determines the demand curve for accommodation. In our empirical estimation, variation in α across different home games is captured by hotel prices and game characteristics such as team rankings.

Rental income in equation (7) is maximized at $\frac{1}{4\alpha}$ by setting the listing price to $P = \frac{1}{2\alpha}$. Thus, rental income is half the listing price as host occupancy equals 50%.

To incorporate a non-pecuniary preference regarding team affiliations, let $P_R = P + D$ denote the host's listing price on games against rival visiting teams. $D \geq 0$ quantifies the price premium a host requires to overcome their non-pecuniary preference against rival fans. D differs from α along two dimensions. First, our empirical implementation has D only being non-zero on games against rivals, while $\alpha > 0$ varies across different home game. Second, in contrast to α , D can vary across hosts. Overall, there is a one-to-one correspondence between a host's non-pecuniary preference and the host's listing price after accounting for the demand for accommodation.

Rental income of $\frac{1}{4\alpha} - \alpha D^2$ on games against rivals is reduced by the host's non-pecuniary preference, which increases their listing price by D . For completeness, the constraint $D \leq \frac{1}{2\alpha}$ prevents the host's occupancy, and rental income, from being negative by preventing the host from setting a listing price that is twice the amount justified by demand.

Appendix C: Variable Description

Variable	Description
Rival	An indicator variable that equals one if the home game is against a rival opponent, and zero otherwise.
Listing Premium	A unit's listing price on a specific game minus the average listing price for all home games in the same football season.
Prime Time Game	An indicator variable that equals one if the home game occurs at 5pm or later, and zero otherwise.
Homecoming	An indicator variable that equals one if the home game coincides with the homecoming weekend, and zero otherwise.
Opponent's Rank	The visiting team's ranking prior to the game. If the opponent is unranked, this rank is set to 50.
Home Team's Rank	The home team's ranking prior to the game. If the home team is unranked, this rank is set to 50.
Pre-Season Top 25 Opponent	An indicator variable that equals one if the opponent was ranked a top 25 team before the start of the season, and zero otherwise. Pre-Season ranking is obtained from the AP Poll.
Number of Units	The number of entire units listed on Airbnb in a college town.
Hotel Premium	The average hotel price on a specific game minus the average hotel price across all home games in the same football season.
Financially Unconstrained	Units listed in a zip code whose average credit utilization score is below the median score of all zip codes in the college town.
Financially Constrained	Units listed in a zip code whose average credit utilization score is above the median score of all zip codes in the college town.
Professional Hosts	Professional Hosts have more than one property listed on Airbnb.
Distance	Distance is measured as the log number of miles between the location of the home team's stadium and the location of the visiting team's stadium.