Do Local Businesses Benefit from Sports Facilities? The Case of Major League Sports Stadiums and Arenas

Timur Abbiasov[1] and Dmitry Sedov[2]

[1]Senseable City Laboratory, MIT, Cambridge, USA
[2]Department of Economics, Northwestern University, Evanston, USA

May 8, 2022

Abstract

The construction of sports facilities, which can cost hundreds of millions of dollars, is often subsidized by public sources. In many cases, subsidies are allocated on the premise that sports venues benefit the local economy by bringing new customers to nearby businesses. We use daily foot traffic data covering major league sports facilities and the surrounding commercial establishments to pin down the size and the spatial distribution of such spillovers. By employing the fixed effects and the IV estimation strategies, we show that the spillover benefits are heterogeneous across sports and business sectors. We find that 100 baseball stadium visits generate roughly 29 visits to nearby food & accommodation businesses and about 6 visits to local retail establishments. While the estimates for football stadiums are comparable, basketball & hockey arenas do not appear to generate significant spillovers for the surrounding businesses.Using our spillover estimates, we also approximate the additional spending of sports facility visitors at nearby businesses. The median value of such spillover expenditures stands at $12.5 million. Additionally, the data on subsidies allocated to facilities in our sample allows us to also show that, in most cases, these spillover expenditures are substantially smaller than the corresponding subsidy amounts.

Keywords: Sports Facilities; Spatial Spillovers; Establishment-level Data.

JEL codes: H23, H71, R58, Z20.

E-mail addresses: abbiasov@mit.edu (T. Abbiasov), dsedov@u.northwestern.edu (D. Sedov)
Corresponding author: Timur Abbiasov, Senseable City Laboratory, MIT, 77 Massachusetts Avenue, Cambridge, MA 02139 USA

1 Introduction

Facilities hosting professional sports teams have received more than $12 billion in subsidies between 2000 and 2010[1]. The proponents of subsidies argue that stadiums and arenas catalyze local economic development (see, e.g., The Atlantic or NBC Sports), and yet, according to the 2017 survey by IGM and Whaples (2006), the economics profession generally agrees that the grounds for subsidizing professional sports are weak. As reviewed by Coates and Humphreys (2008), this consensus has to a large extent been driven by the empirical evidence based on data aggregated at a relatively crude geographic level. At the same time, recent reports by the Associated Press and CNN Business suggest that businesses located near sports facilities – which often depend on the sports fans' expenditures – have been suffering disproportionately more from the COVID-19 pandemic. This anecdotal evidence highlights that the spillover effects from professional sports stadiums and arenas may be localized and thus difficult to detect using aggregate data.

How large are these local spillover effects? How do they differ across business industries? Do stadiums and arenas attract new consumers to local businesses or simply reallocate them from more distant businesses? In this paper, we provide new empirical evidence on these issues using daily data on foot traffic to 92 sports facilities and local businesses in their surrounding areas, as well as sports events in the four major professional sports leagues in the US: MLB, NBA, NFL and NHL. The assembled dataset allows us to estimate fixed effects and instrumental variable specifications that capture the changes in visits to local businesses generated by the visits to the sports facilities. We find these spillover effects to be heterogeneous across leagues and business industries. Baseball and football stadiums generate traffic for local food & accommodation and retail trade businesses, while the corresponding effects for other sectors are substantially lower. For example, we find that 100 additional baseball (football) stadium visits lead to roughly 29 (40) additional visits to food & accommodation businesses within 3 kilometers of the stadium. These effects are highly localized with most additional visits happening within 1 kilometer of the facility. While basketball & hockey arenas appear to generate some spillovers in the 1-kilometer range as well, these additional visits get

[1] Long (2013)

compensated by a corresponding small reduction in visits to further businesses, suggesting a spatial redistribution of consumption. As a result, estimates of the overall local spillovers from basketball & hockey arenas are statistically insignificant for all of the studied business sectors.

These results are rendered possible by the rich dataset we assembled from several sources. First, we partnered with SafeGraph, a company specializing in location data. SafeGraph provided us with a database of US points of interest (including stadiums and businesses across a variety of industries) and their daily visit counts coming from mobile devices with participating apps installed. Second, we collected data from `sports-reference.com` to get information on the stadiums and arenas hosting the four major US sports leagues (MLB, NFL, NBA and NHL) including the facility names and game dates.

The assembled dataset allows us to exploit the day-to-day variation in visits to sports facilities and the corresponding changes in visits to local businesses to estimate the causal spillover effects. We use two estimation strategies – a fixed-effects appoach and an instrumental variable approach. In both approaches, the total visits count to businesses located near sports facilities plays the role of the dependent variable, while the number of facility visits is the independent variable. For the FE strategy, we introduce a facility×month×day-of-week and date fixed effects to flexibly account for facility-specific unobserved seasonality (across months and days of the week) as well as date-specific demand shocks common across stadiums and arenas (like public holidays). For the IV strategy, we use the game-day indicator as an instrument for facility visits to reduce the concerns of (1) local non-sports events attracting large crowds driving visits to both stadiums and businesses, and (2) measurement error. While game days substantially affect foot traffic to stadiums, they are set well in advance and are unlikely to be correlated with the transitory demand conditions, thus alleviating the endogeneity concerns.

The obtained results indicate that baseball and football stadiums generate spillover visits to businesses in a subset of industries, while the null of no spillover effects cannot be rejected for the basketball & hockey arenas. Based on our preferred IV specifications, baseball stadiums induce spillovers for nearby food & accommodation and retail trade businesses, with spillovers mostly concentrated in the

1-kilometer range of the stadiums. Football stadiums appear to additionally affect foot traffic to local recreation facilities and other services, with spillovers propagating to further neighborhoods up to 2.5 kilometers away from the facilities. The localized nature of the effects potentially explains the difficulty of detecting spillovers that earlier research on this topic has experienced using aggregate data.

Having estimated the local spillover effects, we perform a simple back-of-the-envelope calculation to put the magnitude of foot traffic spillovers generated by sports facilities in perspective relative to the typical subsidy amounts. We use the data on the number of games, average event attendance statistics, and an assumption regarding the spending of a typical consumer in local businesses after visiting a sports event, to approximate the additional spillover spending due to foot traffic externalities from sports facilities. Our results indicate that spillover revenues created by the sports facilities for the local businesses in most cases are quite small relative to the public costs associated with their building and financing (as reflected in the data on sports facility subsidies obtained from (Long, 2013)). We estimate that among sports facilities receiving subsidies the median difference between the spillover revenues and the subsidy costs is about 100 million dollars. However, for the top 25% baseball stadiums attracting the largest attendance, foot traffic spillovers are projected to be larger than the costs of subsidies, suggesting that the most utilized facilities may provide sizable externality benefits to the businesses operating in their vicinity. Since we can not account for all public benefits of sports facilities not internalized by stadium owners, we should highlight that this comparison is provided simply as a way to interpret the relative size of foot-traffic externalities generated by sports facilites, and is not sufficient for drawing conclusions about the overall economic viability of subsidizing sports facilities.

The rest of the paper is organized as follows. Section 2 summarizes the relevant literature. Section 3 describes our data sources. Section 4 outlines our empirical strategy and the estimation results. Section 5 provides an additional perspective on the economic magnitude of our estimates. Section 6 concludes.

2 Background and literature

In the light of the continued public financial support for the construction and operation of professional sports facilities, a sizable body of work has been developed to investigate whether such expenditures are economically justified. Most of the early evidence in the literature appears to unambiguously suggest that facilities hosting sports events have no tangible impact on the incomes and employment in their surrounding context (Coates, 2007) and that proponents of stadium and arena construction generally fail to account for the substitution of spending between different types of entertainment. Although these results have led many academics in the profession to settle on the unfavorable conclusion regarding stadium subsidies (Coates and Humphreys, 2008), several of the more recently published studies seek to find alternative ways to evaluate the benefits of sports facilities and franchises to the host cities.

The first argument, which was brought to attention by Nelson (2001) and later developed in Santo (2005), contends that the more recently built stadiums and arenas are different from the earlier ones because they are often purposefully integrated into the downtown area as opposed to being surrounded by suburban parking lots, and this difference in contexts may confound the impact found in earlier studies. While later discussions in the literature (Wassmer, 2001; Coates, 2007) have found that the central claims made by Nelson and Santo are not substantiated, these, among other works, have drawn attention to the differences present within and across locations where the stadiums choose to locate, as well as to the issue of pinning down the actual winners and losers from the stimulus provided to sports centers. Following the latter line, Coates and Humphreys (2003) examine employment statistics for 37 MSAs over the period from 1969 to 1997 and show that professional sports have a small positive effect on wages in one sector, namely, amusements and recreation, and an offsetting negative effect on both earnings and employment in eating and drinking and on employment in services and retail trade sectors.

Another commonly contested issue is that much of the early evidence comes from the data aggregated to the county or MSA level (with sports-related activities measured mostly at the annual frequency), which might not be sufficient to capture the temporal and localized effects of interest (Baade et al., 2008). In response to these concerns, Coates and Depken (2011) study the impact of sports events on the local economy using monthly sales taxes for 23 Texas towns and cities from January 1990 through December 2008 and again conclude that "an additional regular-season game has, at best, a modest effect on sales tax collections" (Coates, 2007).

Despite the noticeable shift towards research designs that allow for richer descriptions of the local business environments, only a few studies to date are based on establishment-level data. Notably, Harger et al. (2016) use 13 new facilities that opened between 2002 and 2006 in 12 MSAs as natural experiments to estimate the effect of entry on nearby business activity in terms of the number of new businesses and workers. Based on their analysis of the data from Dun and Bradstreet MarketPlace, they conclude that there's no tangible effect on new business openings and that the effect on employment is weakly positive for the new businesses in the eating and drinking industry within 1 mile from the new facilities.

Finally, the most up-to-date piece of evidence on the topic is offered in Stitzel and Rogers (2019)[2], who use annual establishment-level sales data from the National Establishment Time-Series (NETS) to estimate the impact of the relocation of the National Basketball Association's Seattle franchise to Oklahoma City on local businesses. Stitzel and Rogers confirm the role of the consumption substitution channel by showing that while food establishments located between 1 and 2 miles from the arena show an increase in sales, there is a similar fall in entertainment sales in the same distance range, while the combined impact on sales for all related industries is insignificant.

The present study builds on the recent trend to employ detailed establishment-level data to uncover the spatially heterogeneous effects of professional sports facilities on the local economy. One major departure of this paper from the existing studies is the use of daily foot traffic levels for sports facilities and nearby businesses, obtained through a commercial provider of mobile device positioning data, as the outcome of interest. Most importantly, the high geographic and temporal resolution of both treatment and outcome variables allows us to estimate the spatial externality gains caused by additional foot traffic attracted to major sports events while controlling for a rich set of location and time fixed

[2] Propheter (2020). The author uses a panel of establishments in Sacramento, CA, active from 2004 through 2018, and finds that retail establishments within a half-mile of the Golden 1 Center have survival times 53% shorter than otherwise similar retail establishments further away.

effects.

3 Data

We use several data sources to study the spillover effects generated by the sports facilities. First, we collected data from `sports-reference.com` to get information on the stadiums and arenas of the four major US professional sports leagues (MLB, NFL, NBA and NHL) including the facility names and game dates for the calendar year of 2018. Second, we partnered with SafeGraph, a company specializing in location data, which provided us with a database of points of interest – defined as places outside of home where people spend time and money – across the US, and their corresponding visit counts on the daily level. The foot traffic information gathered by SafeGraph comes from the location data of mobile devices with installed participating applications. Developers of such applications share anonymized location information with SafeGraph, which further aggregates the data to arrive at the visits counts on the point-of-interest level. From the full SafeGraph points of interest dataset we selected sports facilities that match with the `sports-reference.com` data and nearby businesses located within 3 kilometers of each stadium. Additionally, we obtained the distribution of demographic characteristics across Census Block Groups (CBGs) and Census Tracts (CTs) from the 2018 American Community Survey 5-Year data. For location-specific weather data we used Meteostat API, which provides free access to historical weather and climate data[3]. Finally, we scraped data on the capacity of sports facilities in our sample off Wikipedia and used the sports subsidies data from Long (2013) described in more detail in Section 5.

The rest of this section is organized as follows. Section 3.1 present the details on the assembled sample of sports facilities. In Section 3.2 we demonstrate the variation in facility visits and sports events over time that is essential for our empirical strategy. Section 3.3 provides information about businesses in the areas surrounging the sports facilities. Then, in Section 3.4 we provide descriptive information on attendance and visitor characteristics across sports facilities. Section 3.5 explains the construction of the final estimation sample. Section 3.6 concludes the data description part of the

[3] `https://dev.meteostat.net/api/`

paper by discussing the representativeness of our data.

3.1 Sports facilities

According to the data collected from `sports-reference.com`, a website dedicated to professional sports data, there were 30, 29, 31 and 31 arenas and stadiums used in MLB, NBA, NFL and NHL respectively between January and December 2018. We started from this set of facilities and selected points of interest from the SafeGraph dataset that are located in the same state and share a similar name[4]. We also confirmed that, according to the SafeGraph data, the selected points of interest fall into the recreation category[5], manually checked the exact location of a subset of facilities and verified that the areas of the matched points of interest are consistent with a typical sports facility area. After the match, we obtain a sample with 26, 25, 30 and 21 facilities in the baseball, basketball, football and hockey leagues respectively. It should be noted that 7 of the NHL arenas belong to Canadian teams and were thus not available to us in the SafeGraph dataset, explaining the relatively lower match rate for hockey arenas. Next, we used the SafeGraph database to select all points of interest located within 3 kilometers of each sample facility. As a result, for the facilities in our sample, we have the data on daily visit counts measured by SafeGraph, game dates for the calendar year of 2018, and a set of nearby businesses with their corresponding daily visits. The seating capacity information was scraped off Wikipedia and matched to the constructed sample by facility name.

To provide a first glance into the context in which facilities in our sample operate, Figure 1 displays every facility by sport category on the map of the United States. Expectedly, Figure 1 reveals that sports facilities are primarily scattered across the major metropolitan areas: in fact, 29 of the highest populated 30 metropolitan areas have at least one stadium within their boundary.

Table 1a provides the summary statistics for the sample sports facilities, broken down by sport category. Arenas hosting basketball & hockey games saw roughly 44 games of these sports on average in 2018. An average baseball arena hosted about 80 games in 2018, while there were only around

[4]For a subset of facilities that were recently renamed, we also matched on the former arena name, as part of the SafeGraph data was collected prior to the stadium name change

[5]Two football stadiums, Ford Field and Mercedes Benz Superdome fell instead into the retail trade category, which appears to be an artifact of a machine learning approach used to categorizing some points of interest.

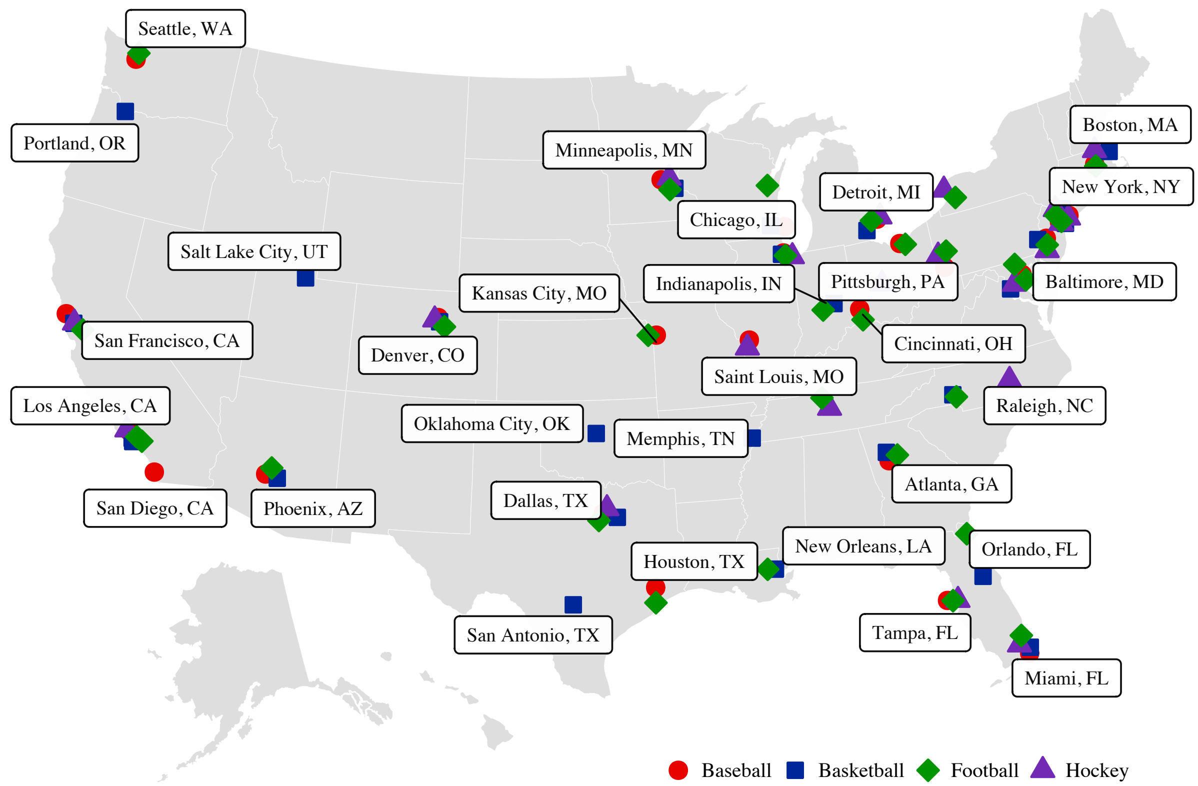

Figure 1: Sample sports facilities on the map of the United States, by sport. Small amount of noise was added to the facilities' coordinates for better clarity.

