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The impact of professional sports facilities on housing values: Evidence from census block group data

Xia Feng [a], Brad R. Humphreys [b,*]

[a] College of William and Mary, Virginia, United States
[b] University of Alberta, Cananda

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ABSTRACT

We estimate the effect of proximity on residential property values in US cities using a hedonic housing price model with spatial autocorrelation. Estimates based on all 1990 and 2000 Census block groups within five miles of every NFL, NBA, MLB, and NHL facility in the US suggest that the median house value in block groups is higher in block groups closer to facilities, suggesting that positive externalities from professional sports facilities may be capitalized into residential real estate prices. The existence of external benefits may justify some of the large public subsidies for construction and operation of professional sports facilities.

Introduction

Despite a lack of evidence that sports facilities generate tangible positive economic benefits, cities continue to subsidize the construction of new sports facilities in order to attract new teams or keep existing ones. The persistent subsidies indicate that professional sports facilities may generate some benefits and suggest looking beyond direct economic impact, in terms of income, jobs, and taxes, for evidence.[1] One place to look for evidence of intangible benefits is in the value of fixed assets like real estate. The value of some non-market public goods like open space, good air quality, high quality schools, etc., appears to be capitalized into housing values and reflected in wages in the form of compensating differentials, based on empirical estimates from standard hedonic models. If air quality and green space affect wages and housing values, then non-economic benefits generated by sports facilities and teams might also be capitalized into these prices.

The literature examining the economic impact of sports contains relatively few studies that examine the effect of sports facilities on housing values, even though intangible benefits are frequently mentioned as potentially important benefits generated by sports facilities. Only a handful of papers investigate the effects of sports facilities on housing values or rents: Ahlfeldt and Kavetsos (2011), Ahlfeld and Maennig (2010), Carlino and Coulson (2004), Dehring, Depken, and Ward (2007), Kiel, Matheson, and Sullivan (2010) and Tu (2005). We examine the effects of spatial proximity to a sports facility on housing values using cross-sectional data from the 1990 and 2000 United States Censuses. This research differs from existing studies in several ways. First, it uses data from a relatively small geographic scope- census block group level data. This has several advantages over more aggregated data in that it allows us to control for spatial heterogeneity across cities. The effect of spatial proximity to a sports facility on housing values can also be examined more precisely in block group level data because a variable reflecting the distance from a facility to each block group can be incorporated in the empirical model. Second, the sample contains data from all Metropolitan Statistical Areas (MSAs) with a franchise in any of the four major professional sports leagues, the National Football League (NFL), the National Basketball Association (NBA), the National Hockey League (NHL) and Major League Baseball (MLB). The effect of different types of sports facilities on housing values may vary because of different event scheduling patterns for the facilities. For example, among the four professional sports facilities, NBA and/or HNL

* Corresponding author. Address: Department of Economics, 8-14 Tory, Edmonton, AB, Canada T6G 2H4. Tel.: +1 780 492 5143; fax: +1 780 492 3300.
E-mail address: brad.humphreys@ualberta.ca (B.R. Humphreys).

[1] Alternatively, public subsidies may continue to be provided because monopoly sports leagues have significantly more bargaining power than cities. If leagues exercise monopoly power by keeping viable markets bereft of teams, existing team owners can exploit this to extract subsidies from cities by threatening to move.

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arenas and MLB stadiums are used more frequently than NFL stadiums because there are at least 41 NBA and NHL regular season home games a year and 81 MLB regular season home games a year but only 8 NFL regular season home games. Most facilities also hose some pre-season games on a regular basis. Moreover, arenas host many other activities like concerts and trade shows, and some arenas are home to both NBA and NHL teams, which may enhance their desirability. Finally, our empirical methodology explicitly controls for spatial dependence in the data by accounting for spatial autocorrelation. This important element has been ignored in most of the existing literature on the spatial economic impact of professional sports facilities. We find evidence that the median residential house value in a census block group decreases as the block group gets farther from a sports facility, even after controlling for block group characteristics and spatial dependence in the data. This suggests that professional sports facilities may generate intangible benefits that are capitalized in housing values.

