

How Do Households Set Prices? Evidence from Airbnb*

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Abstract

We find Airbnb hosts in college towns increase their listing prices more than hotels on games against rival football teams. These high listing prices lower the rental incomes of Airbnb hosts, indicating that household financial decisions are influenced by non-pecuniary preferences. In particular, preferences regarding college team affiliations confound the listing prices set by households. However, financial constraints mitigate these preferences as the inverse relation between listing prices and rental incomes is limited to financially unconstrained hosts.

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The “sharing economy” allows households to monetize idle assets. Whether its their house (Airbnb.com), backyard (Dogvacay.com), car (Getaround.com) or spare cash (Prosper.com), households are deploying – many for the first time – assets for the purpose of generating income. According to Pricewaterhouse Coopers, the international sharing economy totaled \$15 billion in online transactions in 2014 and is on track to reach \$335 billion by 2025.¹

The sharing economy requires households to make an important financial decision: how to set prices on their income-generating assets? The behavioral finance literature has revealed a myriad of peculiarities that confound investment decisions (Hirshleifer, 2001). While internal and external governance mechanisms exist in corporations to mitigate idiosyncratic non-pecuniary preferences that are inconsistent with income maximization, these mechanisms are not available to constrain household preferences. Therefore, the prices set by households may be more sensitive to their idiosyncratic non-pecuniary preferences than the prices set by corporations. This sensitivity implies the objective of hosts is not to maximize rental income. The purpose of this paper is to study the prices set by households for their income-generating assets and their respective rental incomes.

The listing prices set by households on Airbnb in college towns around home football games provides an ideal laboratory for studying household finance. Airbnb is an online marketplace that enables households to rent accommodation at their specified listing price.²

Using Airbnb data to study the financial decisions of households is advantageous for several reasons. First, football rivalries evoke strong emotions, which provides an ideal laboratory to study whether non-pecuniary household preferences interfere with the maximization of rental income. Cikara, Botvinick, Fiske (2011) find that “us versus them” behavior spreads beyond competitors to fans.³ Second, we observe hotel prices in each college town on the same day as the Airbnb listing prices set by households. Thus, we can compare the price-setting of households to benchmark hotel prices set by corporations. Third, we observe listing prices on Airbnb set by the same household on different home games, enabling us to observe the same household’s listing price and rental income on home games against rival teams (e.g., University of Florida at Florida State) and on home games against non-rival teams (e.g., Notre Dame at Florida State). This allows us to hold the household fixed and vary their preference toward the opposing team.

Our data consist of 1,321 entire units on Airbnb in 26 college towns encompassing 232 games during the 2014-2015 football season. Entire units resemble hotel rooms, and provide

¹The Pricewaterhouse Coopers report can be accessed at: <http://www.pwc.com/us/en/technology/publications/assets/pwc-consumer-intelligence-series-the-sharing-economy.pdf>

²Besides generating income, online tools have the ability to impact the financial decisions of households by providing information. Levi (2014) demonstrates the effectiveness of an online tool at decreasing consumption by providing an easy-to-interpret summary of a household’s net worth.

³Edmans, Garcia, and Norli (2007) document the effect of national soccer team results on investor decisions.

self-contained accommodation. Thus, interactions between Airbnb hosts and guests typically involve no reciprocity nor personal contact since guests and hosts are physically separated. College football games are an important determinant of an Airbnb host’s rental income in our sample of college towns. Over 60% of the total rental income earned by Airbnb hosts during the football season occurs on six weekends (Friday and Saturday nights) with home games. For each home game, we create a rival indicator variable that equals one for each game against a “rival” visiting team. Appendix A summarizes the college football rivalries in our study. 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 along with several other proxies such as the visiting team’s rank, we find that Airbnb hosts set higher listing prices on games against rival teams. 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 report a positive unconditional relation between the listing price and rental income of individual units. However, the interaction between unit-level listing prices and the rival indicator variable exerts a negative impact on rental incomes. Consequently, the high listing prices set by households on games against rivals are suboptimal.