9 NFL games (including the playoff stage) played in an average football stadium. However, football stadiums are larger and more capacious compared to the other sports arenas: with an average capacity of about 71 thousand seats, they scale more than three times larger than average basketball or hockey stadiums, and about 67% larger than an average baseball arena.

3.2 Temporal variation in sports visits

Stadiums and arenas host a variety of events from sports games to music concerts to trade shows, events are spread out through the year and are different in attendance, which results in the day-to-day variation in facility visits measured by SafeGraph and displayed in the upper part of Figure 2. Although the day-to-day facility visits variation is high, as suggested by the rugged pattern of the transparent lines showing raw total daily visits, the seasonality of visits is also apparent from the bold lines depicting weekly moving averages of total visits. In fact, in line with our expectations, the weekly moving

		Means				Average daily SG visits	
Sport	Facilities	Games	Area	Capacity	Bus. nearby	No-game day	Game day
Baseball	26	79.8	43,911.1	42,196.5	2,029.7	83.3	1,258.6
Basketball	25	44.9	21,049.9	18,944.8	3,000.3	200.0	612.6
Football	30	8.6	59,743.8	70,625.7	1,316.8	159.8	3,248.5
Hockey	21	43.9	21,357.5	18,292.8	3,082.6	231.5	760.5

(a) Facility sample summary statistics. 1 facility is shared by multiple basketball teams. 1 facility is shared by multiple football teams. 10 facilities are shared by a basketball and a hockey team. Facility area measured in square meters. Businesses in a 3 km radius defined as nearby businesses.

	Mean business count within 3km of facilities				Mean yearly local business visits (thsd.)			
Industry	Baseball	Basketball	Football	Hockey	Baseball	Basketball	Football	Hockey
Admin. Services	6.7	9.7	5.7	9.3	3.5	5.0	3.7	3.3
Construction	0.3	0.3	0.3	0.3	0.1	0.1	0.2	0.1
Education	100.2	127.2	57.5	133.7	175.2	252.7	159.3	253.0
Finance	116.8	160.4	83.3	170.0	39.8	47.2	25.8	53.5
Food & Accommodation	570.7	852.6	373.2	860.4	2453.5	4070.0	1674.8	4207.2
Health	318.6	501.1	218.3	523.5	346.2	467.3	232.6	447.4
Information	43.9	58.0	28.4	61.9	66.7	110.0	48.2	111.6
Manufacturing	15.8	24.8	10.6	25.1	24.9	30.8	16.3	31.2
Other Services	291.5	411.0	173.0	418.0	275.6	317.2	147.6	323.3
Professional Services	28.3	36.8	17.2	37.8	16.3	20.9	8.8	19.0
Public Administration	5.7	8.2	3.1	8.0	11.0	11.7	7.2	10.3
Real Estate	21.0	24.6	16.1	23.2	60.9	63.8	48.1	69.2
Recreation	100.7	158.8	65.0	164.0	471.1	726.6	331.7	776.4
Retail Trade	382.2	587.3	246.1	608.2	1190.4	1647.5	719.7	1714.2
Transportation	21.8	29.7	13.7	30.7	38.5	43.7	26.5	44.5
Wholesale Trade	5.3	9.6	5.2	8.4	5.5	14.0	7.8	11.0
Utilities	0.1	0.2	0.1	0.1	0.1	0.8	0.3	0.4

(b) Summary statisitcs on businesses within 3km of facilities.

Table 1: Descriptive statistics on facilities and their vicinities.

average attendance appears to primarily follow the respective sports seasons displayed in the lower part of Figure 2 by the total daily game count timeline for each sport. At the same time, it should again be noted that sports facilities attract substantial crowds even when the sports season is off. For example, the daily total visits to basketball or hockey arenas vary between 2.5 and 5 thousand during the late summer of 2018, when there are no NBA or NHL games. A similar observation can be made for football stadiums and, to a lesser extent, for baseball.

The temporal variation in facility visits and sports events depicted in Figure 2 is key to our identification strategy. The following subsection explains how we construct our estimation sample.

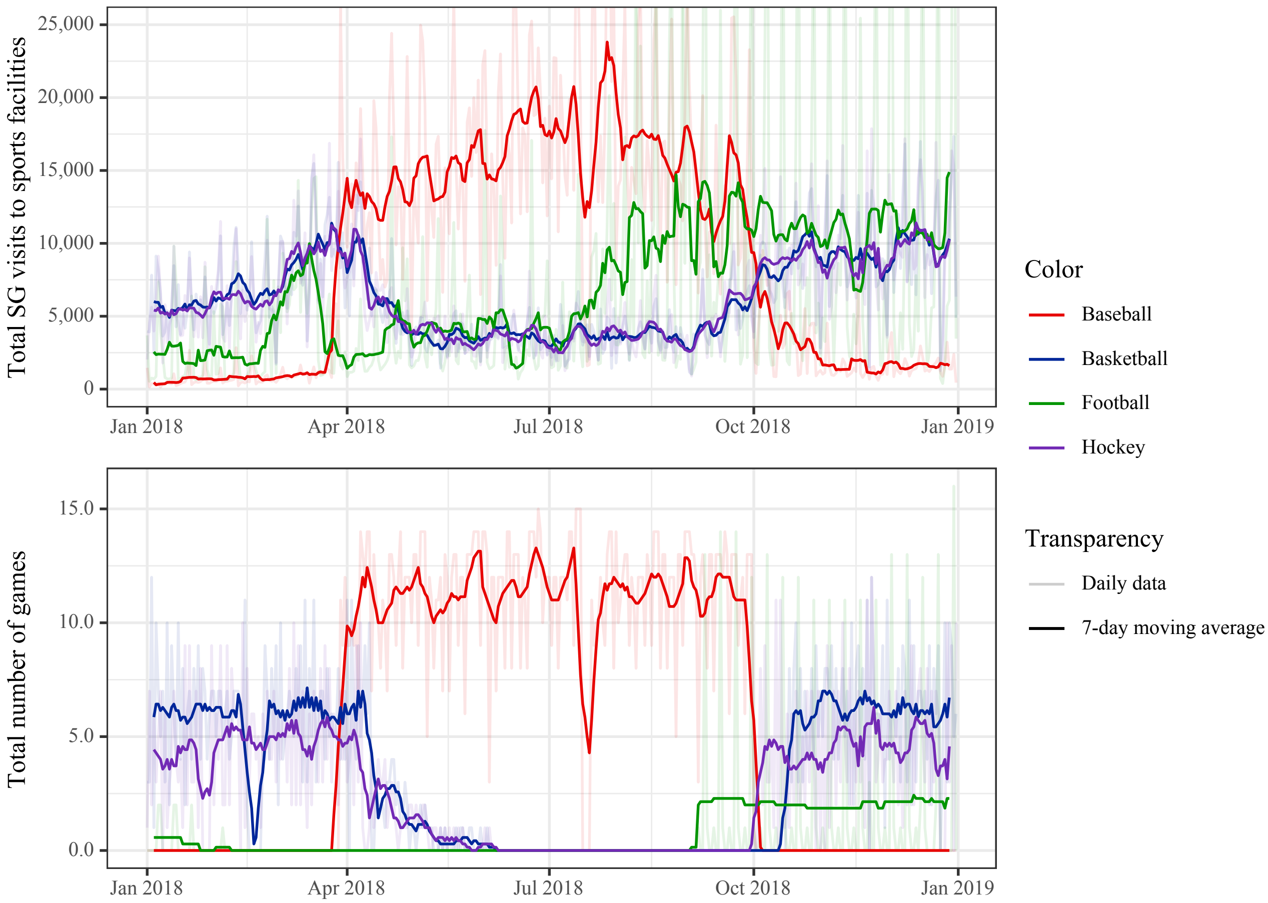

Figure 2: Game events and the corresponding visits inferred from SafeGraph.

3.3 Businesses around sports facilities

When we consider the distribution of businesses around sports facilities, we find that football stadiums are located in less busy parts of the urban landscape. As shown in Table 1a, football stadiums have the lowest mean number of businesses nearby, 1.3 thousand in the 3km radius, compared to about 3 thousand businesses operating near an average hockey or basketball facility, and 2 thousand businesses near a typical baseball arena. Additionally, Table 1b provides a sectoral breakdown of business establishments within the 3km range from the facilities. Focusing on the 2-digits NAICS classification[6], we find a substantial presence of businesses related to food & accommodation, retail trade, and health near stadiums. The same business categories are also the most visited ones, as

[6]We group 2-digit NAICS codes 31, 32 and 33 into a single Manufacturing group; 44 and 44 codes into a retail trade group; 48 and 49 codes into Transportation group; and omit the 11 and 21 codes entirely due to negligible presence in the stadium vicinities.

displayed in the right panel of Table 1b. Figure A.8 illustrates the distributional differences in business visits across categories, while Figure A.10 displays variation in average visits across days of the week by industry and sport.

While the discussion so far has distinguished between four different sports hosted by the sample facilities, in the remaining text we group together the arenas that host basketball & hockey games. There are two reasons for that. First, we see that basketball and hockey arenas are quite similar in average area, capacity, number of games per year, and composition of the surrounding businesses. Second, 10 arenas in our sample are home to both an NBA and an NHL team playing in the professional leagues. Thus grouping basketball & hockey arenas together allows us to concentrate on spillovers caused by the arenas, rather than by the respective sports.

To further explore the heterogeneity in neighborhood characteristics in which sports facilities operate, in Figure A.4 we use measures of distance from the city center, population density, and business opening hours to compare Census Tracts where facilities are located across sports. We find that basketball & hockey arenas usually locate closest to the urban cores, while football stadiums are located in less dense, more suburban areas. The other differences in observable characteristics of stadium locations appear to be small.

3.4 Attendance and visitor characteristics across sports

In terms of attendance, football events attract the largest crowds as measured by the SafeGraph visit counts. We observe more than 3,200 SafeGraph visitors on an average football game day, while basketball & hockey games attract only about 600 and 800 SafeGraph visitors respectively. At the same time, basketball & hockey arenas also display substantial traffic of roughly 200 SafeGraph visitors on no-game days, suggesting that non-sport events hosted by stadiums can generate a flow of potential consumers to the stadium neighborhood. Baseball and football stadiums, which are more popular on the game days compared to basketball & hockey arenas, are less visited when there are no sports events with around 80 and 160 visitors on an average no-game date. Figure A.7 provides an additional illustration of the differences in SafeGraph-measured facility attendance between game and non-game days, while Figure A.9 shows the variation across days of the week.

To better understand how visitors of sport facilities differ across sports, we use the breakdown of facility visit counts from each home CBGs provided by SafeGraph data. In panel (a) of Figure A.5 we compare the distributions of visitors' median traveled distances from home across sports. Similarly, Panel (b) of Figure A.5 depicts the shares of facility visitors who visit from outside the metropolitan area (CBSA) across sports. We find that visitors of basketball & hockey arenas are mostly locals, who usually travel shorter distances to the facility. Traveling from another urban area is more characteristic of football visitors: football stadiums are observed to have the highest median share of visitors from outside the CBSA, and the highest median distance traveled. We provide additional information on the characteristics of sports facility visitors in the remaining panels of Figure A.5, but find only small differences beyond the traveling patterns.

3.5 Estimation sample

Estimation samples used across the majority of empirical specifications are at the facility-day level. For each facility-day observation, we construct total visit counts to nearby businesses as measured by SafeGraph. As mentioned before, each observation also includes information on stadium visits and the indicator of whether the stadium hosted a sports event on a respective day.

Also, we focus our attention on the business categories that display a substantial presence near sports facilities according to Table 1b. Thus for estimation purposes, we only consider visits to businesses in 7 sectors: education, finance, food & accommodation, health, other services, recreation and retail trade.

3.6 Data representativeness

Before proceeding to the description of our approach to the spillover effects estimation, it is worth discussing whether our data is generally representative of sports visitors in the US. The representativeness of location intelligence data provided by SafeGraph has been discussed in prior studies related to ours. For example, Coston et al. (2021) find that in North Carolina, older and non-white individuals are less likely to be captured in the SafeGraph data. On the other hand, Brough, Freedman, and Phillips (2021) consider CBGs in King County and show that SafeGraph coverage rates are not strongly correlated with socioeconomic characteristics. Similarly, a report by Squire (2019) concludes that SafeGraph data are broadly representative across several demographic dimensions.

Focusing on CBGs located in urban areas (CBSAs) with at least one sport facility from our sample, we also investigated demographic selection in our data. Using regression analysis (Table A.1), we find that more affluent residents are slightly underrepresented in the SafeGraph data, while other demographic variables such as educational attainment, share of white population, share of female population, and share of population in age 21-39, are not significantly correlated with SafeGraph sample coverage at the level of CBGs (measured as the ratio of Safegraph users to Census population). We conclude that quantitatively the differences between SafeGraph users and Census population are fairly small, and overall demographic characteristics of Safegraph users are distributed similarly to Census. (Figure A.2[7]). Nevertheless, it is important to bear in mind the nature of the cell phone data and the potential selection in SafeGraph's user sample when interpreting the results.

Additionally, to verify the coverage of businesses captured in SafeGraph data in the sectors of interest (i.e. education, finance, food & accommodation, health, other services, recreation and retail trade), we compare the establishment counts in SafeGraph with the corresponding counts in the Census County Business Patterns dataset. Figure A.3 in the Appendix illustrates the distribution (across the counties in which stadiums are located) of the ratio of SafeGraph business count to the Census business count. For the food & accommodation and retail sectors, the most important ones in our analysis, such ratios are close to 1. The following section describes the empirical specifications that we estimate in order to understand how sports facility visits translate into additional visits to businesses in the sectors of interest.

[7]To view data representativeness from another angle, in Figure A.2 we plot the distributions of Safegraph users' home CBG demographic characteristics according to 2018 American Community Survey 5-Year Data and compare them to the distribution of residential demographics in Census population. To construct these distributions, to each SafeGraph user and to each Census individual we assign the demographic variable corresponding to their residence CBG. The units of observation are, hence, individuals or users. Overall, we find that the two distributions are fairly similar, although some moderate selection in the same direction as suggested by our regression analysis should be noted.

4 Empirical strategy and results

This section focuses on our empirical strategy for estimating foot traffic spillovers from sports facilities to the nearby businesses and on the resulting estimates. We begin by discussing the key empirical challenges and presenting the baseline estimates from a fixed effects specification in Section 4.1. To alleviate the remaining endogeneity concerns, in Section 4.2 we employ an instrumental variables strategy using sports game dates as an instrument for facility visits. Section 4.3 discusses the differences in FE and IV estimates. Next, in Section 4.4 we extend our IV specification and estimate the spatial distribution of spillovers across businesses at different distances from the sports facilities. We then provide an interpretation for the the differences of estimated spillover effects across sports in Section 4.5. Finally, Section Section 4.6 addresses the robustness of our results and the remaining limitations of our identification strategy.

4.1 Fixed effects appoach

Our first empirical approach to estimating spillover effects relies on the day-to-day variation in visits to sports facilities and the corresponding variation in visits to nearby businesses. This baseline strategy relies on introducing a rich set of fixed effects into the regression specifications, since there are several natural reasons to expect an unconditional positive correlation between arena or stadium visits and local business visits beyond the facility-generated spillovers.

First, there are differences between sports facilities in terms of accessibility for urban residents. If some facilities are more accessible to the local population, resulting in higher stadium visits, the same accessibility is likely reflected in higher visits to local businesses. Second, public demand for sports events and consumption demand for local goods or services are likely to fluctuate season to season and day to day. Observationally, this may lead to a positive relationship between facility visits and visits to nearby businesses.

Such considerations constitute a threat to the identification of the spillover effects via a naive regression without controls. In our baseline approach, we attempt to deal with this threat by estimating the facility-date level specification that includes the facility × month × day-of-the-week and date fixed effects, which allow us to control for unobserved static heterogeneity between facilities, facility-specific seasonality effects, and common time-specific shocks:

$$\text{BusinessVisits}^{i}_{ds} = \beta^{Si}\text{FacilityVisits}_{ds} + \gamma^{i}_{smw} + \delta^{Si}_{d} + \varepsilon^{i}_{ds} \tag{1}$$

In eq. (1) $\text{BusinessVisits}^{i}_{ds}$ is the sum of visits to businesses in category i near facility s of sport S on date d, $\text{FacilityVisits}_{ds}$ is the observed count of visits to the facility s itself on date d, γ^{i}_{smw} is the business category specific facility × month × day-of-the-week fixed effect, and δ^{Si}_{d} is the date fixed effect shared by businesses in category i around all facilities. We estimate eq. (1) separately for each sport category S and each 2-digits NAICS industry code i of the businesses near the sports facilities.

Columns (1), (3) and (5) of Table 2 present the resulting estimates. In that table, each coefficient comes from a separate regression estimated on a subset of data. Column groups indicate the sport, by which the data was filtered, with columns (1), (3) and (5) corresponding to baseball, basketball & hockey and football facilities respectively. In turn, table panels indicate the industry of the businesses near sports facilities that were included in the estimation sample. That is, the coefficient in column S and panel i is the estimate of β^{Si}.