Related literature

A few papers have examined the effect of sports facilities on rents and property values. Carlino and Coulson (2004) found evidence that NFL teams and facilities generate non-economic benefits in central cities and their associated MSAs. Given that professional sports are, at some level, a non-excludable public good, Carlino and Coulson (2004) posited that the intangible benefits from the NFL manifest themselves as compensating differentials the same way as other contributors to the quality of life in a community, such as clean air, low crime, and pleasant weather. Cities that gain an NFL team will have higher quality of life than cities that do not, producing higher rents or lower wages. Carlino and Coulson (2004) estimated two hedonic price models, one for housing rents and the other for wages, using data from 53 of the 60 largest MSAs in 1993 and 1999, at three different levels of geographic aggregation: central city level, MSA level, and Consolidated Metropolitan Statistical Area (CMSA) level. Their results indicated that the presence of an NFL franchise raised rent by approximately 8% in central cities. Unlike other studies using hedonic models to measure the effects of attributes on housing prices in a specific location with individual housing data, this study was the first to employ cross-sectional data across major central cities and their associated MSAs using data from the American Housing Survey.

Carlino and Coulson (2004) did not address any potential negative effects generated by an NFL franchise on rent. Professional sports facilities may generate negative externalities because they also produce disamenities, such as traffic jams, noise, and trash. The net effect of sports facilities on housing values depends on the relative size of the positive and negative effects. If the positive effect dominates negative effect, then the net effect will be positive. In other words, the sign of the net effect cannot be determined *a priori*.

Carlino and Coulson's (2004) estimates are not robust to changes in the geographic scope of the sample, suggesting that intangible benefits may exhibit spatial heterogeneity. The effect of sports facilities located in the urban core of cities may not spillover substantially to suburban areas. While suburban residents might derive benefits from living in a MSA that is home to a team, these benefits may diminish as the distance from the facility increases. So expanding the geographic scope from central cities to MSA, or even bigger CMSA, without controlling for spatial heterogeneity may not identify the effects of the presence of an NFL team on property values.

Spatial heterogeneity has been shown to be an important element of urban housing markets. Spatial heterogeneity exists in cities because housing values depend on surrounding amenities like good school quality and low crime rates. Variation in these amenities across space may affect housing values. So distance from a sports facility can be expected to affect housing values. We hypothesize that the economic impacts on housing values would be higher near a sports facility than far from the facility, and decline as the distance from the facility increases, given other things equal.

Kiel et al. (2010) performed a study similar to Carlino and Coulson (2004), but examined housing prices, not rent. This study also used data from the American Housing Survey in 1993 and 1999. Like Carlino and Coulson (2004), Kiel et al. (2010) estimated a hedonic model where the log of the owner-reported housing value was the dependent variable. They did not account for spatial dependence in the data. Kiel et al. (2010) found no relationship between residential housing values and proximity to NFL stadiums, after controlling for other factors affecting housing values.

Four similar case studies on the spatial economic impact of sports facilities have recently been published: Ahlfeldt and Kavetsos (2011), Ahlfeldt and Maennig (2010), Dehring et al. (2007), and Tu (2005). The first two examined the effects of an NFL stadium on property values while the third and fourth examined the effect of sports stadiums on property values in Europe. Tu (2005) analyzed the impact of FedEx Field, home of NFL's Washington Redskins, on housing values in Price George's County, Maryland. Dehring et al. (2007) analyzed the impacts of announcements about a potential football stadium for the Dallas Cowboys in Arlington, Texas on housing values. Ahlfeld and Maennig (2010) analyzed the effect of three stadiums on assessed land value in Berlin. Ahlfeldt and Kavetsos (2011) analyzed the effect of the new Wembley stadium and Emirates stadium, on property values in London. These four papers reached different conclusions. Tu (2005) found a positive effect of FedEx Field on housing values within three miles of the stadium; Ahlfeld and Maennig (2007) found both positive and negative effects of stadiums on housing values in Berlin; Dehring et al. (2007) found a negative aggregate impact of the three announcements on property values. Ahlfeldt and Kavetsos (2011) found a positive effect of new stadium announcements on property values.