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 Notre Dame, Airbnb units in Tallahassee were listed for an average listing price of \$201. As each unit was booked for this game, average rental income was also \$201. However, five weeks later, on the home game against the unranked University of Florida team, which is a rival of Florida State, the average listing price in Tallahassee was increased to \$267 but average rental income declined to \$67.

To examine variation in listing prices, we construct a unit-level Airbnb listing premium as the listing price on a specific game minus the average listing price across all home games. Variation in the listing premium may reflect variation in host preferences regarding the opposing team as well as variation in demand. To isolate demand, a similar college-level hotel listing premium is computed as the average hotel price on a specific game minus the average hotel price across all home games.

Figure 1 illustrates the listing price increases 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, namely Alumni. In contrast to games against rivals, Airbnb listing prices on homecoming do not have an inverse relation with rental incomes. To generalize the above example involving visits by

Notre Dame and the University of Florida to Tallahassee, Figure 2 illustrates that for every dollar in rental income earned by Airbnb hosts on a highly ranked non-rival game, only \$0.71 is earned on games against rivals. For comparison, hotels experience a negligible decline to \$0.96 on games against rivals.⁴

The low occupancy rate of Airbnb hosts on games against rivals can be explained by hotel rooms and entire units listed on Airbnb being substitutes in conjunction with an occupancy rate below 100% for hotels. For emphasis, nearly all the Airbnb units in our sample are available for immediate booking using Airbnb’s Instant Book feature. Therefore, the low occupancy rate of Airbnb hosts on games against rivals is not due to guests being denied accommodation by hosts. Instead, hosts use the price mechanism to express their preference against rival fans.

Hosts with more than one Airbnb listing as classified as a professional. As with hotels, we find no evidence that professional hosts set suboptimal listing prices on games against rivals. Additional tests condition on unit and host characteristics to confirm that the inverse relation between listing prices and rental incomes on games against rivals is not due to the overestimation of demand. Indeed, hosts have several months to lower their listing price to obtain a successful booking before each home game.

In contrast to entire units, shared units on Airbnb that have common facilities (bathroom, kitchen, etc) are suitable for visiting fans of the home team. Hosts of shared units do not increase their listing prices on games against rivals. Therefore, fans of the home team can avoid the high listing prices for entire units on Airbnb by booking shared accommodation on games against rivals.

A further analysis reveals that the financial constraints of hosts influence listing prices. We divide the zip codes within each college town into areas whose average credit utilization score is either above or below the median credit utilization score of the respective college town. The credit utilization score divides outstanding credit card debt by the total available credit, with the availability of credit reflecting household income. Zip codes whose average credit utilization score is above the college town’s median are classified as having financially constrained hosts, while zip codes whose average credit utilization is below this median are classified as having financially unconstrained hosts.⁵

On games against rivals, the listing prices of financially unconstrained hosts are nearly 60% higher than those of financially constrained hosts. As a consequence of setting more competitive

⁴We compute the total Airbnb rental income and hotel revenue in each college town on home games against top 25 ranked non-rival teams and on home games against rival teams. The total on rival games are then normalized by the respective totals on highly ranked non-rival games, with Figure 2 illustrating the average of these two ratios.

⁵We verify that hosts with multiple Airbnb units concentrate their units in the same zip code. This geographic concentration is consistent with short-term accommodation rentals requiring frequent monitoring.

(lower) listing prices, financially constrained hosts do not earn less rental income on games against rivals. Intuitively, financially constrained hosts do not require as large a price premium to overcome their preference against rival fans.⁶ To clarify, unit fixed effects control for differences in the quality of accommodation, hence the possibility that financially unconstrained hosts have higher quality units with higher listing prices.

To illustrate the economic implications of financial constraints, financially unconstrained hosts and financially constrained hosts earn similar rental income; averaging \$189 and \$187, 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 unchanged at \$183. Therefore, financial constraints improve the financial decisions of households with respect to setting listing prices.