For each sport, facility visits are strongly correlated with the visits to local food & accommodation businesses conditional on the employed fixed effects. An additional visit to a baseball stadium is associated with 0.3260 additional visits to nearby food & accommodation places. The corresponding coefficients for basketball & hockey and football facility stand at 0.7129 and 0.2890 respectively. The observed association is substantially lower in magnitude for the retail businesses: an additional facility visit corresponds to 0.0716 (0.1795, 0.0868) additional retail visits for the case of baseball (basketball & hockey, football). Additionally, visits to businesses in the recreation category appear to be related to basketball & hockey and football stadiums visits, the respective coefficient estimates are 0.1058 and 0.0703 respectively. The remaining fixed effects estimates in columns (1), (3) and (5) of Table 2 are either statistically insignificant or very modest in magnitude. Thus the observed associations between sports facility visits and visits to nearby businesses in other services, health, finance and education

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Food & Accommodation						
Facility visits	0.3260***	0.2929***	0.7129**	0.1963	0.2890***	0.3978***
	(0.0538)	(0.0612)	(0.2169)	(0.1153)	(0.0436)	(0.0685)
Retail Trade						
Facility visits	0.0716**	0.0648**	0.1795*	0.0097	0.0868***	0.1258***
	(0.0248)	(0.0228)	(0.0870)	(0.0316)	(0.0147)	(0.0258)
Recreation						
Facility visits	0.0307	0.0089	0.1058*	−0.0406	0.0703**	0.0663***
	(0.0179)	(0.0226)	(0.0447)	(0.0525)	(0.0228)	(0.0130)
Other Services						
Facility visits	0.0134**	0.0139*	0.0267**	0.0064	0.0217***	0.0346***
	(0.0037)	(0.0056)	(0.0084)	(0.0079)	(0.0050)	(0.0072)
Health						
Facility visits	0.0115	0.0092	0.0405*	0.0125	0.0374	0.0617*
	(0.0071)	(0.0075)	(0.0160)	(0.0172)	(0.0237)	(0.0301)
Finance						
Facility visits	0.0027	0.0015	0.0015	0.0052	0.0040**	0.0060***
	(0.0014)	(0.0013)	(0.0029)	(0.0032)	(0.0012)	(0.0013)
Education						
Facility visits	−0.0011	−0.0061	0.0120	0.0078	0.0047	0.0216
	(0.0031)	(0.0036)	(0.0062)	(0.0151)	(0.0036)	(0.0117)
Facility×Month×DoW FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
F-stat	-	182.3	-	247.5	-	177.9
1st stage coef.	-	1127.6	-	454.0	-	3122.3
Observations	9,490	9,490	13,140	13,140	10,950	10,950

Note: *p<0.05; **p<0.01; ***p<0.001

Table 2: OLS FE and IV FE estimates. Each coefficient in the table represents an estimate from a regression specification on a subset of data by facility sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and date clustering are reported in parentheses.

sectors appear to be negligible.

4.2 Instrumental variables approach

Although the fixed effects specifications partly resolve the issues complicating the estimation of the true causal spillover effect, two threats to identification remain. First, if unobserved demand shocks such as weather and local events (festivals, parades, or conventions) affect the visit counts of both sports facilities and nearby businesses, the fixed effects specifications can overestimate the causal effect of interest. Second, the measurement error due to imperfect attribution of visits to points of interest using mobile phone data may result in a downward bias[8] of the FE coefficient estimates. The actual direction of bias in our FE estimates for each sports category depends on the balance between these two countervailing forces.

To deal with these remaining threats to identification, we employ an instrumental variable strategy with sports game date indicator being an instrument for sports facility visits in addition to using the same set of fixed effects as in the previous section. In light of the identification issues outlined above, we think that our resulting IV estimates capture the spillover coefficient more accurately relative to the FE estimates. First, game dates are set well in advance. MLB released the 2018 MLB season schedule on January 9, 2018, more than 2 months before the first scheduled game. A similar gap between the schedule announcement and the season start is observed in NBA, while NHL and NFL announce the schedules even earlier, more than 3 months before the first season game. The game dates thus cannot be correlated with the unobserved demand shocks such as weather or local festivals that are not anticipated far in advance. Second, using game date indicator as an instrument should alleviate the issue of measurement error due to imperfect attribution of visits using mobile phone data. While the remainder of this section focuses specifically on the IV spillover coefficient estimates, we also refer the reader to Section 4.6 for a discussion of the remaining limitations of our IV approach.

The game date indicator is a strong predictor of facility attendance as measured by the SafeGraph sample visit counts across all of the sports groups, as indicated by the first stage estimation results

[8] Formally, this is a case of attenuation bias, but given that the true spillover effects are likely positive, this bias has a downward direction.

summarized in the lower part of Table 2. Conditional on the facility × month × day-of-the-week and date fixed effects, game dates are observed to have 1,128 visits more than non-game dates for baseball stadiums. The first stage coefficients for basketball & hockey and football facilities correspond to 454 and 3,122 additional visits on game dates respectively. The first stage F statistics are 182.3 (247.5, 177.9) for baseball (basketball & hockey, football) visits, suggesting that the game day indicator is a strong instrument.

Columns (2), (4) and (6) of Table 2 present the spillover effect estimates resulting from the instrumental variable specification with the same set of fixed effects as before. These estimates indicate that there exists a strong link between the facility and local business visits for a subset of sports (baseball and football) and industries (food & accommodation and retail).

Specifically, in line with the fixed effects specifications, for football and baseball stadiums the estimated coefficients indicate a positive spillover effect for food & accommodation and retail businesses. For the most affected food & accommodation industry, 100 additional baseball stadium visits are estimated to spillover into additional 29.3 business visits, while additional 100 football stadium visits translate into 39.8 additional business visits. Similar estimates for the retail sector stand at 6.5 and 12.5 additional visits for baseball and football stadiums respectively. As in the earlier reported fixed effect specifications, the remaining estimates of baseball stadiums spillovers to recreation, other services, health, finance and education industries are either statistically or economically insignificant[9]. In turn, football stadiums appear to affect nearby businesses across a larger variety of industries. Specifically, 100 additional football stadium visits are estimated to generate 6.63 visits to recreation facilities and 3.46 visits to other services businesses. The 0.0617 coefficient estimate of spillovers generated for health-related businesses is also marginally significant, while the finance and education visits are not substantially affected.

Spillover estimates corresponding to the basketball & hockey arenas are all rendered insignificant by the instrumental variable strategy. Also, the point estimate for the effect on food & accommodation businesses stands at 0.1963, much lower than the fixed-effects appoach estimate of 0.7129. A similar

[9] For the other services sector the coefficient estimate indicates that for 100 additional baseball stadium visits only 1.39 additional business visits are made.

note applies to the businesses in the retail sector: the point estimate in the IV specification is only 0.0097, a substantial decline from the FE estimate of 0.1795. The decrease in point estimate from the FE to the IV specification is also observed for the businesses near baseball stadiums. On the other hand, the IV estimates for football spillover effects are higher than the FE estimates. In the next section, we discuss the differences between FE and IV estimates in more detail.

4.3 Differences between FE and IV estimates

As mentioned above, we believe that the FE estimates are biased relative to the true spillovers, and the direction of this bias for each sports category depends on the balance between two countervailing forces: the endogeneity due to local events and the measurement error due to imperfect attribution of visits using mobile phone data. To the extent that our IV solves these issues, one could expect the corresponding estimates to move down or up (relative to the FE estimates) depending on which of the two issues is relatively more pronounced for a particular sport. Below we briefly reiterate on both the endogeneity and the measurement error concerns, and describe why the endogeneity issue is likely to be relatively more pronounced for basketball & hockey facilities, while being less important for football (and baseball being an in-between case). We believe that this comparative importance of the endogeneity issue explains the fact that IV estimates are higher than FE for football and lower for the other sports.

First, recall that the endogeneity concern in estimating spillover effects arises primarily due to temporal local demand shocks causing changes in both visits to sports facilities and to businesses nearby. More specifically, we think that local events (e.g. festivals, parades, or conventions) that attract additional local demand can lead to a positive bias in our FE estimates relative to the true causal spillovers. The size of this bias depends on the prevalence of local events near the facility of each sport. We think such positive bias is likely to be larger for basketball & hockey arenas compared to football stadiums (while baseball stadiums are an in-between case) since basketball & hockey arenas are more often located in downtown areas (see Figure A.4). We believe that major non-sports events are more frequent and generate larger demand shocks specifically in central city areas. Hence, if the endogeneity due to local events was the only problem of the FE strategy, we would expect IV estimates for all sports to be lower than the FE estimates, but even more so for the basketball & hockey arenas relative to other sports.

However, measurement error is also an issue for the FE approach. In our case, measurement error in the facility visits variable can arise due to the misattribution of visits using mobile phone data. Since the true spillover effects are likely positive, the attenuation bias induced by the measurement error pushes the FE estimates down relative to the actual spillovers. If the measurement error was the only issue that affected our FE approach, we would expect the IV estimates to be lower than the FE estimates across all sports categories. However, the positive bias due to endogeneity described above leads to the ambiguity of the expected change in IV compared to FE estimates.

Hence, we think that the differential results between the FE and IV strategies reflect the balance between the negative FE bias due to measurement error and the positive FE bias due to unobserved local demand shocks. While the measurement error pushes the FE estimates down relative to the true spillover estimates for all sports, the strength of the endogeneity issue determines the sign of the resulting bias relative to true spillovers. We think that the endogeneity issue due to local demand shocks is strongest for the basketball & hockey arenas (because of their more central locations) and the weakest for football stadiums (because they are the most remotely located), while baseball stadiums are an in-between case. This argument aligns with the fact that our basketball & hockey spillover estimates decrease the most as we switch from FE to IV specification. In turn, the fact that our IV estimates for football are higher than FE (unlike the other sports categories) is consistent with measurement error bias dominating the endogeneity bias in the FE estimates for football. Finally, baseball is a less clear case in terms of the FE bias direction. Baseball stadiums are less centrally located than basketball and hockey arenas, but not quite as suburban as football stadiums, which is consistent with the baseball spillover estimates being similar in FE and IV specifications.

Figure 3: Regression coefficients, estimation sample broken down by distance range around the sports facilities.

4.4 Spatial heterogeneity in spillovers

Now that we have discussed our general IV approach, we turn to exploring the spillovers heterogeneity with respect to the distance to the sports facilities. To do so, we estimate the IV specifications while breaking down the affected businesses into groups defined by the distance to the nearby facility. Specifically, we compute total visits to businesses in half-kilometer distance bins around the facilities, ranging from 0-0.5km bin to 2.5-3km bin. We then use these total visit counts as an outcome variable in separate regressions with sports facility visits as the independent variable.

Figure 3 presents the resulting estimates for the two most affected industries, food & accommodation and retail. The patterns of heterogeneity across distance ranges are similar for baseball and basketball & hockey arenas. Most of the generated spillovers affect businesses in the closest proximity to the sports facility: the coefficient estimates are significant for the 0-0.5km and 0.5-1km distance ranges in case of food & accommodation businesses, and in the 0-0.5km bin only for the retail businesses. The spillover effects of football stadiums, however, are more spread out: positive spillovers are observed across all explored distance ranges for the food & accommodation industry, and for 0-0.5 to 1.5-2km distance ranges for the retail sector. Still, the effects fade out fast, an additional football stadium visit translates into 0.11 additional food & accommodation visits in the 0-0.5km distance range and only into 0.0226 additional visits in the 2-2.5km distance range.

It is worth pointing out that Figure 3 also provides some evidence of spatial reallocation of consumption. Specifically, the negative (although insignificant) spillover estimates for the businesses located 1-2.5km away from the basketball & hockey arenas indicate that the businesses near sports facilities get new customers by stealing them from businesses located further away from the action.

We also explore the possibility of temporal reallocation of consumption. Here, we think of temporal reallocation as a consumption pattern characterized by consumers shifting business visits across days of the week. For example, a sports fan can go to a game, subsequently visit a nearby restaurant, but also refrain from going to another restaurant during the same week (a restaurant they would have visited in the absence of the sports game). We estimate regressions using the data aggregated at the weekly level[10] in an attempt to capture such behavior. If the corresponding spillover coefficient estimates were indistinguishable from zero, we would have suggestive evidence of fans visiting more businesses on game days by reducing visits on other days. However, the results presented in Table A.3 for food & accommodation and retail trade sectors do not point to reallocation: the spillover coefficients for baseball and football stadiums are still positive and significant.

While we do not find evidence of consumption reallocation across time, we believe that the spatial reallocation described above (which is characteristic of basketball & hockey arenas) is one of the reasons why the IV estimates are lowest for basketball & hockey among all of the sports. The following section provides a more in-depth discussion of spillover differences across sports.

[10]Otherwise, the specifications estimated using aggreageted data are analogous to those at the daily level.

4.5 Spillover differences across sports

Having explored the spatial heterogeneity of spillover effects, we now turn to the spillover differences across sports. Why is the football spillover estimate to food & accommodation businesses (0.3978) more than two times higher than the basketball & hockey estimate (0.1963) in our preferred IV specification? Why do baseball stadiums exhibit an intermediate level of spillovers for most of the sectors of interest? The rest of the section discusses the heterogeneity of visitor characteristics and facility locations of different sports leagues, which can, perhaps, provide some insights about these differences in spillovers.

The first important driver of the across-sports differences in spillover patterns is the heterogeneity of sports facility vistors' geographic origins. Specifically, as we show in Figure A.5 (panels a,b), visitors of basketball & hockey arenas are more likely to be locals (those traveling shorter distances to the facility). Baseball and football visitors, on the other hand, are more likely to be outsiders (those traveling longer distances, often from outside of the metropolitan area). There are two reasons why we expect the spillovers from locals and outsiders to be different. First, locals are more likely to simply relocate their visits within the city, closer to sports facility areas. This shifting pattern is consistent with the fact that, for basketball & hockey, spillover estimates are highest in the immediate area around the facility, but are lower and even negative in further away areas within the 3km range, leading to the ambiguity in the total spillover effect. Second, we think that outsiders are more likely to spend more time near the sports facilities given the fixed cost of traveling. This behavior is consistent with estimated spillovers for football being highest among sports, and more spread out, both in space and across business categories.

Second, it is worth highlighting the differences in facilities' locations across sports. As discussed before, we find that basketball & hockey arenas typically locate closer to the urban cores, where business density is high, while football stadiums are located in less dense, more suburban areas (Figure A.4). While one might expect this to result in higher spillovers for basketball & hockey relative to football or baseball, our preferred IV estimates for basketball & hockey turn out to be lower (see Table 2). We think there are two potential reasons why more centrally located facilities may actually generate lower spillovers. First, businesses located near the downtown facilities may be often visited by central city office workers, who avoid the same businesses when there is a large sports crowd, leading to a displacement effect.[11] Hence, basketball & hockey facilities may produce lower net spillovers due to stronger displacement effects occurring in more central locations. Second, while there may be fewer businesses near football and baseball stadiums, these businesses are more likely to be specifically designed to serve sports fans, and hence may be more dependent on them. This specialization on sports fans is another factor that can make the marginal impact of an additional football visit higher than that of an additional basketball & hockey visit. Although our data on individual sports visits is not detailed enough to pin down the importance of these two latter mechanisms, we think it is useful to keep these suggestive explanations in mind when interpreting our results.

4.6 Robustness and remaining limitations

To provide additional support for our main estimates from the IV specifications, we run several robustness checks. This section discusses the corresponding results. We first focus on the concern that some businesses in our sample may be affected by multiple sports facilities, and provide several additional specifications that explicitly account for the possibility of multiple treatments. We next discuss specifications with additional control variables. The section then concludes with a discussion of the remaining limitations of our empirical strategy.

First, we address the concern that some businesses can potentially be treated by multiple sports facilities, if those are located sufficiently close to each other. More specifically, SUTVA may be violated in eq. (1) if our sample includes businesses located less than 3km away from two or more sports facilities of the same sport category (or, in other words, if some facilities of the same sport are closer than 6km from each other). However, we have found that in our estimation sample, none of the businesses are within a 3km radius from more than one facility of the *same* sport. Yet, in a broader sense, if some businesses are located in close proximity to facilities of *multiple* sport categories, not accounting for visits to facilities of other sports in eq. (1) might cause an omitted variable bias. In

[11] This argument came to our attention from the helpful comments offered by the referee from the Jouran of Urban Economics.

fact, 55 facilities across sports in our sample have at least one neighboring facility less than 6km away. To address this issue, we rerun our main specification with total visit counts to other nearby sports facilities (i.e. those within 6km of the "main" facility) added as a control with the resulting spillover coefficient estimates reported in Table A.7. To alleviate concerns about endogeneity, we also estimate a specification with total games in nearby facilities as an instrument for the new variable – similar to our approach for the main regressor. Overall, the comparison of our main results (Table 2) and Table A.7 indicates that introducing visits to nearby facilities to our baseline specifications does not substantially alter our results. After taking visits to other nearby facilities into account, all of the estimates remain similar to the estimates from the baseline model.