Tu (2005) did not account for spatial dependence, which exists in spatial cross-sectional data, but instead modeled spatial proximity to FedEx Field by including a distance variable and three distance dummy variables indicating if the property is located in "impact areas" with three different radii: one-mile, two-miles, and three-miles..

Tu (2005) estimated a series of standard hedonic models to measure the price differentials between houses located in close proximity to FedEx Field and those with similar attributes but located at a distance from the stadium, and found that houses within a one-mile radius from the stadium are priced lower than comparable units outside the three-mile impact area. Tu (2005) also used a difference-in-difference approach to examine changes in the impact of FedEx Field on property values over three time periods: pre-development, development, and post-development.

Dehring et al. (2007) investigated two sets of stadium announcements concerning a new stadium for the NFL's Dallas Cowboys: a proposal to build a new stadium in Dallas Fair Park which was ultimately abandoned; and a proposal to build a stadium in Arlington that was undertaken. Dehring et al. (2007) employed a standard hedonic housing price model and a difference-in-difference approach to estimate the effects of these announcements on nearby residential property values. For the Dallas Fair Park case, they found that property values increased near Dallas Fair Park after the announcement of the new stadium proposal. However, in Dallas County, which would have paid for the stadium with increased sales taxes, residential property values decreased after the announcement. These patterns reversed when the proposal was abandoned. Three additional announcements concerning the proposed stadium in Arlington all had a negative impact on property values, but each was individually insignificant. The aggregate impact of the three announcements was negative and statistically significant. The accumulated net impact corresponded to an approximate 1.5% decline in property values in Arlington, which was almost equal to the anticipated household sales tax burden.

Again, both models in these two papers may be misspecified due to their failure to correct for spatial autocorrelation, leading to biased estimates. By explicitly accounting for spatial autocorrelation, this study should produce unbiased and consistent estimates of the effect of sports facilities on housing values.

Alhfeldt and Maennig (2010) examined the effect of three multipurpose sports facilities on property values in Berlin. This case study is of considerable interest, as these facilities were built as urban redevelopment anchors in blighted neighborhoods. This study controlled for spatial dependence in the data. Alhfeldt and Maennig (2007) present evidence that sports facilities raise the assessed value of some properties within 3000 m of sports facilities, although the impact declines with distance and the data also contain some evidence of a negative impact.

Some recent empirical evidence suggests that the non-pecuniary impacts of professional sports teams and facilities may vary across space (Coates & Humphreys, 2005). By analyzing voting on subsidies for professional sports facilities in two cities, Houston, Texas and Green Bay, Wisconsin, Coates and Humphreys (2005) found that voters living in close proximity to facilities tend to favor subsidies more than voters living farther from the facilities. Also they showed precincts with more renters in Green Bay cast a large share of "yes" votes for a subsidy for Lambeau Field while precincts with more renters in Houston cast a smaller share of "yes" votes for subsidies for a new basketball arena, which is consistent with Carlino and Coulson (2004) result in that it suggests a relationship between renters and benefits from sports. This evidence indicates that the benefits generated by professional sports are distributed unevenly not only across space within one city but also across cities and implies the existence of spatial heterogeneity both within a city and across cities.

In summary, the existing literature contains some evidence that professional sports facilities generate externalities. The net effect of these externalities can be either positive or negative. The existing evidence is based on detailed case studies of specific cities and facilities, and most does not account for spatial dependence in the data. We extend this literature by developing a comprehensive data set containing observations from many cities containing a wide variety of sports facilities. We also extend the commonly used hedonic housing price model to include spatial autocorrelation, a common feature in these data.