Overall, suboptimal pricing on games against rival fans is limited to non-professional financially unconstrained hosts.⁷ These host characteristics are difficult to reconcile with alternative explanations for our results such as the overestimation of demand or a higher cost for accommodating rival fans. Instead, preferences regarding college football team affiliations appear to cause a subset of hosts to set suboptimal listing prices. This subset is economically significant since 40% of the entire units listed on Airbnb have non-professional financially unconstrained hosts.

To clarify, the cost of providing accommodation to rival fans is not higher because of a higher propensity to cause damage. The probability a unit incurs damage is unrelated to host characteristics such as financial constraints that induce cross-sectional variation in listing prices. Moreover, hotel prices are not significantly higher on games against rivals despite hotel rooms also being susceptible to damage. Furthermore, Airbnb hosts do not require higher damage deposits on games against rivals, nor are hosts more likely to block their units from being rented. Airbnb also insures hosts for a million dollars in property damage.⁸ Finally, the probability that units booked on games against rivals subsequently become unavailable for rent is not higher than for units booked on games against non-rivals. Thus, providing accommodation to rival fans is not associated with damage that prevents subsequent rental income.

Finally, a placebo test verifies that suboptimal pricing offers the best explanation for our empirical results. The placebo test attempts to replicate our results in urban areas that have more than 1,000 Airbnb listings such as Los Angeles. Consistent with college football games representing a less salient increase in the demand for accommodation in urban areas, we find no evidence of suboptimal pricing in urban areas on games against rivals.

⁶This interpretation is more likely than financially constrained hosts having a weaker preference against rival fans.

⁷Entire units are as likely to have a financially constrained host as a financially unconstrained host.

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

The growing importance of the sharing economy has attracted the attention of academics, with Duarte, Siegel, and Young (2012) as well as Iyer, Khwaja, Luttmer, and Shue (2015) examining online peer-to-peer lending markets. In contrast to peer-to-peer lending, the Airbnb hosts we examine are sellers not buyers whose pricing power derives from their properties being relatively unique. Intuitively, Airbnb hosts have more discretion when setting listing prices than lenders have setting interest rates. Moreover, the demand for Airbnb accommodation is concentrated on a few weekends, with the opportunity to obtain rental income expiring if the property is unoccupied on a home game. In contrast, lenders have multiple opportunities to deploy their savings.

1 Data

Our analysis uses Airbnb data for units near college football stadiums. A guest can book a unit on Airbnb at the listing prices specified by the host on specific dates. Airbnb receives a 3% fee from the host for each completed booking and an additional service charge from guests. In our sample of college towns, Airbnb earnings are concentrated on home games where guests typically book two to three nights of accommodation.

Variation in listing prices during the football season is dramatic for Airbnb units located in college towns since home games represent large anticipated increases in demand for accommodation. We examine units whose listing price changes at least once during the football season to ensure the Airbnb hosts in our sample are active. Initially, we focus on entire units that resemble large hotel rooms with self-contained facilities. Entire units are appropriate for rival fans who prefer being physically separate from fans of the home team. A later empirical test examines shared units on Airbnb.

We identify the top 30 ranked college football programs for the 2014 and 2015 football seasons. The 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.

We limit our main analysis to college towns with fewer than 1,000 entire unit listings on Airbnb per football season to exclude teams in urban areas such as Los Angeles (teams excluded:

USC, UCLA, Stanford, and Texas). Urban areas are examined separately in a later placebo test. We also restrict our sample of Airbnb listings to units located within 15 miles from the stadium.

Next, we identify pairs of rivals and require at least 50 prior games between these 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 232 unique home games that contain 42 games against a rival. Appendix A contains a complete list of rivals.

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 alternative benchmarks such as the average price for all home games against non-rival teams. Besides Airbnb data, our study utilizes data on 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. As with the Airbnb Listing Premium, Hotel Listing Premium is computed as the average hotel price on a specific game minus the average hotel price across all home games.