Alternatively, the possibility of multiple treatments may be addressed by estimating the effects of sports facility visits on business visits at the level of individual businesses, with treatment intensity measured as the total number of visits to all sports facilities in the vicinity of each establishment (similar to Pennington (2021), for example). Hence, in Table A.8 we report estimates for the following regression specification:

$$\text{BusinessVisits}^i_{jd} = \sum_{S \in \text{Sports}} \beta^i_S \text{SumFacilityVisits}^S_{jd} + \gamma^i_{mwc} + \mu^i_j + \delta^i_d + \varepsilon^i_{jd} \tag{2}$$

In this case, $\text{BusinessVisits}^i_{jd}$ corresponds to visits to business j (in category i) on date d, $\text{SumFacilityVisits}^S_{jd}$ is the sum of visits to all sports facilities of sport S that are less than 3km away from j on date d, γ^i_{mwc} is the month × day of week × census tract fixed effect, μ^i_j is the establishment-level fixed effect, and δ^i_d is the date fixed effect. Similar to our main IV approach, to alleviate the concerns about endogeneity we instrument total sports visits with the total number of games held at the corresponding facilities less than 3km away from j. As shown in Table A.8, the results of estimating Equation 2 generally confirm our main findings. For food & accommodation and retail businesses, football and baseball visits exhibit positive and significant spillovers, while the estimates for basketball and hockey are insignificant. Football visits produce the largest spillovers and impact a wider set of business categories including recreation, other services and health establishments. Table A.8 also reveals negative, albeit small, effects of basketball and hockey arenas on visits to health, finance and education businesses, pointing to the possibility of displacement effects occurring in downtown areas, where basketball and hockey arenas locate more often (as discussed in the previous section). Finally, we run a specification similar to (2) that allows for spatial heterogeneity of spillovers across a range of distances from the facility. The results shown in Table A.9 are in line with our main results.

Second, we show that our main results are robust to accounting for playoff games and local weather. For playoffs, game dates are usually set closer to the actual event. This potentially increases the ability of the sports organizers to adjust game schedules to local demand shocks, and presents a threat to our identification strategy. Table A.5 reports our estimates of eq. (1) with local weather conditions (daily temperature and precipitation) and playoff dates added as controls[12]. As evident from the comparison with our baseline results (Table 2), accounting for weather and playoff status does not substantially alter our estimates, and all conclusions remain the same. We also show that controlling for facility-specific within-week trends and excluding national holidays on top of the other FE does not substantially alter our results (Table A.11). It is worth pointing out, however, that in the latter case the relative magnitudes of baseball and football spillovers switch places relative to our main specification, suggesting that the point estimate difference between football and baseball found in our baseline specification is small relative to the uncertainty of the estimates.

To conclude this section, we want to highlight some important considerations on our main IV strategy and its limitations. As game dates in most cases are set far in advance, our instrument is necessarily orthogonal to local demand shocks that are not anticipated at least a few months before the game, such as within-month variation in weather or small local festivals and celebrations. Second, the co-variation in sports and business visits due to national holidays is picked up by the date fixed effects we use across all of our specifications. Finally, the facility-specific month-day of week fixed effects factor out seasonal variation in local demand such as seasonal changes in fans activity. In general, these arguments are supported by the robustness checks described in this section. However, local short-term shocks anticipated by sports leagues long before the actual game dates, such as festivals or parades that

[12]For football, all games occurring in the period between Jan 6, 2018 and Feb 4, 2018 are marked as playoff games. Correspondingly, for basketball & hockey we use the period from Apr 11, 2018 to June 8, 2018 to mark playoff games. For baseball, the postseason began on Oct 2, 2018 and our data on baseball games do not feature any games after that date.

attract large enough crowds, remain a potential concern. Since game dates can be potentially affected by the scheduling of such big events, this can, in principle, confound our identification strategy, which remains a limitation of our approach.

5 Putting the spillover estimates in perspective

Now that we have estimated and discussed the local spillover effect coefficients, in this section, we provide an additional perspective on the overall magnitude of foot traffic spillover benefits generated by sports facilities for nearby businesses. Using a simple back-of-the-envelope calculation, we approximate the incremental spending at businesses close to each facility in our sample due to foot traffic spillovers. To put these additional revenues into context, we then compare them to the public subsidies these facilities received. Since, in this latter exercise, we want to compare positive foot traffic externalities from sports facilities to public costs, we focus only on the subsidized portion of facilities' costs, and internalized prices such as ticket sales and rental fees are left out from our calculations. Moreover, we should highlight that there are other mechanisms through which sports facilities can benefit the local community, e.g. by creating jobs and new business opportunities, or through amenity effects. We thus do not aim to perform a full cost-benefit analysis.

As a preview, we estimate that a median sports facility generates roughly \$12.5M of additional revenues for the local food & accommodation and retail businesses each year. However, we find that only the top 25% of baseball stadiums may generate enough foot traffic spillovers alone to offset total public costs. We now turn to describing the details of the spillover expenditures approximation and the comparison to subsidies.

First, using the data provided in Long (2013), for every facility in our dataset that was commissioned prior to 2010, we obtained the records of public costs allocated to cover the construction or operation of these facilities. Total public cost is the main variable of interest and corresponds to the net present value at 2010 of public capital, net annual ongoing public costs, and foregone property taxes associated with financing and building each facility. The median value of sports facility subsidy in our sample is

\$240M (measured in 2010 dollars), also see Figure A.6 for the distribution of the subsidy amounts.

Correspondingly, for each facility that received a subsidy, we compute the spillover revenues at the local food & accommodation and retail businesses as follows:

$$\text{Est.AnnualSpilloverRevenues}_s = \text{Est.Attendance}_s \times (\text{DollarPerVisit}_{F\&A} + \text{DollarPerVisit}_{Retail})$$

where

$$\text{DollarPerVisit}_i = \hat{\beta}^{Si} \times E$$

is the approximated spending per additional customer, $\hat{\beta}^{Si}$ is the number of additional visits to the businesses in category i for each stadium or arena visitor during game dates (using the results from the first row in Table 2 for each sport category), and E corresponds to the average amount of dollars each generated customer spends on the services of the surrounding businesses. For our baseline, we use the value of $E = \$15$ and explore the consequences of the more generous \$20 assumption in the Appendix. The total annual attendance is approximated using the information on each facility's capacity, the number of games in 2018, and the average share of visitors who attend the facility on the days without sports events:[13]

$$\begin{aligned}
\text{Est.Attendance}_s &= \text{Est.Attendance}_s^{\textit{game days}} + \text{Est.Attendance}_s^{\textit{other days}} \\
\text{Est.Attendance}_s^{\textit{game days}} &= \text{TotalGames}_s \times \text{VisitorCapacity}_s \times f_s \\
\text{Est.Attendance}_s^{\textit{other days}} &= \text{ShareVisitors}_s^{\textit{other days}} \times \text{Est.Attendance}_s^{\textit{game days}}
\end{aligned}$$

In the above, f_s denotes the average facility capacity load, which we define separately for each sport category based on the data from Wikipedia.

Based on our calculations presented in Table 3, a median arena receiving subsidies generates roughly \$12.5M of annual spillover revenues to the businesses in the food & accommodation and retail

[13] For each facility, $\text{ShareVisitors}_s^{\textit{other days}}$ is computed as the facility's average attendance on no-game days divided by the average attendance game dates, with both estimates obtained from SafeGraph daily visit counts.

	Mean	Q25	Med.	Q75
All facilities receiving subsidies				
Annual attendance (m)	2.23	1.69	2.04	2.77
Annual spillover revenues from foot traffic ($M)	11.73	6.96	12.55	15.48
Spillover revenues net of public costs ($M)	-113.37	-169.47	-104.15	-40.95
Public costs at 2010 ($M)	274.80	190.00	240.00	329.00
Baseball				
Annual attendance (m)	2.84	2.56	2.84	2.98
Annual spillover revenues from foot traffic ($M)	15.23	13.76	15.23	16.00
Spillover revenues net of public costs ($M)	-75.19	-154.45	-67.20	12.23
Public costs at 2010 ($M)	284.83	195.00	260.00	374.00
Football				
Annual attendance (m)	1.66	1.30	1.62	1.98
Annual spillover revenues from foot traffic ($M)	13.02	10.21	12.75	15.58
Spillover revenues net of public costs ($M)	-156.12	-217.79	-100.52	-53.53
Public costs at 2010 ($M)	335.33	240.00	285.00	384.00
Hockey & Basketball				
Annual attendance (m)	2.14	1.78	1.98	2.22
Annual spillover revenues from foot traffic ($M)	6.60	5.49	6.11	6.86
Spillover revenues net of public costs ($M)	-112.44	-150.56	-111.59	-70.76
Public costs at 2010 ($M)	203.29	160.00	198.00	235.00

Table 3: Public Costs and Estimated Spillover Revenues for Stadiums Receiving Public Funds. Assuming an average of value of 15$ per generated customer. To maintain consistency in our calculations, in computing spillover revenues net of public costs, we assume an average lease duration of 30 years and an interest rate of 6 percent following Long (2013).

categories. Notably, baseball stadiums appear to exhibit the most pronounced spillovers with roughly $15.2M of generated foot traffic spillovers in the median case, followed by football stadiums that generate about $12.7M. A median hockey or basketball arena, on the other hand, generates only $6.1M of spillover spending from foot traffic, which is in line with the fact that in our baseline specification we could not reject the null hypothesis of no spillovers for the surrounding businesses for this sports category.

To provide an additional perspective on the foot-traffic externalities, we also compare the spillover revenues to public costs. More specifically, for each facility, we also computed *Spillover revenues net of public costs*, which denotes the difference between the foot-traffic revenue spillovers and the estimated net public costs documented in Long (2013) over the projected facility's lifespan. To maintain consistency in our calculations, we assume an average lease duration of 30 years and an interest rate of 6 percent following Long (2013).

As follows from the results in Table 3, in the vast majority of cases, the values of allocated subsidies are substantially larger than the additiona revenues from foot traffic spillovers to businesses. Assuming that the average per-consumer spending is $15, we estimate that a median facility subsidy leads to negative revenue spillovers net of public costs of $104M. Notably, baseball is the only sport category for which we find the upper quartile of spillovers net of public costs to be positive at about $12.2M. In Table A.12 in the Appendix, we allow for a higher per-customer spending value of $20 and obtain qualitatively similar results. We find that the upper quartile spillover revenues net of public costs for hockey and basketball remain negative. For football, stadiums in the upper quartile generate small positive net difference of $25M. Still, baseball stadiums in the top quartile generate the largest foot traffic externalities net of public costs of $81M.[14]

We think that our results reveal a number of important patterns. First of all, for the vast majority of sports facilities, we find a significant gap between the magnitudes of the subsidies and the additional revenues from foot traffic spillovers that we estimate from the data. We interpret this as suggesting that spillover foot traffic alone in most cases is not sufficient to offset the public costs of sports subsidies. When comparing the results across sports, we can see that spending spillovers from foot traffic reflect both the sport-specific strength of spillover effects and the annual number of visitors for each sports category. For basketball & hockey arenas our baseline spillover estimates are not statistically significant and, based on the point estimates, we find that they generate the smallest median revenues for the surrounding businesses. On the other hand, we find that baseball stadiums appear to generate the largest spillover spending. The main reason is that baseball games attract twice as many people as basketball & hockey games, and happen ten times more often than football games. While our baseline spillover estimates for football are slightly higher than for baseball, the median annual attendance of

[14] As another robustness check, Table A.13 in the Appendix replicates Table 3 but with the spillover estimates re-scaled to account for the fact that the total number of businesses in each category covered by SafeGraph can differ systematically from the actual number of businesses in the same category as measured by the Census County Business Patterns data (recall the discussion in Section 3 and the corresponding Figure A.3 in the Appendix). The results obtained this way remain very similar to the baseline.

a football stadium is 43% smaller. As a result, the most utilized baseball stadiums generate more additional spending from the foot traffic spillovers than facilities of other sports. The policy takeaway here is rather simple: chances that a community can economically benefit from a sports facility via the spillover channel are higher if the facility hosts a popular team and is visited frequently enough.

6 Conclusion

Historically, local and state governments in the US have allocated substantial amounts of public funds to support the construction and maintenance of sports facilities. At least in part, these public investments were motivated by the positive spillover effects stadiums and arenas can generate for the local businesses. However, the lack of detailed data has rendered difficult the task of actually estimating these local spillovers. In this paper, we use daily foot-traffic data for major league sports facilities and their surrounding businesses to estimate such spillover effects. We also explore the heterogeneity of spillover benefits across sports, business sectors, and distance from sports facilities.

Our results indicate positive spillovers from baseball and football stadiums that are concentrated largely in entertainment-related businesses in the closest proximity to the facilities. On the other hand, we find that the spillover estimates for basketball & hockey arenas are not statistically significant in our preferred specifications. While the positive spillover effects of basketball & hockey arenas can be detected in the inner-most area around the facility, they come at the cost of reduced visits to businesses located further away, so the net effect is ambiguous.

To put our spillovers estimates into perspective, we perform a simple back-of-the-envelope calculation and approximate the additional spending from spillover foot traffic at businesses in the vicinity of sports facilities. We find that a median facility generates approximately $12.5 million of additional expenditures per year. At the same time, we find that these additional expenditures are, in most cases, substantially smaller than the value of the subsidies that sports facilities receive over their typical lifetimes. Hence, we conclude that, in the majority of cases, foot traffic externalities alone are not large enough to offset the public costs of sports subsidies.

Acknowledgements

We thank Anna Algina, Donald Davis, Gaston Illanes, Riccardo Marchingiglio, Robert Porter, Mar Reguant, Molly Schnell, Dmitry Sorokin and seminar participants at Northwestern University for helpful comments and discussions. Special thanks to Jonathan Wolf and the SafeGraph team for access to data, clarifications and thoughtful remarks.

References

Baade, R. A., R. Baumann, and V. A. Matheson (2008). Selling the game: Estimating the economic impact of professional sports through taxable sales. *Southern Economic Journal 74*(3), 794–810.

Brough, R., M. Freedman, and D. C. Phillips (2021). Understanding socioeconomic disparities in travel behavior during the covid-19 pandemic. *Journal of Regional Science 61*(4), 753–774.

Chauncey Alcorn, CNN Business (2020, August). College towns face a potentially devastating economic blow this fall: No football. Accessed: 2020-09-23. Archived at https://web.archive.org/web/20200821174709/https://edition.cnn.com/2020/08/14/business/college-football-economic-impact/index.html.

Coates, D. (2007). Stadiums and arenas: Economic development or economic redistribution? *Contemporary Economic Policy 25*(4), 565–577.

Coates, D. and C. A. Depken (2011). Mega-events: Is Baylor Football to Waco what the Super Bowl is to Houston? *Journal of Sports Economics 12*(6), 599–620.

Coates, D. and B. Humphreys (2003). The effect of professional sports on earnings and employment in the services and retail sectors in US cities. *Regional Science and Urban Economics 33*(2), 175–198.

Coates, D. and B. R. Humphreys (2008). Do economists reach a conclusion on subsidies for sports franchises, stadiums, and mega-events? *Econ Journal Watch 5*(3), 294–315.

Coston, A., N. Guha, D. Ouyang, L. Lu, A. Chouldechova, and D. E. Ho (2021). Leveraging administrative data for bias audits: Assessing disparate coverage with mobility data for covid-19 policy. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pp. 173–184.

Harger, K., B. R. Humphreys, and A. Ross (2016). Do new sports facilities attract new businesses? *Journal of Sports Economics 17*(5), 483–500.

Long, J. (2013). *Public/private Partnerships for Major League Sports Facilities*. Routledge Research in Sport Business and Management. Routledge.

Mark Newman, MLB (2018, January). MLB releases game times for 2018 schedule. Accessed: 2020-09-10. Archived at https://web.archive.org/web/20200923112119/https://www.mlb.com/news/game-times-announced-for-2018-mlb-season-c264451646.

Mike Florio, NBC Sports (2015, April). Carson stadium would generate millions of dollars, create thousands of jobs. Accessed: 2020-09-01. Archived at https://web.archive.org/web/20201030200739/https://profootballtalk.nbcsports.com/2015/04/02/carson-stadium-would-generate-millions-of-dollars-create-thousands-of-jobs/.

Nelson, A. C. (2001). Prosperity or blight? A question of major league stadia locations. *Economic Development Quarterly 15*(3), 255–265.

NHL (2017, June). 2017-18 NHL schedule released. Accessed: 2020-09-10. Archived at https://web.archive.org/web/20190912175830/https://www.nhl.com/news/2017-18-nhl-schedule-for-regular-season/c-290045466.

Pennington, K. (2021). Does building new housing cause displacement?: The supply and demand effects of construction in san francisco. *The Supply and Demand Effects of Construction in San Francisco (June 15, 2021)*.

Propheter, G. (2020). Does proximity to a new sports facility affect existing businesses' survival time? *Journal of Sports Economics 21*(5), 451–476.

R.J. White, CBS Sports (2017, April). 2017 NFL schedule release: Here's the time and date for all 256 games. Accessed: 2020-09-10. Archived at https://web.archive.org/web/20190112062956/https://www.cbssports.com/nfl/news/2017-nfl-schedule-release-heres-the-time-and-date-for-all-256-games/.

Santo, C. (2005). The economic impact of sports stadiums: Recasting the analysis in context. *Journal of Urban Affairs 27*(2), 177–192.

Sekou Smith, NBA (2017, August). 2017-18 NHL schedule released. Accessed: 2020-09-10. Archived at https://web.archive.org/web/20190725033149/https://www.nba.com/article/2017/08/14/complete-nba-schedule-early-start-recovery-time.

Squire, R. F. (2019). What about bias in the SafeGraph dataset? Safegraph.com. Accessed: 2022-04-19. Archived at http://web.archive.org/web/20220315052916/https://www.safegraph.com/blog/what-about-bias-in-the-safegraph-dataset.

Stitzel, B. and C. L. Rogers (2019). NBA sweet spots: Distance-based impacts on establishment-level sales. *Growth and Change 50*(1), 335–351.

The Atlantic (2012, September). If you build it, they might not come: The risky economics of sports stadiums. Accessed: 2020-09-01. Archived at https://web.archive.org/web/20200930222336/https://www.theatlantic.com/business/archive/2012/09/if-you-build-it-they-might-not-come-the-risky-economics-of-sports-stadiums/260900/.