Empirical model

The standard hedonic housing price model relates the market value of a residential property, usually measured by sales price, to measures of housing unit attributes and neighborhood characteristics that determine the property values. When estimating a hedonic housing price model, an empirical researcher faces a choice among a number of possible functional forms for the empirical model. The existing literature uses linear functional forms (Palmquist, 1984), semi-log functional forms (Carlino & Coulson, 2004; Kiel et al., 2010), and log–log functional forms (Basu & Thibodeau, 1998). Each has advantages and disadvantages. For example, from an economic perspective, both the log-linear and log–log forms permit the marginal implicit price of a particular attribute to vary across the observations while the linear form forces a constant effect. The advantage of the linear form is that it is intuitive and provides a direct estimate of the marginal implicit price of an attribute- the coefficient estimate on the attribute variable in the equation. The empirical hedonic model specification used here is

$$Y = \alpha + X\beta + \varepsilon \tag{1}$$

where Y denotes an *nx1* vector of housing values or log of the housing values, X is an *nxk* matrix of explanatory variables representing housing structure attributes, individual sports facility characteristics, and locational attributes. Some variables in X are expressed in log forms. X is assumed to be uncorrelated with the error term ε. α and β are vectors of unknown parameters to be estimated. ε is the standard random error term, which is uncorrelated with the explanatory variables, with mean zero and variance constant.

Spatial autocorrelation

Spatial autocorrelation can be loosely defined as the coincidence of value similarity and locational similarity (Anselin & Bera, 1998). Formally, spatial autocorrelation can be expressed by the moment condition

$$Cov(y_i, y_j) = E(y_i y_j) - E(y_i) \cdot E(y_j) \neq 0 \text{ for } i \neq j \tag{2}$$

where i and j refer to individual locations, y_i and y_j refer to the values of a random variable at that location. Spatial autocorrelation can be positive where similar values (high or low) for a random variable tend to cluster in space or negative where locations tend to be surrounded by neighbors with very dissimilar values. Of the two types, positive spatial autocorrelation is more intuitive and is observed much more in reality than negative spatial autocorrelation. Spatial autocorrelation exists in cross-sectional data because the variables examined share locational characteristics. Housing prices are spatially autocorrelated for the same reason. Economists have long called attention to spatial autocorrelation when evaluating housing prices (Basu & Thibodeau, 1998; Can, 1992; Dubin, 1992; Kim, Phipps, and Anselin, 2003). Despite the recent advances in spatial data analysis and spatial econometrics (Anselin, 1988, 2003a; Anselin, Florax, and Rey, 2004), spatial autocorrelation has not been considered in existing hedonic housing studies of the impacts of spatial facilities. The existence of spatial autocorrelation in the data set implies a loss of information. By including a spatial lagged dependent variable or error term into the model, the loss of information can be explicitly addressed (Anselin & Bera, 1998).

A crucial issue in modeling spatial autocorrelation is to define the locations for which the values of the equation error term are correlated, i.e., neighbors. Neighbors can be defined by both geographical features, e.g., distance, contiguity, and demographic or economic characteristics, e.g., population density, trade flow. However, house prices are assumed to capitalize the locational amenities which may be spatially autocorrelated. Therefore, the identification of neighbors for observations on housing prices should be based on geographic features.

Spatial lags

In general, spatial lag models are analogous to autoregressive model used in time-series analysis. But there is an important distinction between these two models. In spatial data, the autoregressive term induces simultaneity due to the two-way interaction among neighbors, i.e., the spatial shift operator or spatial lag operator takes forms of both y_{i-1} and y_{i+1} , while there is no counterpart to time series data.

Following Anselin (1988), the formal spatial lag hedonic model, or spatial autoregressive (SAR) lag model can be represented as follows (Anselin, 1988):

$$y = \rho W y + X\beta + \varepsilon \tag{3}$$

where ρ is the spatial autoregressive parameter with $|\rho| < 1$, W is an $n \times n$ row-standardized spatial weights matrix that represents the neighbor structure with spatial lag Wy as a weighted average of neighboring values, and the other variables are as in Eq. (1). After some manipulation, the reduced form of the spatial lag model can be expressed