Table 1 reports the average number of units listed, listing price, rental income, listing premium, and occupancy rate on different home games for Airbnb units. In addition, the average listing price, rental income, listing premium, and occupancy rate of hotels are also reported. Observe that games against rivals are associated with the highest average listing price of \$277.06 on Airbnb, which corresponds to the highest Airbnb listing premium of \$28.77, and the lowest occupancy of 65.03%. Therefore, despite having the highest average listing price, games against rivals fail to generate the highest average rental income due to the lower occupancy rate.⁹ 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.

In contrast to Airbnb units, hotel prices are not highest on games against rivals. Hotel occupancy is also not highest on games against rivals. Thus, games involving a rival visiting team are not associated with an unusually high demand for accommodation.

Observe that entire Airbnb units are more expensive than hotel rooms, on average. Thus, the lower rental income earned by Airbnb hosts on games against rivals is difficult to attribute to wealthy football fans who prefer hotel accommodation. Instead, consistent with the lower rental income earned by Airbnb hosts on games against rivals, visiting football fans are price sensitive with respect to accommodation.

⁹A lottery preference cannot explain the variation in listing prices on different home games. The lottery preference predicts that hosts accept the low probability of obtaining a booking by setting a high listing price on every game.

2 Empirical Results

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). Standard errors are clustered at the team level. The β_1 coefficient in this specification determines whether games against rivals are associated with a larger listing premiums after controlling for a multitude of demand proxies.

The demand proxies include indicator variables for games during prime time and on homecoming weekend. 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. Most important, Hotel Listing 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.

The positive β_1 coefficients in Panel A of Table 2 indicate that Airbnb hosts increase their listing prices on games against rivals. For example, the 24.756 coefficient (t -statistic of 5.982) in last column with all control variables indicates that listing prices are nearly \$25 higher on games against rivals compared to the average home game. Thus, after controlling for multiple demand proxies, including hotel prices, we find that games against rivals are associated with higher listing prices on Airbnb.

The positive coefficients for Hotel Listing Premium indicate that Airbnb listing prices comove 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 hotel prices. Intuitively, prime time games are more important, and therefore increase Airbnb listing prices. The negative coefficients for the Prime Time Game indicator may arise from the inclusion of Hotel Listing Premium that is higher for prime time games according to Panel B of Table 2.

Hotel prices are unlikely to be influenced by preferences regarding team affiliations due to the diversity of their employees and operations. Instead, hotel prices proxy for the demand for accommodation. Therefore, we repeat the estimation of equation (1) using Hotel Listing Premium as the dependent variable instead of Airbnb Listing Premium.

Panel B of Table 2 reports that hotel prices are consistently higher on homecoming games but not games against rivals. The coefficient for the Rival indicator variable is occasionally significant

at the 10% level but is often insignificant. In contrast to games against rivals, homecoming is clearly stated on every college football schedule. Furthermore, Alumni returning for homecoming can participate in several events besides the football game. Therefore, homecoming is associated with a high demand for accommodation.

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 a smaller listing premium 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 the listing premium since the willingness of their fans to travel with the team is greater.

2.1 Occupancy Rate

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

$$1_{\text{Booking}_{i,t}} = \beta_1 \text{Airbnb Listing Premium}_{i,t} + \beta_2 \text{Rival}_{i,t} + \beta_3 \text{Airbnb Listing Premium}_{i,t} \times \text{Rival}_{i,t} + \gamma X_t + \epsilon_{i,t}. \quad (2)$$

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 accommodation, a negative β_3 coefficient indicates that high listing premiums on games against rivals lower the likelihood of a booking.

Table 3 reports negative β_3 that indicate listing price increases on games against rivals reduce the likelihood that a host obtains a booking. The non-negative β_2 coefficients are consistent with hosts not rejecting bookings by rival fans. Indeed, 95.5% of hosts activate Airbnb’s Instant Book feature, which enables guests to 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.¹⁰ The positive coefficients for Hotel Listing Premium and Hotel Occupancy indicate that the occupancy of Airbnb hosts increases with the demand for hotel accommodation. Thus, Airbnb units and hotel rooms have a common response to increases in demand.