The Initiative on Global Markets (2017). Sports stadiums. Accessed: 2020-09-23. Archived at https://web.archive.org/web/20200701235444/https://www.igmchicago.org/surveys/sports-stadiums/.

Wassmer, R. W. (2001). Metropolitan prosperity from major league sports in the CBD: Stadia locations or just strength of the central city? A reply to Arthur C. Nelson. *Economic Development Quarterly 15*(3), 266–271.

Whaples, R. (2006). Do economists agree on anything? Yes! *The Economists' Voice 3*(9), 1–6.

Will Graves, The Associated Press (2020, September). As MLB plays on, the businesses it feeds fight for survival. Accessed: 2020-09-23. Archived at https://web.archive.org/web/20200919095601/https://apnews.com/141ea2b8c6fe5bc33fdd941dea868716.

Appendix

A Tables and Figures

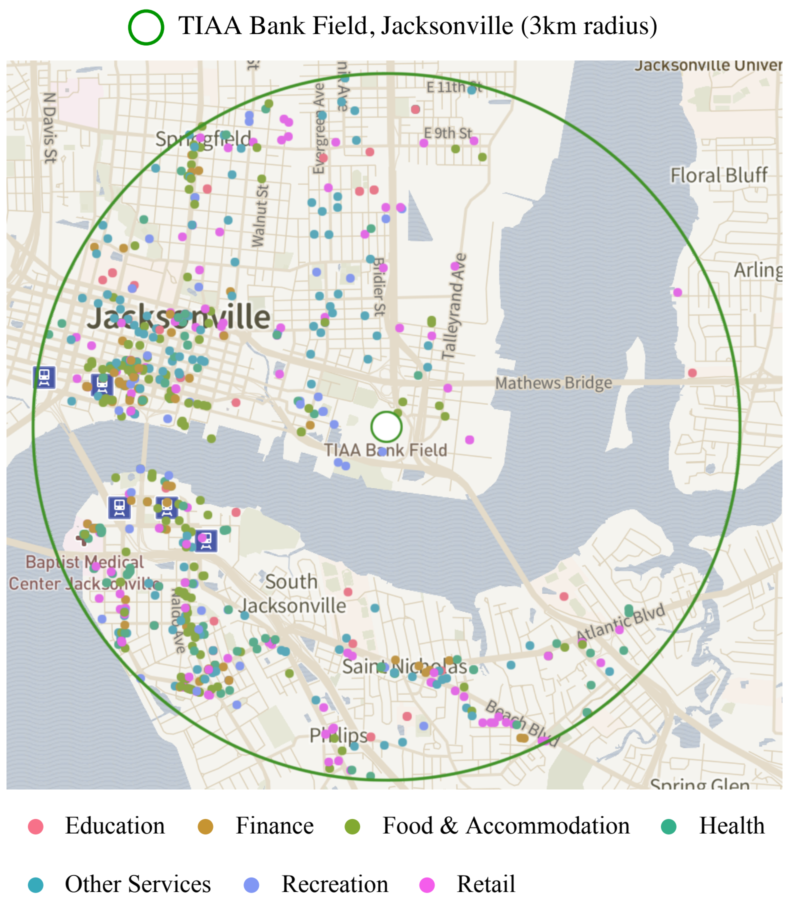

Figure A.1: Establishments by category, in the 3km radius around TIAA Bank Field in Jacksonville, Florida.

	Dependent variable:				
	Safegraph Census Coverage % (p.p)				
	(1)	(2)	(3)	(4)	(5)
Median HH Income ($k)	-0.041^{***}				
	(0.003)				
% Pop. Bachelor And Higher (pp)		-0.085			
		(0.062)			
% Pop. White (pp)			-0.032		
			(0.039)		
% Pop. Age 21-39 (pp)				0.559^{*}	
				(0.322)	
% Pop. Female (pp)					0.595
					(0.926)
Observations	97,476	100,488	100,498	100,498	100,498
R^2	0.007	0.0001	0.00001	0.001	0.0002
Adjusted R^2	0.007	0.00005	0.00000	0.001	0.0002
Residual Std. Error	19.946	259.590	262.801	262.726	262.775
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table A.1: Safegraph Sample Coverage across CBGs. The sample consists of all CBGs located in core-based statistical areas (CBSAs) with at least one sports facility in our dataset. Each CBG is assigned demographic variables using 2018 American Community Survey 5-Year Data.

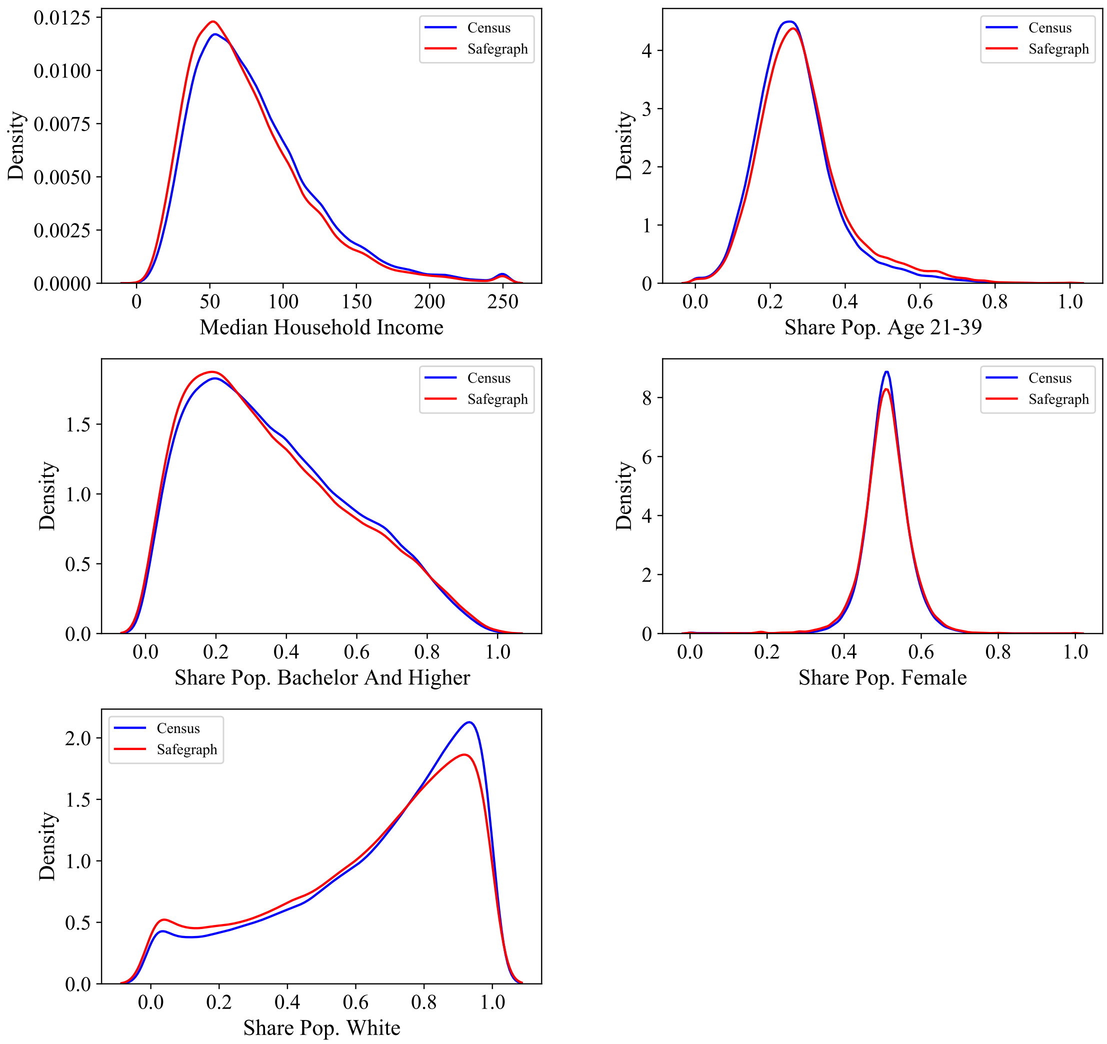

Figure A.2: Distribution of key demographic variables in SafeGraph and Census samples. The sample consists of census population and Safegraph users located in core-based statistical areas (CBSAs) with at least one sports facility in our dataset. The densities correspond to distributions of individual's home CBG demographic characteristics according to 2018 American Community Survey 5-Year Data. To construct these distributions, to each SafeGraph user and to each Census individual we assign the demographic variable corresponding to their residence CBG. The units of observation are individuals or users.

	Dependent varible: business visits					
	Distance range					
	0-0.5 km	0.5-1 km	1-1.5 km	1.5-2 km	2-2.5 km	2.5-3 km
Football						
FoodAccommodation	0.1100***	0.1436***	0.0619**	0.0386**	0.0226*	0.0150**
	(0.0243)	(0.0266)	(0.0189)	(0.0128)	(0.0101)	(0.0053)
Retail	0.0380**	0.0423***	0.0205**	0.0105**	−0.0017	0.0154
	(0.0124)	(0.0066)	(0.0059)	(0.0031)	(0.0039)	(0.0077)
F-stat	180.9	180.9	180.9	180.9	180.9	180.9
Obs.	10,950	10,950	10,950	10,950	10,950	10,950
Baseball						
FoodAccommodation	0.2208***	0.0395*	0.0195*	0.0140	−0.0059	0.0051
	(0.0361)	(0.0149)	(0.0090)	(0.0114)	(0.0089)	(0.0077)
Retail	0.0526**	0.0085	0.0040	0.0031	−0.0018	−0.0016
	(0.0174)	(0.0049)	(0.0037)	(0.0047)	(0.0045)	(0.0036)
F-stat	190.6	190.6	190.6	190.6	190.6	190.6
Obs.	9,490	9,490	9,490	9,490	9,490	9,490
Basketball & Hockey						
FoodAccommodation	0.2473***	0.0604*	−0.0021	−0.0386	−0.0584	−0.0124
	(0.0420)	(0.0238)	(0.0342)	(0.0370)	(0.0370)	(0.0192)
Retail	0.0605***	0.0016	−0.0118	−0.0065	−0.0377	0.0037
	(0.0157)	(0.0119)	(0.0131)	(0.0078)	(0.0294)	(0.0100)
F-stat	264.5	264.5	264.5	264.5	264.5	264.5
Obs.	13,140	13,140	13,140	13,140	13,140	13,140
Note:				*p<0.05; **p<0.01; ***p<0.001		

Table A.2: IV FE estimates. Each coefficient in the table represents an estimate from a regression specification on a subset of data by distance range (columns), facility sport (panels) and business industry (rows). All specifications include facility-month-dayofweek and date fixed effects. Standard errors robust to heteroskedasticity and facility clustering are reported in parentheses.

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
Food & Accommodation						
Facility visits	0.2761***	0.2703***	0.8602*	−0.0514	0.3619***	0.6040**
	(0.0611)	(0.0661)	(0.3418)	(0.4734)	(0.0767)	(0.1746)
Retail Trade						
Facility visits	0.0409	0.0601**	0.1350	−0.2622	0.0924**	0.1648*
	(0.0334)	(0.0199)	(0.1812)	(0.2040)	(0.0284)	(0.0629)
Facility×Month FE	✓	✓	✓	✓	✓	✓
Week FE	✓	✓	✓	✓	✓	✓
F-stat	-	172.3	-	101.3	-	187.4
1st stage coef.	-	1136.8	-	379.5	-	3213.8
Observations	1,352	1,352	1,872	1,872	1,560	1,560
Note:				*p<0.05; **p<0.01; ***p<0.001		

Table A.3: OLS FE and IV FE estimates with the weekly level of visits aggregation. The number of games during a given week serves as the instrument in the IV specification. Each coefficient in the table represents an estimate from a regression specification on a subset of data by facility sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and week clustering are reported in parentheses.

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
Food & Accommodation						
Facility visits	0.3299***	0.2933***	0.8282**	0.2458**	0.2812***	0.3916***
	(0.0491)	(0.0612)	(0.2831)	(0.0894)	(0.0427)	(0.0705)
Retail Trade						
Facility visits	0.0821***	0.0645**	0.2153*	0.0304	0.0856***	0.1249***
	(0.0215)	(0.0228)	(0.0999)	(0.0279)	(0.0148)	(0.0262)
Recreation						
Facility visits	0.0318	0.0090	0.1280*	−0.0473	0.0683**	0.0629***
	(0.0189)	(0.0226)	(0.0580)	(0.0561)	(0.0236)	(0.0133)
Other Services						
Facility visits	0.0127**	0.0140*	0.0318**	0.0097	0.0206***	0.0326***
	(0.0039)	(0.0056)	(0.0107)	(0.0081)	(0.0046)	(0.0066)
Health						
Facility visits	0.0118	0.0092	0.0538**	0.0200	0.0353	0.0622
	(0.0068)	(0.0076)	(0.0196)	(0.0173)	(0.0225)	(0.0312)
Finance						
Facility visits	0.0026	0.0015	0.0019	0.0060	0.0040**	0.0059***
	(0.0014)	(0.0013)	(0.0038)	(0.0036)	(0.0012)	(0.0014)
Education						
Facility visits	−0.0015	−0.0060	0.0182*	0.0147	0.0049	0.0206
	(0.0029)	(0.0036)	(0.0074)	(0.0155)	(0.0038)	(0.0112)
Facility×Month×DoW FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
F-stat	-	182.2	-	255.9	-	173.9
1st stage coef.	-	1127.4	-	417.5	-	3131.1
Observations	8,684	8,684	9,864	9,864	9,180	9,180
Note:						*p<0.05; **p<0.01; ***p<0.001

Table A.4: OLS FE and IV FE estimates without playoff months (Apr-Jun excluded for basketball and hockey, Oct excluded for baseball, Jan-Feb excluded for football). Each coefficient in the table represents an estimate from a regression specification on a subset of data by facility sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and date clustering are reported in parentheses.

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
Food & Accommodation						
Facility visits	0.3160***	0.2856***	0.7215**	0.1815	0.2872***	0.3953***
	(0.0552)	(0.0612)	(0.2192)	(0.1203)	(0.0435)	(0.0684)
Retail Trade						
Facility visits	0.0698*	0.0618*	0.1834*	0.0038	0.0857***	0.1241***
	(0.0269)	(0.0235)	(0.0883)	(0.0338)	(0.0144)	(0.0256)
Recreation						
Facility visits	0.0312	0.0086	0.1090*	−0.0446	0.0697**	0.0656***
	(0.0184)	(0.0226)	(0.0451)	(0.0554)	(0.0230)	(0.0128)
Other Services						
Facility visits	0.0133**	0.0134*	0.0269**	0.0051	0.0215***	0.0344***
	(0.0039)	(0.0058)	(0.0084)	(0.0080)	(0.0050)	(0.0071)
Health						
Facility visits	0.0096	0.0083	0.0414*	0.0116	0.0373	0.0615
	(0.0066)	(0.0075)	(0.0162)	(0.0173)	(0.0238)	(0.0302)
Finance						
Facility visits	0.0023	0.0014	0.0011	0.0047	0.0040**	0.0059***
	(0.0013)	(0.0012)	(0.0029)	(0.0033)	(0.0012)	(0.0013)
Education						
Facility visits	−0.0017	−0.0065	0.0130*	0.0090	0.0045	0.0213
	(0.0031)	(0.0036)	(0.0063)	(0.0158)	(0.0036)	(0.0117)
Facility×Month×DoW FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
F-stat	-	63.8	-	84.0	-	59.4
1st stage coef.	-	1117.6	-	448.3	-	3120.5
Observations	9,355	9,355	12,978	12,978	10,947	10,947
Note:						*p<0.05; **p<0.01; ***p<0.001

Table A.5: Robustness checks for the main OLS FE and IV FE estimates: with local weather variables added as controls. Each coefficient in the table represents an estimate from a regression specification on a subset of data by facility sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and date clustering are reported in parentheses.

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
Food & Accommodation						
Facility visits	0.3160***	0.2856***	0.7644**	0.1994	0.2833***	0.3893***
	(0.0552)	(0.0612)	(0.2367)	(0.1092)	(0.0433)	(0.0705)
Retail Trade						
Facility visits	0.0698*	0.0618*	0.2015*	0.0181	0.0847***	0.1233***
	(0.0269)	(0.0235)	(0.0931)	(0.0319)	(0.0145)	(0.0261)
Recreation						
Facility visits	0.0312	0.0086	0.1139*	−0.0556	0.0687**	0.0620***
	(0.0184)	(0.0226)	(0.0481)	(0.0572)	(0.0236)	(0.0131)
Other Services						
Facility visits	0.0133**	0.0134*	0.0288**	0.0063	0.0206***	0.0323***
	(0.0039)	(0.0058)	(0.0087)	(0.0081)	(0.0047)	(0.0065)
Health						
Facility visits	0.0096	0.0083	0.0465**	0.0186	0.0370	0.0620
	(0.0066)	(0.0075)	(0.0165)	(0.0168)	(0.0240)	(0.0313)
Finance						
Facility visits	0.0023	0.0014	0.0009	0.0047	0.0040**	0.0059***
	(0.0013)	(0.0012)	(0.0030)	(0.0034)	(0.0012)	(0.0014)
Education						
Facility visits	−0.0017	−0.0065	0.0137*	0.0101	0.0039	0.0204
	(0.0031)	(0.0036)	(0.0067)	(0.0157)	(0.0035)	(0.0112)
Facility×Month×DoW FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
F-stat	-	63.8	-	92.6	-	58.1
1st stage coef.	-	1117.6	-	424.4	-	3129.3
Observations	9,355	9,355	12,978	12,978	10,947	10,947
Note:						*p<0.05; **p<0.01; ***p<0.001

Table A.6: Robustness checks for the main OLS FE and IV FE estimates: with local weather variables added as controls and play-off games excluded. Each coefficient in the table represents an estimate from a regression specification on a subset of data by facility sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and date clustering are reported in parentheses.