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon \tag{4}$$

where the "Leontief Inverse" $(I - \rho W)^{-1}$ links the dependent variable y to all the x_i in the system through a *spatial multiplier*. Note that expanding the "Leontief Inverse" matrix leads to an expanded form given that $|\rho| < 1$ and w_{ij}, the element of W, is less than 1 for row-standardized spatial weights:

$$(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \dots \tag{5}$$

where each observation of dependent variable is linked to all observations of the explanatory variables through this spatial multiplier. In addition, Eqs. (4) and (5) show how the dependent variable y at location i is related to the error terms at all locations in the system through the same spatial multiplier in the SAR process. So this SAR process generates a global range of spillovers, which is referred as a type of global autocorrelation since it relates all the locations in the system to each other (Anselin, 2003b). This SAR process well captures the features of housing market in that there are neighboring spillover effects on houses each other due to shared neighborhood amenities. So each house price affects all the other houses in the neighborhood, but with distance decay. This simultaneity due to the two-way spatial interaction makes the spatial lag term Wy correlated with the equation error term, which makes the OLS estimators biased and inconsistent. Anselin (1988) develops maximum likelihood and instrumental variables estimators to correct for this problem. The following section discusses these estimators.

Spatial errors

There are two different specifications for the error terms: spatial autoregressive errors and spatial moving average errors. Accordingly, two types of spatial error models can be specified. The spatial autoregressive (SAR) error model is similar to Eq. (3) but with a spatial lag in the error term (Anselin, 1988):

$$\varepsilon = \lambda W\varepsilon + u \tag{6}$$

where λ is the spatial autoregressive parameter with $|\lambda| < 1$, W is the weights matrix, and u is a vector of *i.i.d.* errors. Like the spatial lag model solved for y, the above error term can be expressed:

$$\varepsilon = [I - \lambda W]^{-1} u \tag{7}$$

where similarly, for $|\lambda| < 1$ and $w_{ij} < 1$, the expansion of the "Leontief Inverse" matrix is:

$$(I - \lambda W)^{-1} = I + \lambda W + \lambda^2 W^2 + \dots \tag{8}$$

The variance–covariance matrix for the vector of error terms is

$$\begin{aligned} E(\varepsilon\varepsilon') &= \sigma^2[(I - \lambda W)'(I - \lambda W)]^{-1} \\ &= \sigma^2\left[(I - \lambda W)^{-1}(I - \lambda W)^{-1'}\right] \end{aligned} \tag{9}$$

which is the product of the Leontief expansion and its transpose. Again this type of variance–covariance structure is referred as global by Anselin (2003b), since it relates all locations in the system to each other. This global nature implies that, for this SAR error process, a shock in the error u at any location in the housing market will propagate to all other locations according to the above Leontief expansion. The OLS estimator, while still unbiased, will be no longer efficient under this error structure. So the estimation of spatial autoregressive error model should be based on maximum likelihood or instrumental variables method (Anselin, 1988).

The spatial moving average (SMA) error model can be expressed as

$$\varepsilon = \gamma W u + u \tag{10}$$

where γ is the SMA parameter, and the other variables are the same as in Eq. (6). The SMA error process is quite different from the spatial autoregressive error model in that SMA only produces a local range of spillover effects, because Eq. (10) is already a reduced form and does not contain the inverse matrix term (Anselin, 2003b). Formally, it can be expressed:

$$E(\varepsilon\varepsilon') = \sigma^2\left[(I+\gamma W)(I+\gamma W)'\right] \\ = \sigma^2\left[I+\gamma(W+W') + \gamma^2 WW'\right] \tag{11}$$

From Eq. (11), the variance–covariance structure of SMA depends only on the first and second order neighbors instead of all the observations as in spatial autoregressive error model. Beyond two "bands" of neighbors, the spatial covariance is zero. Again OLS estimation of the SMA model will still remain unbiased but be inefficient due to the resulting error covariance structure.