The next analysis provides more compelling evidence that the listing prices set by households are confounded by preferences regarding team affiliations.

¹⁰Airbnb has embarked on a program to combat the denial of accommodation. Edelman, Luca, and Svirsky (2016) 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.

2.2 Rental Income

Our next analysis examines the impact of unit-level listing premiums on rental incomes using the following panel regression

$$\begin{aligned} \text{Rental Income}_{i,t} = & \beta_1 \text{Airbnb Listing Premium}_{i,t} + \beta_2 \text{Rival}_{i,t} \\ & + \beta_3 \text{Airbnb Listing Premium}_{i,t} \times \text{Rival}_{i,t} + \gamma X_t + \epsilon_{i,t}, \end{aligned} \quad (3)$$

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.¹¹ Appendix B contains a illustrative model that demonstrates the rental income reduction attributable to having listing prices exceed demand.

The positive β_1 coefficients in Table 4 are consistent with hosts earning higher rental income by setting higher listing prices due to 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 rental income.¹² In the specification with all control variables, the β_3 coefficient equals -0.284 (t -statistic of -2.248). Thus, preferences regarding team affiliations confound the listing prices set by households.

The positive coefficients for the Homecoming and Pre-Season Top 25 Opponent indicator variables are consistent with greater demand, hence higher rental income. The average number of units listed on Airbnb has a positive relation with both listing prices and rental incomes at the unit level. As entire units on Airbnb are a substitute for hotel rooms, more Airbnb units in a college town may signify that the number of hotel rooms is inadequate.

Overall, the listing prices set by Airbnb hosts on games against rivals cannot be attributed to higher demand for Airbnb accommodation due to the inverse relation between unit-level listing premiums and rental incomes. Instead, preferences regarding team affiliations confound the listing prices set by households.

3 Financial Constraints

Heterogeneity among Airbnb hosts and the potential for competition motivates our analysis of financial constraints. The average credit utilization score for individual zip codes provided

¹¹The results are robust to the inclusion of both squared and cubed listing premiums that capture nonlinearities in the income function.

¹²Alternatively, hosts may derive utility from price gouging rival fans rather than disutility from providing them accommodation.

by Experian proxies for financial constraints. 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.¹³

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 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, with right skewness indicating that residents in several zip codes have significantly less available credit. The difference between the average credit utilization score of financially constrained and financially unconstrained hosts exceeds 5 in our sample of college towns.

Equation (1) and equation (3) are re-estimated separately for financially constrained and financially unconstrained hosts. 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. To partially verify 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, evidence of suboptimal pricing strengthens after removing the 317 observations where the financial constraints of professional hosts are ambiguous due to listings in both financially constrained and financially unconstrained zip codes. Indeed, the misidentification of financial constraints would weaken the relation between financial constraints and listing prices.

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.

Moreover, in terms of rental income, Panel C of Table 5 indicates that among financially unconstrained hosts, the β_3 coefficient in equation (3) 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 B of Table 5, the β_3 coefficient is insignificant among financially

¹³Results are similar if the median credit utilization score of the entire sample rather is used to classify hosts.

constrained hosts. Thus, the listing price decisions of financially constrained hosts are not confounded by preferences regarding team affiliations.

The difference in the occupancy rates of financially constrained versus financially unconstrained hosts captures competition. In unreported results, by setting lower (more competitive) listing prices on games against rivals, financially constrained hosts have a higher occupancy than financially unconstrained hosts on these games.

The raw data provides the following in-sample averages that summarize the economic implications of financial constraints. Financially unconstrained hosts have similar rental incomes as financially constrained hosts on games against highly ranked non-rival teams; \$189.42 compared to \$187.23, respectively. Thus, financial constraints do not determine rental income on games against non-rival teams. However, on games against rival teams, the rental income of financially unconstrained hosts declines by over 20% to \$149.24, while the rental income of financially constrained hosts is almost unchanged at \$182.56. In summary, financially constrained hosts set lower listing prices and earn higher rental income on games against rivals than financially unconstrained hosts.