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
Food & Accommodation						
Facility visits	0.3282***	0.2995***	0.7137**	0.2005	0.2916***	0.3974***
	(0.0539)	(0.0603)	(0.2165)	(0.1177)	(0.0439)	(0.0680)
Retail Trade						
Facility visits	0.0721**	0.0665**	0.1798*	0.0113	0.0873***	0.1257***
	(0.0249)	(0.0227)	(0.0869)	(0.0323)	(0.0147)	(0.0257)
Recreation						
Facility visits	0.0371*	0.0219	0.1073*	−0.0317	0.0770**	0.0651***
	(0.0155)	(0.0167)	(0.0417)	(0.0510)	(0.0218)	(0.0116)
Other Services						
Facility visits	0.0136**	0.0143*	0.0267**	0.0067	0.0218***	0.0346***
	(0.0037)	(0.0056)	(0.0083)	(0.0080)	(0.0050)	(0.0072)
Health						
Facility visits	0.0118	0.0099	0.0406*	0.0127	0.0376	0.0617*
	(0.0071)	(0.0075)	(0.0159)	(0.0173)	(0.0237)	(0.0301)
Finance						
Facility visits	0.0027	0.0016	0.0015	0.0052	0.0040**	0.0060***
	(0.0014)	(0.0013)	(0.0029)	(0.0032)	(0.0012)	(0.0013)
Education						
Facility visits	−0.0010	−0.0058	0.0120	0.0078	0.0047	0.0216
	(0.0031)	(0.0035)	(0.0062)	(0.0150)	(0.0036)	(0.0118)
Facility×Month×DoW FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
F-stat	-	219.0	-	251.5	-	179.0
1st stage coef.	-	1127.7	-	454.0	-	3122.2
Observations	9,490	9,490	13,140	13,140	10,950	10,950
Note:						*p<0.05; **p<0.01; ***p<0.001

Table A.7: Robustness checks for the main OLS FE and IV FE estimates: with visits to nearby sports facilities added as control for multiple treatments. Each coefficient in the table represents an estimate from a regression specification on a subset of data by facility sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and date clustering are reported in parentheses.

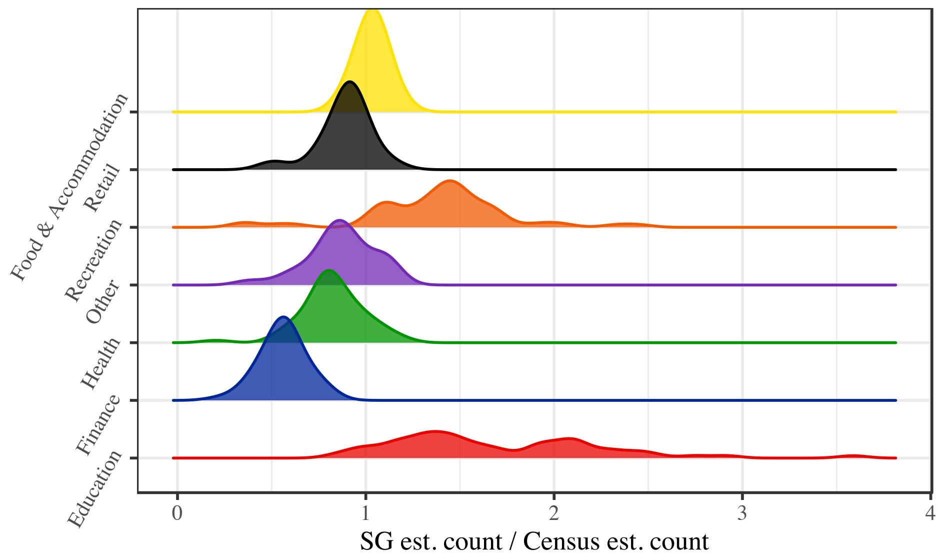

Figure A.3: Coverage of SafeGraph data as compared to the Census County Business Patterns dataset.

	Dependent variable: business visits						
	Model: IV						
	Food & Acc.	Retail	Recreation	Other	Health	Finance	Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseball	0.00067***	0.00028***	−0.00075	0.00001	−0.00004	0.00009	−0.00001
	(0.00013)	(0.00010)	(0.00107)	(0.00002)	(0.00005)	(0.00008)	(0.00009)
Football	0.00122***	0.00042***	0.00275***	0.00019***	0.00018***	0.00022*	0.00055
	(0.00017)	(0.00012)	(0.00102)	(0.00007)	(0.00005)	(0.00013)	(0.00035)
Basketball & Hockey	0.00027	−0.00260	−0.04270	−0.00154	−0.00496**	−0.00498**	−0.00553***
	(0.00334)	(0.00171)	(0.04472)	(0.00104)	(0.00244)	(0.00225)	(0.00150)
Month×Dow×CensusTract FE	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓
Observations	1,083,320	726,715	182,500	365,365	376,315	89,060	120,815

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.8: Robustness checks: the table reports IV estimates for the effects of sports facility visits on business visits at the level of individual businesses. Treatment intensity measured as the total number of visits to all sports facilities in the 3km radius of each business. Total sports visits are instrumented with the total number of games held at the corresponding facilities. Standard errors robust to heteroskedasticity and establishment and date clustering are reported in parentheses.

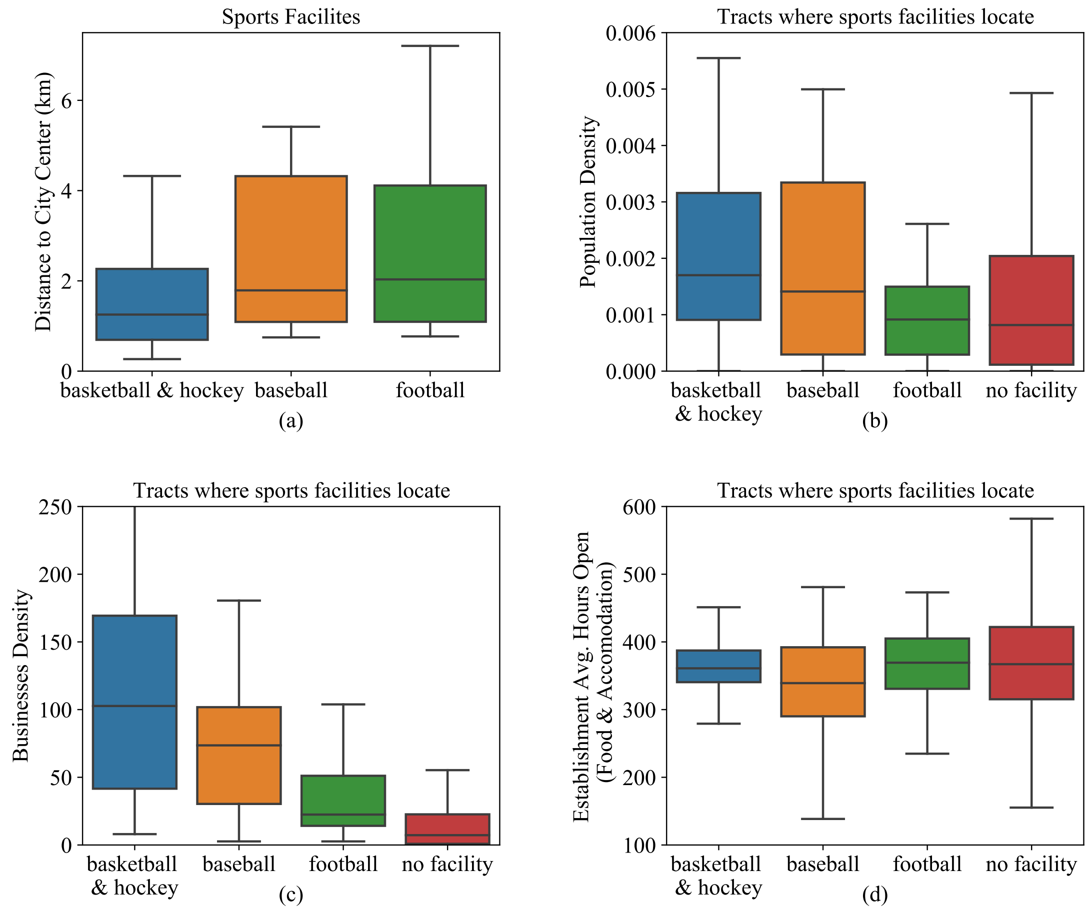

Figure A.4: Characteristics of facility locations by sport. The sample consists of all Census tracts located in core-based statistical areas (CBSAs) with at least one sports facility in our dataset. Each tract is assigned demographic variables using data at the census block group level from 2017 American Community Survey 5-Year Data, aggregated to tract level. Tract-level business density (panel c) corresponds to the total number of businesses across major categories (Retail, Finance, Education, Health, Recreation, Food and Accommodation, and Other Services) per sq. km. Average number of hours open per month for each business in Food & Accomodation cateogory (panel d) is provided by SafeGraph.

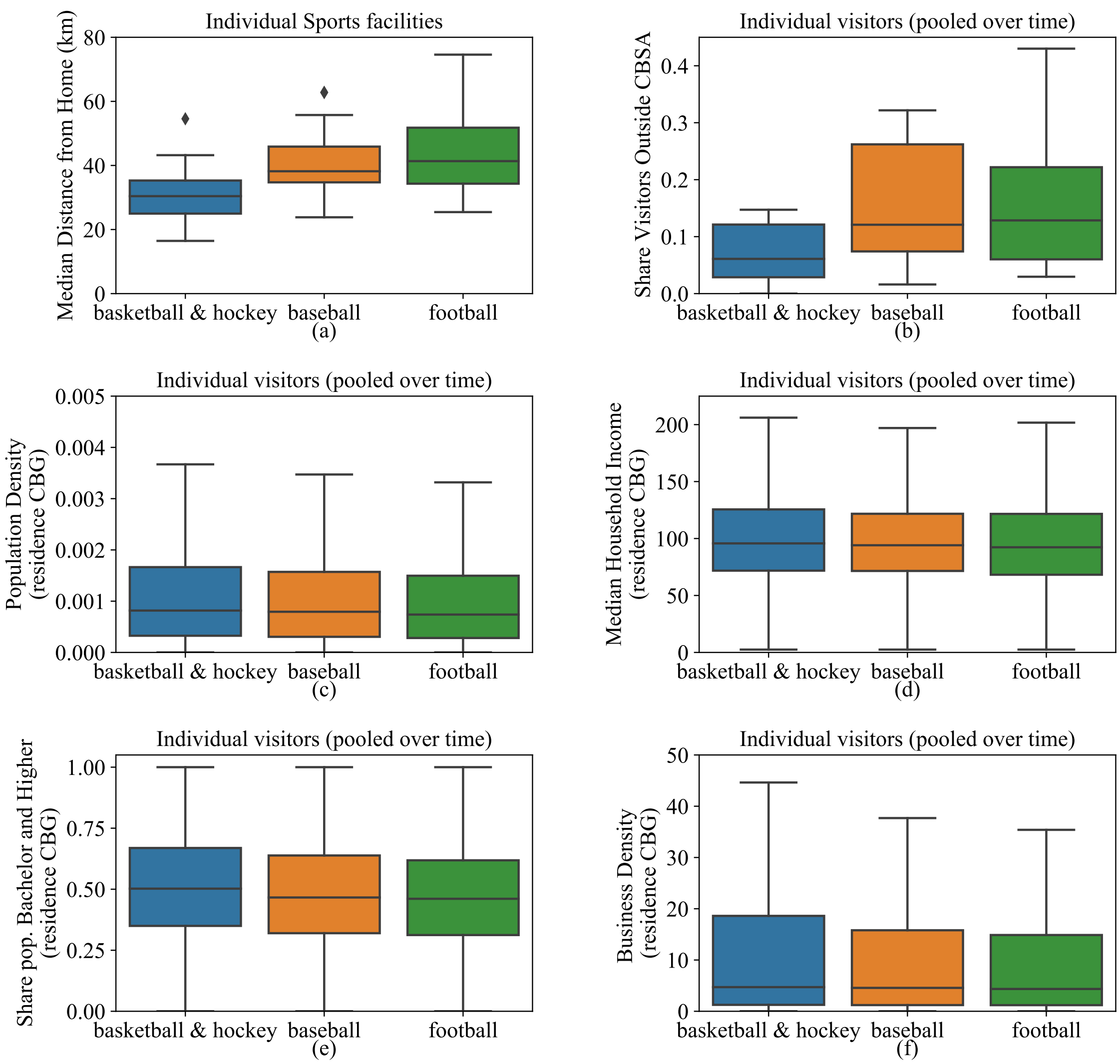

Figure A.5: Distribution of key demographic variables for visitors of sports facilites. In panels (a)-(b) the sample consists of all sports facilites in our data, and median distance across each facilties' visitors is provided by Safegraph. In panels (b)-(d), the sample is the all Safegraph users that visit sports facilities, and demographics associated with each user's home location (CBG) are obtained using 2017 American Community Survey 5-Year Data. Business density in visitors' home CBGs (panel e) corresponds to the total number of businesses across major categories (Retail, Finance, Education, Health, Recreation, Food and Accommodation, and Other Services) per sq. km.

	Dependent variable: business visits						
	Model: IV						
	Food & Acc.	Retail	Recreation	Other	Health	Finance	Education
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseball (0-1km)	0.00287***	0.00168***	−0.00736	0.00012	0.00020	0.00038	−0.00003
	(0.00065)	(0.00050)	(0.00459)	(0.00013)	(0.00014)	(0.00031)	(0.00054)
Baseball (1-2km)	0.00016	0.00006	0.00040	−0.00001	0.00006**	−0.00007	0.00010
	(0.00011)	(0.00009)	(0.00070)	(0.00005)	(0.00003)	(0.00012)	(0.00013)
Baseball (2-3km)	0.00018*	0.00006	0.00056	0.00001	−0.00018*	−0.00017	−0.00009
	(0.00010)	(0.00009)	(0.00113)	(0.00001)	(0.00010)	(0.00014)	(0.00013)
Football (0-1km)	0.00431***	0.00247***	0.01460***	0.00142**	0.00299**	0.00155**	0.00536**
	(0.00073)	(0.00047)	(0.00493)	(0.00057)	(0.00131)	(0.00069)	(0.00270)
Football (1-2km)	0.00113***	0.00059***	0.00016	0.00004	0.00001	−0.00015	−0.00039
	(0.00023)	(0.00015)	(0.00093)	(0.00011)	(0.00024)	(0.00011)	(0.00053)
Football (2-3km)	0.00019***	−0.00011	0.00090	0.00007	−0.00004	0.00002	0.00035*
	(0.00005)	(0.00015)	(0.00101)	(0.00005)	(0.00008)	(0.00008)	(0.00020)
Basketball & Hockey (0-1km)	0.00502	0.00136	0.00464	−0.00373	0.00635	0.00305	−0.01973*
	(0.00685)	(0.00724)	(0.02807)	(0.00751)	(0.01037)	(0.00757)	(0.01014)
Basketball & Hockey (1-2km)	−0.00458	−0.00467	−0.05633	−0.00285	−0.00458	−0.00945**	0.00141
	(0.00667)	(0.00321)	(0.05031)	(0.00192)	(0.00535)	(0.00438)	(0.00553)
Basketball & Hockey (2-3km)	0.00112	−0.00200	−0.07021	0.00015	−0.00815**	0.02370*	−0.00313
	(0.00622)	(0.00379)	(0.07233)	(0.00145)	(0.00370)	(0.01378)	(0.00542)
Month×Dow×CensusTract FE	✓	✓	✓	✓	✓	✓	✓
Establishment FE	✓	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓	✓
Observations	1,083,320	726,715	182,500	365,365	376,315	89,060	120,815
Note:							*p<0.1; **p<0.05; ***p<0.01

Table A.9: Robustness checks: the table reports IV estimates for the effects of sports facility visits on business visits at the level of individual businesses, with effects estimated seperately for distance bands 0-1km, 1-2km, and 2-3km around each establishment. Treatment intensity measured as the total number of visits to all sports facilities within a corresponding distance from each business. Total sports visits are instrumented with the total number of games held at the corresponding facilities. Standard errors robust to heteroskedasticity and establishment and date clustering are reported in parentheses.

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
Food & Accommodation						
Facility visits	0.3497***	0.3162***	0.7269**	0.2006	0.2817***	0.3891***
	(0.0530)	(0.0621)	(0.2255)	(0.1485)	(0.0453)	(0.0611)
Retail Trade						
Facility visits	0.0910***	0.0798***	0.1861*	0.0214	0.0878***	0.1198***
	(0.0182)	(0.0212)	(0.0845)	(0.0379)	(0.0156)	(0.0233)
Recreation						
Facility visits	0.0372*	0.0190	0.1218*	−0.0242	0.0602**	0.0654***
	(0.0176)	(0.0227)	(0.0455)	(0.0559)	(0.0165)	(0.0129)
Other Services						
Facility visits	0.0170***	0.0183***	0.0304***	0.0103	0.0213***	0.0345***
	(0.0038)	(0.0046)	(0.0082)	(0.0102)	(0.0051)	(0.0072)
Health						
Facility visits	0.0141*	0.0115	0.0401*	0.0120	0.0399	0.0600*
	(0.0067)	(0.0072)	(0.0149)	(0.0168)	(0.0227)	(0.0276)
Finance						
Facility visits	0.0030*	0.0021	0.0019	0.0034	0.0042**	0.0062***
	(0.0014)	(0.0012)	(0.0030)	(0.0035)	(0.0012)	(0.0014)
Education						
Facility visits	0.0029	0.0007	0.0095	−0.0122	0.0038	0.0204
	(0.0024)	(0.0021)	(0.0058)	(0.0137)	(0.0037)	(0.0122)
Facility×Month×DoW FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
Facility×Month×Day trend	✓	✓	✓	✓	✓	✓
F-stat	-	182.7	-	250.6	-	178.2
1st stage coef.	-	1128.0	-	459.5	-	3134.3
Observations	9,490	9,490	13,140	13,140	10,950	10,950
Note:						*p<0.05; **p<0.01; ***p<0.001

Table A.10: OLS FE and IV FE estimates with facility-month specific time trend on the daily level. Each coefficient in the table represents an estimate from a regression specification on a subset of data by facility sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and date clustering are reported in parentheses.