In both spatial error models, spatial dependence in the error terms may induce heteroskedasticity because the diagonal elements in both Eqs. (9) and (11), the variance of both processes at each location, depend on the diagonal elements in W^2, WW', W'^2, and so on, which are directly related to the number of neighbors for each location. So if the neighborhood structure is not constant across space, then heteroskedastic errors result. One way to avoid this result is to define a k-nearest neighbor spatial weights matrix where the number of neighbors is a constant or using spatial two-stage least squares estimation to correct for heteroskedastic errors (Anselin, 1988). Compared to the spatial autoregressive error model, SMA is not used often as it only accounts for local externalities in errors. We use a spatial autoregressive error model, described in the following section, in our empirical analysis.

Specification of the spatial weights matrix

A spatial weights matrix is an $n \times n$ positive symmetric matrix, W, which specifies the "neighborhood set" for each observation as nonzero elements. In each row i, a nonzero element w_{ij} defines column j as a neighbor of i. So $w_{ij} = 1$ when $i$and j are neighbors, and $w_{ij} = 0$ otherwise. Conventionally, the diagonal elements of the weights matrix are set to zero, i.e., $w_{ii} = 0$. The weights matrix is row standardized such that the weights of a row sum to one. The row standardized weights matrix makes the spatial lag term an average of all neighboring values and thus allows for spatial smoothing of the neighboring values. It ensures that the spatial parameters in many spatial stochastic processes are comparable between models.

The specification of neighborhood sets, in which elements are set to nonzero values, is important because it captures the extent of spatial interaction and spatial externalities. In the case of housing markets, nonzero elements in the weights matrix represent the spillover effects from each house on its neighbors. Due to the features of both housing markets and housing data, the specification of the neighborhood set for each house is especially important.

A number of definitions of neighborhoods and associated spatial weights matrices have been proposed in the literature. The traditional approach relies on geographic structure or the spatial structure of the observations. In this approach, areal units are defined as "neighbors" if they share a common border, which is called first-order contiguity, or if they are within a given distance of each other; i.e., $w_{ij} = 1$ for $d_{ij} < t$, where d_{ij} is the distance between observations i and j, and t is the distance cut-off value.[2] In GeoDa, a spatial econometrics software program, a spatial weights matrix can be constructed based on border contiguity, distance contiguity, and k-nearest neighbors. For the border contiguity, GeoDa can create first-order and higher-order weights matrices based on rook contiguity (common boundaries) and queen contiguity (both common boundaries and common vertices). Each of these three ways has its own advantages and disadvantages. For example, when there is a high degree of heterogeneity in the spatial distribution of areal units (polygon) or points, the distance based spatial weights matrix will generate non-constant number of neighbors for each observation. As noted above, one way to solve this heterogeneity problem is to constrain the neighbor structure to the k-nearest neighbors. Non-symmetric weights matrix does not capture the two-way interaction existed among the spatial observations because non-symmetry implies subject $i$is a neighbor of subject j but not *vice versa*. Though in some rare cases, spatial effect might be just one-way and irreversible like in time-series analysis, in most cases including examining the housing value, the spatial effect is two-way interaction and the spatial weights matrix, therefore, must be defined as a symmetric one. So it is not appropriate to construct k-nearest neighbor weights matrix in this study. Also k-nearest neighbor weights matrix is very rigid and may not be appropriate in some given situations.[3] So one must carefully choose the way to define spatial weights matrix in empirical applications.

In rural housing markets, a spatial weights matrix based on contiguity may not be appropriate because houses in rural areas may be far apart each other and be separated by some geographic features so that they are not contiguous. A rural spatial weights matrix based on contiguity may include houses with no neighbors or "islands," a disadvantage of using a distance-based spatial weights matrix in rural housing markets. However, in urban areas, houses are more contiguous and lot sizes do not vary much, so both contiguity and distance based spatial weights matrix should be feasible. In the following empirical analysis, we use a spatial weights matrix based on common boundaries or rook contiguity.

Data description

The main sources of data are the Census 1990 and 2000 Long Forms. Census data contain a large amount of economic and demographic information on U.S. households, including detailed geographic information, at various geographical levels from state to census block group. The data used were collected directly from *Census CD + Map 1990* and *Census CD 2000 Long Form SF3* produced by Geolytics, Inc., which provide a geographic interface for 1990 and 2000 Long Form census data.