4 Robustness Tests

We construct a unit-level residual listing premium by regressing the original Airbnb Listing Premium on the Hotel Listing Premium of each college town. Residual Listing Premium is defined by the residual from this regression and captures listing price increases on games against rivals that are due to host preferences rather than demand. Equation (1) and equation (3) are then re-estimated using the Residual Listing Premium in lieu of the original Airbnb Listing Premium.

The results in Table 6 parallel our earlier results as the β_3 coefficient is negative for financially unconstrained hosts and insignificant for financially constrained hosts. Thus, using hotel prices to control for demand, the lower rental income of financially unconstrained hosts on games against rivals is due to suboptimal pricing.

While our analysis focuses on a preference against rival fans, homecoming coincides with a high demand for accommodation due to the influx of home team fans.¹⁴ Table 7 reports insignificant β_3 coefficients for the interaction variable defined as Airbnb Listing Premium \times Homecoming. Therefore, we find no evidence of suboptimal pricing on homecoming.

Fans of the home team such as Alumni also require accommodation. As members of the majority, physical separation from the local population is less important for fans of the home

¹⁴According to Panel B of Table 2, hotel prices increase on homecoming, with the inclusion of hotel prices as a control variable eliminating the impact of homecoming on Airbnb prices in Panel A.

team. Consequently, shared units on Airbnb provide suitable accommodation for fans of the home team.¹⁵ Table 8 reports that listing prices for shared units are not higher on games against rivals. Thus, fans of the home team can avoid the high listing premiums for entire units on games against rivals by booking shared units. However, as members of the minority, fans of the rival visiting team who prefer being physically separate from the local population are required to book hotel accommodation.

Every host on Airbnb is assigned a unique identification number. In unreported results, 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. Professional hosts are as likely to be financially constrained as financially unconstrained, and 94.2% adopt the Instant Book feature. Thus, professional hosts and non-professional hosts have similar characteristics. However, professional hosts do not set suboptimal listing prices on games against rivals. Instead, the inverse relation between unit-level listing premiums and rental incomes is limited to non professional financially unconstrained hosts that manage 40% of the entire Airbnb units in our sample. In unreported results, we also find no evidence of this inverse relation on games against rivals in urban areas that have more than 1,000 Airbnb listings such as Los Angeles. The null result from this placebo test is consistent with college football fans exerting an insignificant impact on the demand for accommodation in urban areas.

Although we identify rivalries between college football teams from the sports media, we identify two determinants of a college football rivalry. Rival teams have been playing 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, most college football fans do not reside in college towns as their graduates pursue career opportunities in other destinations. Moreover, our empirical results are robust to controlling for the distance between college football stadiums.

We also compile data on stadium incidents defined as arrests and ejections to verify our classification of rival teams is appropriate. The identification of rival teams is confirmed by a higher number of stadium incidents (arrests and ejections) on games against rivals according to Table 9.¹⁶ Specifically, the positive coefficient of 16.489 (t -statistic of 2.808) for the Rival indicator variable in the full specification indicates a higher number of incidents on games against rivals. In contrast, homecoming games are associated with fewer stadium incidents due to the negative coefficient of -5.376 (t -statistic of -2.126). The Prime Time Game indicator variable

¹⁵The willingness of rival fans to pay a premium for privacy cannot explain our earlier results for entire units since hotel room prices, which are substitutes for entire units, are not higher on rival games.

¹⁶Rees 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.

has positive coefficients that are consistent with more important college football games eliciting stronger fan emotions. Similarly, higher 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 stadium interactions between fans of opposing teams and therefore stadium incidents.