	Dependent varible: business visits within 3km					
	Baseball		Basketball & Hockey		Football	
	FE	IV	FE	IV	FE	IV
Food & Accommodation						
Facility visits	0.3692***	0.3695***	0.5659**	0.2386*	0.2205***	0.3081***
	(0.0545)	(0.0564)	(0.1607)	(0.1096)	(0.0362)	(0.0574)
Retail Trade						
Facility visits	0.1068***	0.1119***	0.1381*	0.0583	0.0708***	0.1013***
	(0.0207)	(0.0231)	(0.0594)	(0.0341)	(0.0128)	(0.0214)
Recreation						
Facility visits	0.0541*	0.0786*	0.0820*	−0.0083	0.0421**	0.0422**
	(0.0210)	(0.0358)	(0.0350)	(0.0483)	(0.0117)	(0.0146)
Other Services						
Facility visits	0.0149***	0.0149*	0.0248**	0.0154	0.0193***	0.0280***
	(0.0036)	(0.0069)	(0.0071)	(0.0080)	(0.0052)	(0.0068)
Health						
Facility visits	0.0157**	0.0165*	0.0310*	0.0276	0.0442	0.0529
	(0.0047)	(0.0064)	(0.0123)	(0.0210)	(0.0245)	(0.0273)
Finance						
Facility visits	0.0024	0.0025	0.0002	0.0024	0.0039**	0.0056***
	(0.0013)	(0.0014)	(0.0035)	(0.0040)	(0.0013)	(0.0015)
Education						
Facility visits	0.0043	0.0104*	0.0129**	0.0069	−0.0003	−0.0016
	(0.0022)	(0.0042)	(0.0043)	(0.0110)	(0.0043)	(0.0148)
Facility×Month×DoW FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
Within Facility×Week trend	✓	✓	✓	✓	✓	✓
F-stat	-	132.2	-	193.9	-	150.8
1st stage coef.	-	1199.2	-	476.7	-	3261.4
Observations	9,230	9,230	12,780	12,780	10,650	10,650
Note:						*p<0.05; **p<0.01; ***p<0.001

Table A.11: Robustness checks for the main OLS FE and IV FE estimates: with national holidays dates excluded, and facility-specific within-week trends added as additional controls. Each coefficient in the table represents an estimate from a regression specification on a subset of data by sport (columns) and business industry (panels). Standard errors robust to heteroskedasticity and facility and date clustering are reported in parentheses.

	Mean	Q25	Med.	Q75
All stadiums receiving subsidies				
Annual attendance (m)	2.23	1.69	2.04	2.77
Annual spillover revenues from foot traffic ($M)	15.64	9.28	16.74	20.64
Spillover revenues net of public costs ($M)	-59.56	-122.87	-55.31	37.02
Public costs at 2010 ($M)	274.80	190.00	240.00	329.00
Baseball				
Annual attendance (m)	2.84	2.56	2.84	2.98
Annual spillover revenues from foot traffic ($M)	20.31	18.35	20.31	21.34
Spillover revenues net of public costs ($M)	-5.31	-86.12	-2.93	81.04
Public costs at 2010 ($M)	284.83	195.00	260.00	374.00
Football				
Annual attendance (m)	1.66	1.30	1.62	1.98
Annual spillover revenues from foot traffic ($M)	17.36	13.61	17.00	20.78
Spillover revenues net of public costs ($M)	-96.38	-180.72	-46.35	25.40
Public costs at 2010 ($M)	335.33	240.00	285.00	384.00
Hockey & Basketball				
Annual attendance (m)	2.14	1.78	1.98	2.22
Annual spillover revenues from foot traffic ($M)	8.80	7.31	8.14	9.15
Spillover revenues net of public costs ($M)	-82.16	-122.41	-83.19	-44.68
Public costs at 2010 ($M)	203.29	160.00	198.00	235.00

Table A.12: Public Costs and Estimated Spillover Revenues for Stadiums Receiving Public Funds (under alternative assumptions). Assuming an average of value of 20$ per generated customer. To maintain consistency in our calculations, in computing spillover revenues net of public costs, we assume an average lease duration of 30 years and an interest rate of 6 percent following Long (2013)

	Mean	Q25	Med.	Q75
All stadiums receiving subsidies				
Annual attendance (m)	2.23	1.69	2.04	2.77
Annual spillover revenues from foot traffic ($M)	12.87	7.72	13.03	16.50
Spillover revenues net of public costs ($M)	-97.65	-153.72	-99.08	-30.64
Public costs at 2010 ($M)	274.80	190.00	240.00	329.00
Baseball				
Annual attendance (m)	2.84	2.56	2.84	2.98
Annual spillover revenues from foot traffic ($M)	17.27	14.48	16.26	17.88
Spillover revenues net of public costs ($M)	-47.13	-141.36	-52.01	31.58
Public costs at 2010 ($M)	284.83	195.00	260.00	374.00
Football				
Annual attendance (m)	1.66	1.30	1.62	1.98
Annual spillover revenues from foot traffic ($M)	13.78	10.57	13.20	16.26
Spillover revenues net of public costs ($M)	-145.69	-211.47	-79.93	-43.10
Public costs at 2010 ($M)	335.33	240.00	285.00	384.00
Hockey & Basketball				
Annual attendance (m)	2.14	1.78	1.98	2.22
Annual spillover revenues from foot traffic ($M)	7.14	5.96	6.52	7.22
Spillover revenues net of public costs ($M)	-104.95	-128.47	-108.27	-62.29
Public costs at 2010 ($M)	203.29	160.00	198.00	235.00

Table A.13: Public Costs and Estimated Spillover Revenues for Stadiums Receiving Public Funds (under alternative assumptions). Assuming an average of value of 15$ per generated customer and with spillover estimates scaled by the ratio of SafeGraph business count to the Census business count for each county and business category. To maintain consistency in our calculations, in computing spillover revenues net of public costs, we assume an average lease duration of 30 years and an interest rate of 6 percent following Long (2013).

Facility	Sport	Annual attendance (m)	Annual revenue spillovers ($M)	Public costs at 2010 ($M)	Revenue spillovers net of public costs ($M)
Dodger Stadium	baseball	4.01	21.50	65.0	231.01
Globe Life Park In Arlington	baseball	3.30	17.69	213.0	30.47
American Airlines Center	hockey or basketball	5.45	16.83	167.0	64.70
Coors Field	baseball	3.10	16.63	222.0	6.87
Tropicana Field	baseball	2.93	15.74	210.0	6.70
Mercedes Benz Superdome	football	1.99	15.62	190.0	25.02
Everbank Field	football	1.98	15.58	202.0	12.48
At&t Park	baseball	2.88	15.48	20.0	193.04
Oriole Park At Camden Yards	baseball	2.80	15.05	167.0	40.11
Citi Field	baseball	2.77	14.85	142.0	62.45
Comerica Park	baseball	2.50	13.41	180.0	4.54
Los Angeles Memorial Coliseum	football	1.44	11.31	38.0	117.66
Progressive Field	baseball	2.01	10.79	131.0	17.59
Target Center	hockey or basketball	2.36	7.30	97.0	3.51
Talking Stick Resort Arena	hockey or basketball	2.22	6.86	48.0	46.44

Table A.14: List of facilities that generate net positive differnce between the total value of foot-traffic spillovers and total public costs. Assuming an average of value of 15$ per generated customer. To maintain consistency in our calculations, in computing spillover revenues net of public costs, we assume an average lease duration of 30 years and an interest rate of 6 percent.

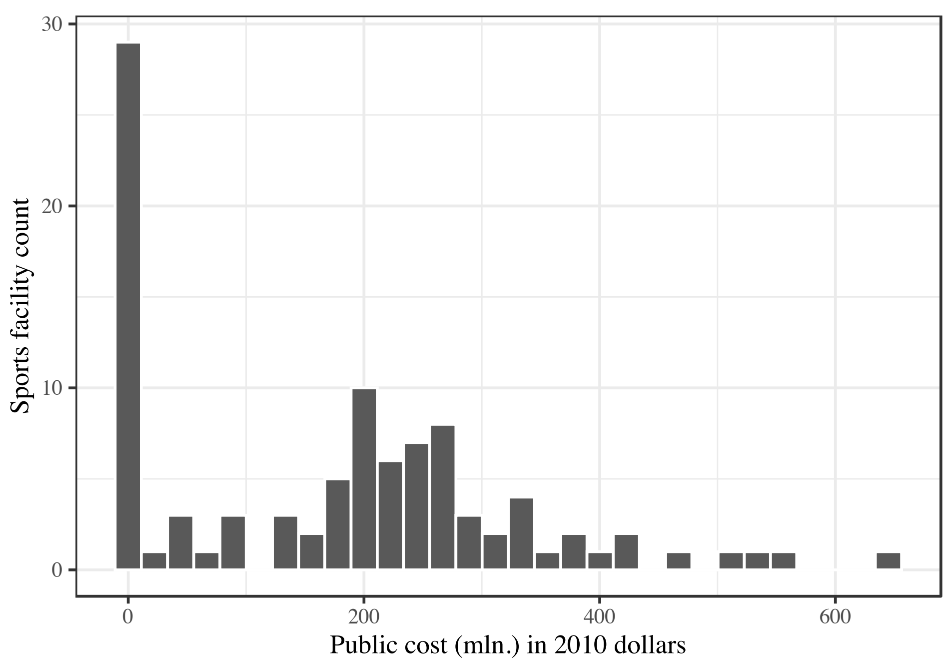

Figure A.6: Distribution of public costs allocated to stadiums.

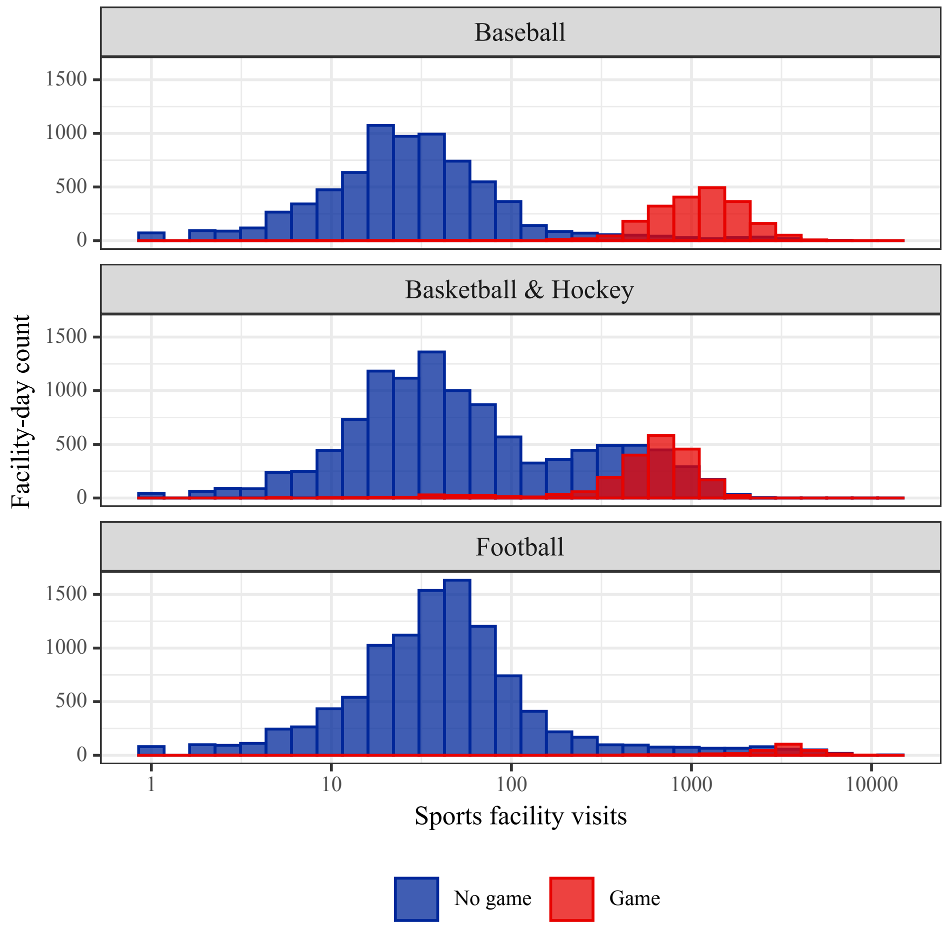

Figure A.7: Distribution of visits to sports facilities by sport and game day status. Each observations is a facility-day.

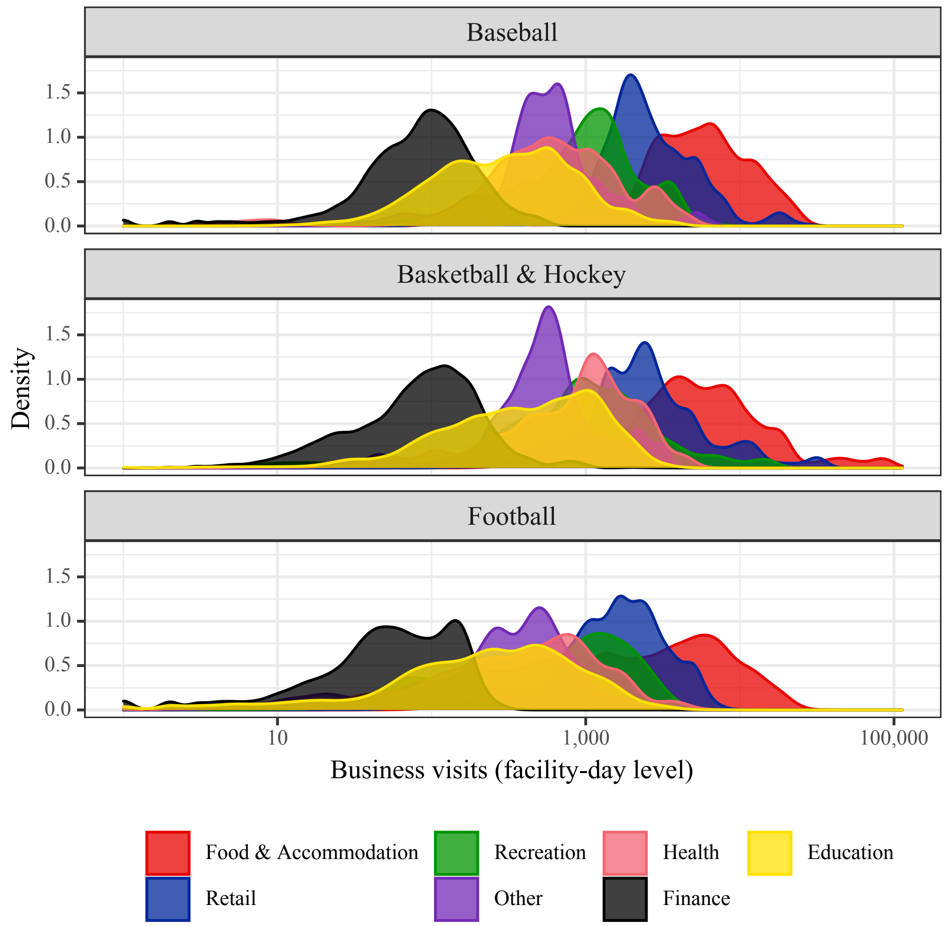

Figure A.8: Distribution of visits to businesses near sports facilities by sport and industry. Each observation is a facility-industry-day.