Although several game and visiting team characteristics influence the number of stadium incidents, Table 2 reports that these characteristics do not increase Airbnb listing prices or hotel prices. Therefore, incidents at the stadium, where opposing fans interact, do not translate into rival fans causing damage to hotel rooms or entire Airbnb units that physically separate fans of the rival team from the local population. Indeed, the inverse relation between unit-level listing premiums and rental incomes cannot be attributed to a higher cost of providing accommodation 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.¹⁷ Moreover, variation in listing prices attributable to host characteristics such as financial constraints is unlikely to explain the propensity of guests to damage a host's unit. Finally, Airbnb allows hosts to block their unit from being booked on specific dates. In unreported results, the propensity of hosts to block their unit is not higher on games against rivals. Moreover, units booked on rivals games are not more likely to be subsequently blocked by the host during the following week. Consequently, it does not appear that units booked by rival fans are more likely to require repairs.

Intuitively, as rival fans are not more likely to cause property damage, our empirical results support taste-based discrimination by Airbnb hosts against rival fans rather than statistical discrimination. In the classic expected utility framework, financial decisions result from preferences and probabilities. Our empirical results are consistent with taste-based discrimination, which operates through the preferences channel (Becker, 1957). This channel implies that hosts accept lower rental income to avoid accommodating fans of the rival football team. Alternatively, statistical discrimination (Arrow, 1973; Phelps, 1972) operates through the probability channel. This channel implies that households require higher listing prices on games against rivals as compensation for the higher likelihood of incurring damage.

¹⁷Guests also rate their host. However, hosts typically have many more ratings than guests. Furthermore, if rival fans were more likely to assign a poor review to hosts as a result of their mutual dislike, all hosts on games against rivals would be susceptible to a bad review. Thus, the competitiveness of a host relative to his peer hosts would not be adversely affected.

5 Conclusion

We study the impact of college football rivalries on the financial decisions of Airbnb hosts. We report that preferences regarding team affiliations confound the listing prices set by hosts. Specifically, listing price increases on games against rivals lead to lower rental income. This inverse relation between listing price increases and rental incomes is concentrated in financially unconstrained hosts. Thus, financial constraints appear to mitigate household preferences that otherwise induce suboptimal pricing decisions.

References

- Arrow, K., 1973, The Theory of Discrimination, in O. Ashenfelter and A. Rees (Eds.), *Discrimination in Labor Markets*, Princeton, NJ: Princeton University Press.
- Becker, G., 1957, *The economics of discrimination*. University of Chicago Press.
- Card, D., and G. Dahl, 2011, Family violence and football: The effect of unexpected emotional cues on violent behavior. *Quarterly Journal of Economics* 126, 103-143.
- Cikara, M., M. Botvinick, and S. Fiske, 2011. Us versus them: Social identity shapes neural responses to intergroup competition and harm. *Psychological Science* 22, 306-313.
- Duarte, J., S. Siegel, and L. Young, 2012, Trust and credit: The role of appearance in peer-to-peer lending. *Review of Financial Studies* 25, 2455-2484.
- Edelman, B., M. Luca, and D. Svirsky, 2016, Racial discrimination in the sharing economy: Evidence from a field experiment. Forthcoming, *American Economic Journal: Applied Economics*.
- Edmans, A., D. García, and Ø. Norli, 2007, Sports sentiment and stock returns. *Journal of Finance* 62, 1967-1998.
- Hirshleifer, D., 2001, Investor psychology and asset pricing. *Journal of Finance* 61, 1533-1597.
- Iyer, R., A. Khwaja, E. Luttmer, and K. Shue, 2015, Screening peers softly: Inferring the quality of small borrowers. *Management Science* 62, 1554-1577.
- Levi, Y., 2014, Information architecture and intertemporal choice: A randomized field experiment in the United States. Working Paper, USC.
- Mian, A., and A. Sufi, 2011, House prices, home equity-based borrowing, and the US household leverage crisis. *American Economic Review* 101, 2132-2156.
- Phelps, E., 1972, The statistical theory of racism and sexism. *American Economic Review* 62, 659-661.
- Rees, D., and K. Schnepel, 2009, College football games and crime. *Journal of Sports Economics* 10, 68-87.

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 optimal listing price based on demand that maximizes a host's rental income. In the absence of non-pecuniary preferences regarding team affiliations, the host sets the listing price to maximize

$$\text{Rental Income} = \text{Listing Price} \times \text{Probability}(\text{Occupancy} | \text{Listing Price}) . \quad (4)$$

This maximization is equivalent to maximizing

$$P \times [1 - \alpha P] \quad (5)$$

provided Occupancy is determined by the following 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 (5) 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 depending on, for example, their financial constraints. Overall, there is a one-to-one correspondence between a host's non-pecuniary preference D against rival fans and the host's listing price, P_R after accounting for the demand for accommodation represented by α .

Rental income of $\frac{1}{4\alpha} - \alpha D^2$ on games against rivals is lower than $\frac{1}{4\alpha}$ on games against non-rivals due to the host's non-pecuniary preference, which increases their listing price. 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.
Number of Units	Pre-Season ranking is obtained from the AP Poll.
Hotel Listing Premium	The number of entire units listed on Airbnb in a college town.
Financially Unconstrained	The average hotel price on a specific game minus the average hotel price across all home games in the same football season.
Financially Constrained	Units listed in a zip code whose average credit utilization score is below the median score of all zip codes in the college town.
Professional Hosts	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 are hosts that have more than one property listed on Airbnb.

Table 1: Summary Statistics

This table reports the average number of units listed on Airbnb as well as their listing price, rental income, listing premium, and occupancy rate on games against rival and non-rival teams. 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 ten 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	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	Listing Price	Rental Income	Listing 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 Listing Premium

	Hotel Listing 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)	-0.588*** (-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)	0.120 (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 Premium and Airbnb Rental Income

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 Listing 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 Listing 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 Income of Financially Unconstrained Airbnb Hosts

	Financially Unconstrained Hosts					
	Airbnb Listing Premium	Airbnb Rental Income				
Hotel Listing 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 Income of Financially Constrained Airbnb Hosts

	Financially Constrained Hosts					
	Airbnb Listing Premium	Airbnb Rental Income				
Hotel Listing 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: Stadium Incidents

This table reports the coefficients from a team fixed effects regression explaining the number of stadium incidents, defined as the sum of stadium arrests and ejections for 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 Arrests and Ejections				
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



Figure 1. 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.

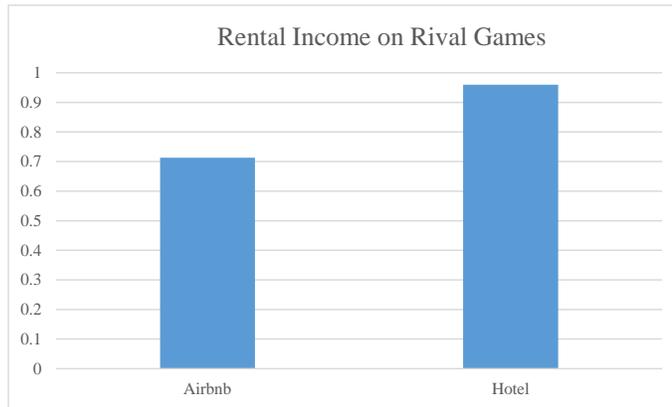


Figure 2. This figure illustrates the reduction in rental income experienced by Airbnb hosts, compared to hotels, on games against rivals. The total dollar-denominated amount of rental income on home games against top 25 ranked non-rival teams and against rival teams are computed. The amount on rival games is then divided by the amount on highly ranked non-rivals. These ratios are computed for Airbnb hosts and hotels in each college town, with their respective averages plotted above. For every dollar in rental income earned by Airbnb hosts on a highly ranked non-rival game, \$0.71 is earned on games against rivals. For comparison, hotels experience a negligible decline to \$0.96 on games against rivals.