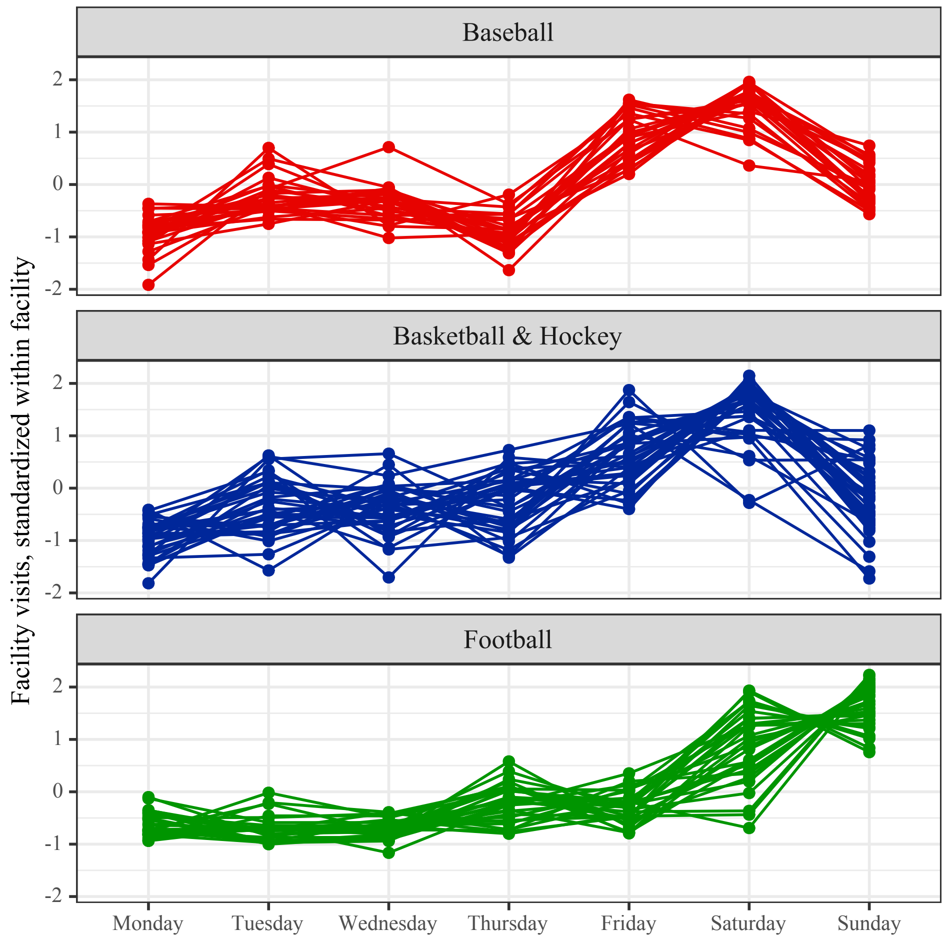

Figure A.9: Comparisons of average visit counts to sports facilities across days of the week. Average visit counts standardized within facility.

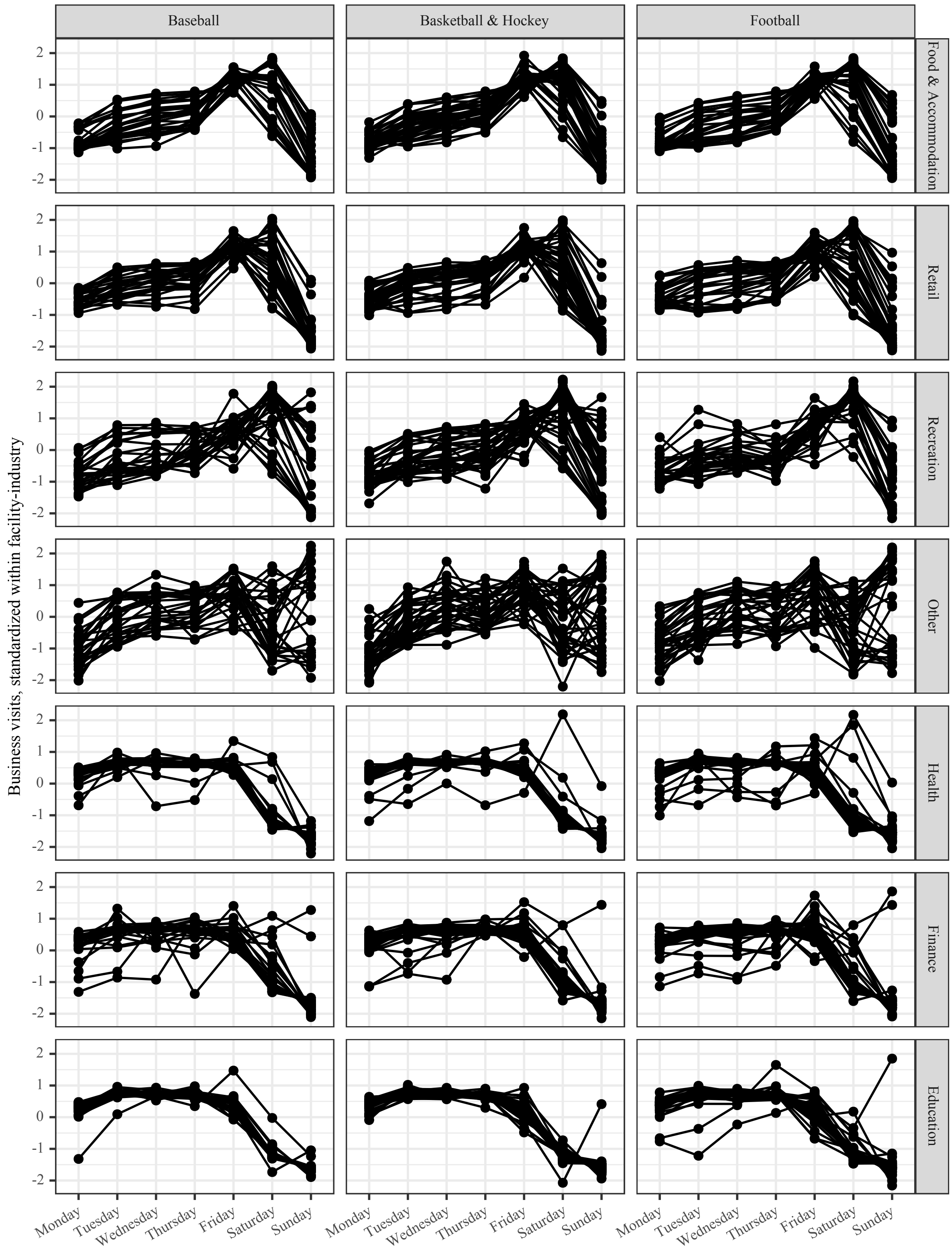

Figure A.10: Comparisons of average visit counts to businesses near sports facilities across days of the week. Average visit counts standardized within facility-industry.

Table A.15: List of all major sports leagues teams and corresponding sports facilities. The “Shared” column indicates whether the facility is shared by multiple teams. The “In sample” column indicates whether the facility is present in the estimation sample (missingness due to the facility non-presence in Safegraph data). The “Pub. cost” column indicates whether the data on facility’s public cost is available in Long (2013).

#	*Team*	*Facility*	*State*	*City*	*Shared*	*In sample*	*Pub. cost*
Baseball							
1.	Arizona Diamondbacks	Chase Field	AZ	Phoenix		✓	✓
2.	Atlanta Braves	SunTrust Park	GA	Atlanta		✓	
3.	Baltimore Orioles	Oriole Park at Camden Yards	MD	Baltimore		✓	✓
4.	Boston Red Sox	Fenway Park	MA	Boston		✓	✓
5.	Chicago Cubs	Wrigley Field	IL	Chicago			
6.	Chicago White Sox	Guaranteed Rate Field	IL	Chicago		✓	✓
7.	Cincinnati Reds	Great American Ball Park	OH	Cincinnati		✓	✓
8.	Cleveland Indians	Progressive Field	OH	Cleveland		✓	✓
9.	Colorado Rockies	Coors Field	CO	Denver		✓	✓
10.	Detroit Tigers	Comerica Park	MI	Detroit		✓	✓
11.	Houston Astros	Minute Maid Park	TX	Houston		✓	✓
12.	Kansas City Royals	Kauffman Stadium	MO	Kansas City		✓	✓
13.	Los Angeles Angels	Angel Stadium of Anaheim	CA	Anaheim			✓
14.	Los Angeles Dodgers	Dodger Stadium	CA	Los Angeles		✓	✓
15.	Miami Marlins	Marlins Park	FL	Miami		✓	
16.	Milwaukee Brewers	Miller Park	WI	Milwaukee		✓	✓
17.	Minnesota Twins	Target Field	MN	Minneapolis		✓	✓
18.	New York Mets	Citi Field	NY	New York City		✓	✓
19.	New York Yankees	Yankee Stadium	NY	New York City		✓	✓
20.	Oakland Athletics	Oakland Alameda County Coliseum	CA	Oakland	✓		
21.	Philadelphia Phillies	Citizens Bank Park	PA	Philadelphia		✓	✓
22.	Pittsburgh Pirates	PNC Park	PA	Pittsburgh		✓	✓
23.	San Diego Padres	Petco Park	CA	San Diego		✓	✓
24.	San Francisco Giants	AT&T Park	CA	San Francisco		✓	✓
25.	Seattle Mariners	Safeco Field	WA	Seattle		✓	✓
26.	St. Louis Cardinals	Busch Stadium	MO	St. Louis		✓	✓
27.	Tampa Bay Rays	Tropicana Field	FL	St. Petersburg		✓	✓
28.	Texas Rangers	Globe Life Park in Arlington	TX	Arlington		✓	✓
29.	Toronto Blue Jays	Rogers Centre		Toronto			
30.	Washington Nationals	Nationals Park	DC	Washington		✓	✓
Basketball							
31.	Atlanta Hawks	Philips Arena	GA	Atlanta		✓	✓
32.	Boston Celtics	TD Garden	MA	Boston	✓	✓	✓
33.	Brooklyn Nets	Barclays Center	NY	New York City	✓	✓	
34.	Charlotte Hornets	Time Warner Cable Arena	NC	Charlotte		✓	✓
35.	Chicago Bulls	United Center	IL	Chicago	✓	✓	✓
36.	Cleveland Cavaliers	Quicken Loans Arena	OH	Cleveland			✓
37.	Dallas Mavericks	American Airlines Center	TX	Dallas	✓	✓	✓
38.	Denver Nuggets	Pepsi Center	CO	Denver	✓	✓	✓
39.	Detroit Pistons	Little Caesars Arena	MI	Detroit	✓	✓	
40.	Golden State Warriors	Oracle Arena	CA	San Francisco		✓	✓
41.	Houston Rockets	Toyota Center	TX	Houston			
42.	Indiana Pacers	Bankers Life Fieldhouse	IN	Indianapolis		✓	✓
43.	Los Angeles Clippers	Staples Center	CA	Los Angeles	✓	✓	✓
44.	Los Angeles Lakers	Staples Center	CA	Los Angeles	✓	✓	✓
45.	Memphis Grizzlies	FedExForum	TN	Memphis		✓	✓
46.	Miami Heat	American Airlines Arena	FL	Miami		✓	✓
47.	Milwaukee Bucks	BMO Harris Bradley Center	WI	Milwaukee		✓	✓
48.	Minnesota Timberwolves	Target Center	MN	Minneapolis		✓	✓
49.	New Orleans Pelicans	Smoothie King Center	LA	New Orleans		✓	✓
50.	New York Knicks	Madison Square Garden	NY	New York City	✓	✓	✓
51.	Oklahoma City Thunder	Chesapeake Energy Arena	OK	Oklahoma City		✓	✓
52.	Orlando Magic	Amway Center	FL	Orlando		✓	✓
53.	Philadelphia 76ers	Wells Fargo Center	PA	Philadelphia	✓	✓	✓
54.	Phoenix Suns	Talking Stick Resort Arena	AZ	Phoenix		✓	✓
55.	Portland Trail Blazers	Moda Center	OR	Portland		✓	✓
56.	Sacramento Kings	Golden 1 Center	CA	Sacramento			
57.	San Antonio Spurs	AT&T Center	TX	San Antonio		✓	✓

Table A.15: List of all major sports leagues teams and corresponding sports facilities. The "Shared" column indicates whether the facility is shared by multiple teams. The "In sample" column indicates whether the facility is present in the estimation sample (missingness due to the facility non-presence in Safegraph data). The "Pub. cost" column indicates whether the data on facility's public cost is available in Long (2013). *(continued)*

#	*Team*	*Facility*	*State*	*City*	*Shared*	*In sample*	*Pub. cost*
58.	Toronto Raptors	Air Canada Centre		Toronto	✓		
59.	Utah Jazz	Vivint Smart Home Arena	UT	Salt Lake City		✓	✓
60.	Washington Wizards	Verizon Center	DC	Washington	✓	✓	✓
Football							
61.	Arizona Cardinals	University of Phoenix Stadium	AZ	Glendale		✓	✓
62.	Atlanta Falcons	Mercedes Benz Stadium	GA	Atlanta		✓	
63.	Baltimore Ravens	M&T Bank Stadium	MD	Baltimore		✓	✓
64.	Buffalo Bills	Ralph Wilson Stadium	NY	Orchard Park		✓	✓
65.	Carolina Panthers	Bank of America Stadium	NC	Charlotte		✓	✓
66.	Chicago Bears	Soldier Field	IL	Chicago		✓	✓
67.	Cincinnati Bengals	Paul Brown Stadium	OH	Cincinnati		✓	✓
68.	Cleveland Browns	FirstEnergy Stadium	OH	Cleveland		✓	✓
69.	Dallas Cowboys	AT&T Stadium	TX	Arlington		✓	✓
70.	Denver Broncos	Sports Authority Field at Mile High	CO	Denver		✓	✓
71.	Detroit Lions	Ford Field	MI	Detroit		✓	✓
72.	Green Bay Packers	Lambeau Field	WI	Green Bay		✓	✓
73.	Houston Texans	NRG Stadium	TX	Houston		✓	✓
74.	Indianapolis Colts	Lucas Oil Stadium	IN	Indianapolis		✓	✓
75.	Jacksonville Jaguars	EverBank Field	FL	Jacksonville		✓	✓
76.	Kansas City Chiefs	Arrowhead Stadium	MO	Kansas City		✓	✓
77.	Los Angeles Chargers	StubHub Center	CA	Inglewood		✓	✓
78.	Los Angeles Rams	Los Angeles Memorial Coliseum	CA	Inglewood		✓	✓
79.	Miami Dolphins	Hard Rock Stadium	FL	Miami Gardens		✓	✓
80.	Minnesota Vikings	US Bank Stadium	MN	Minneapolis		✓	
81.	New England Patriots	Gillette Stadium	MA	Foxborough		✓	✓
82.	New Orleans Saints	Mercedes Benz Superdome	LA	New Orleans		✓	✓
83.	New York Giants	MetLife Stadium	NJ	East Rutherford	✓	✓	✓
84.	New York Jets	MetLife Stadium	NJ	East Rutherford	✓	✓	✓
85.	Oakland Raiders	Oakland Alameda County Coliseum	CA	Oakland	✓		
86.	Philadelphia Eagles	Lincoln Financial Field	PA	Philadelphia		✓	✓
87.	Pittsburgh Steelers	Heinz Field	PA	Pittsburgh		✓	✓
88.	San Francisco 49ers	Levi's Stadium	CA	Santa Clara		✓	
89.	Seattle Seahawks	CenturyLink Field	WA	Seattle		✓	✓
90.	Tampa Bay Buccaneers	Raymond James Stadium	FL	Tampa		✓	✓
91.	Tennessee Titans	Nissan Stadium	TN	Nashville		✓	✓
92.	Washington Redskins	FedExField	MD	Landover		✓	✓
Hockey							
93.	Anaheim Ducks	Honda Center	CA	Anaheim			✓
94.	Arizona Coyotes	Gila River Arena	AZ	Glendale			
95.	Boston Bruins	Td Garden	MA	Boston	✓	✓	✓
96.	Buffalo Sabres	First Niagara Center	NY	Buffalo		✓	✓
97.	Calgary Flames	Scotiabank Saddledome		Calgary			
98.	Carolina Hurricanes	Pnc Arena	NC	Raleigh		✓	✓
99.	Chicago Blackhawks	United Center	IL	Chicago	✓	✓	✓
100.	Colorado Avalanche	Pepsi Center	CO	Denver	✓	✓	✓
101.	Columbus Blue Jackets	Nationwide Arena	OH	Columbus		✓	✓
102.	Dallas Stars	American Airlines Center	TX	Dallas	✓	✓	✓
103.	Detroit Red Wings	Little Caesars Arena	MI	Detroit	✓	✓	
104.	Edmonton Oilers	Rogers Place		Edmonton			
105.	Florida Panthers	Bb&t Cente	FL	Sunrise		✓	✓
106.	Los Angeles Kings	Staples Center	CA	Los Angeles	✓	✓	✓
107.	Minnesota Wild	Xcel Energy Center	MN	Saint Paul		✓	✓
108.	Montreal Canadiens	Bell Centre		Montreal			
109.	Nashville Predators	Bridgestone Arena	TN	Nashville		✓	✓
110.	New Jersey Devils	Prudential Center	NJ	Newark		✓	✓
111.	New York Islanders	Barclays Center	NY	New York City	✓	✓	
112.	New York Rangers	Madison Square Garden	NY	New York City	✓	✓	✓
113.	Ottawa Senators	Canadian Tire Centre		Ottawa			
114.	Philadelphia Flyers	Wells Fargo Center	PA	Philadelphia	✓	✓	✓

Table A.15: List of all major sports leagues teams and corresponding sports facilities. The "Shared" column indicates whether the facility is shared by multiple teams. The "In sample" column indicates whether the facility is present in the estimation sample (missingness due to the facility non-presence in Safegraph data). The "Pub. cost" column indicates whether the data on facility's public cost is available in Long (2013). *(continued)*

#	*Team*	*Facility*	*State*	*City*	*Shared*	*In sample*	*Pub. cost*
115.	Pittsburgh Penguins	PPG Paints Arena	PA	Pittsburgh		✓	✓
116.	San Jose Sharks	Sap Center at San Jose	CA	San Jose		✓	✓
117.	St. Louis Blues	Scottrade Center	MO	St. Louis		✓	✓
118.	Tampa Bay Lightning	Amalie Arena	FL	Tampa		✓	✓
119.	Toronto Maple Leafs	Air Canada Centre		Toronto	✓		
120.	Vancouver Canucks	Rogers Arena		Vancouver			
121.	Vegas Golden Knights	T-Mobile Arena	NV	Paradise			
122.	Washington Capitals	Verizon Center	DC	Washington	✓	✓	✓
123.	Winnipeg Jets	Bell MTS Place		Winnipeg			