We use data from the 1990 and 2000 Decennial Censuses at the block group level. Data at this level of aggrega-

[2] See Anselin (2002) for a full review of contiguity based spatial weights matrix.

[3] For example, when the border is a river, the observations on the both sides of rivers may be neighbors using k-nearest neighbor criterion. But in practice, these observations barely have any spillover effects each other due to the segmentation of the river.

Table 1A
Facilities in sample – MLB and MLB/NFL/NHL.

Facility name	Sport	Team	MSA/CMSA
Chase Field/Bank One Ballpark*	MLB	Diamondbacks	Phoenix, AZ MSA
Turner Field*	MLB	Braves	Atlanta, GA MSA
Oriole Park at Camden Yards*	MLB	Oriloes	Baltimore, MD MSA
Fenway Park	MLB	Red Sox	Boston–Lawrence–Salem, MA-NH CMSA
Wrigley Field	MLB	Cubs	Chicago–Gary–Lake County, IL-IN-WI CMSA
New Comiskey Park*	MLB	White Sox	Chicago–Gary–Lake County, IL-IN-WI CMSA
Comiskey Park#	MLB	White Sox	Chicago–Gary–Lake County, IL-IN-WI CMSA
Jacobs Field*	MLB	Indians	Cleveland–Akron–Lorain, OH CMSA
Coors Field*	MLB	Rockies	Denver–Boulder, CO CMSA
ComericaPark*	MLB	Tigers	Detroit–Ann Arbor, MI CMSA
Tiger Stadium	MLB	Tigers	Detroit–Ann Arbor, MI CMSA
Astros Field*	MLB	Astros	Houston–Galveston–Brazoria, TX CMSA
Kauffman Stadium	MLB	Royals	Kansas City, MO-KS MSA
Dodger Stadium	MLB	Dodgers	Los Angeles–Anaheim–Riverside, CA CMSA
Milwaukee County Stadium	MLB	Brewers	Milwaukee–Racine, WI CMSA
Shea Stadium	MLB	Mets	New York CMSA
Yankee Stadium	MLB	Yankees	New York CMSA
AT&TPark*	MLB	Giants	San Francisco-Oakland-San Jose, CA CMSA
SafeCO Field*	MLB	Mariners	Seattle–Tacoma, WA CMSA
Busch Stadium	MLB	Cardinals	St. Louis, MO-IL MSA
Ballpark at Arlington*	MLB	Rangers	Dallas–Fort Worth, TX CMSA
Arlington Stadium#	MLB	Rangers	Dallas–Fort Worth, TX CMSA
Anaheim Stadium/Edison Field	MLB/NFL	Angels/Rams	Los Angeles–Anaheim–Riverside, CA CMSA
Atlanta–Fulton County Stadium#	MLB/NFL	Braves/Falcons	Atlanta, GA MSA
Baltimore Memorial Stadium	MLB/NFL	Orioles/Colts	Baltimore, MD MSA
Cleveland stadium#	MLB/NFL	Indians/Browns	Cleveland–Akron–Lorain, OH CMSA
Riverfront Stadium/Cinergy Field	MLB/NFL	Reds/Bengals	Cincinnati–Hamilton, OH-KY-IN CMSA
Mile High Stadium	MLB/NFL	Rockies/Broncos	Denver–Boulder, CO CMSA
Dolphin Stadium	MLB/NFL	Marins/ Miami Dolphins	Miami–Fort Lauderdale, FL CMSA
Astrodome	MLB/NFL	Astros/Oilers	Houston–Galveston–Brazoria, TX CMSA
Oakland Coliseum	MLB/NFL	Athletics/Raiders	San Francisco–Oakland–San Jose, CA CMSA
Veterans Stadium	MLB/NFL	Phillies/Eagles	Philadelphia CMSA
Three Rivers Stadium	MLB/NFL	Pirates/Steelers	Pittsburgh–Beaver Valley, PA CMSA
Qualcomm Stadium	MLB/NFL	Padres/Chargers	San Diego, CA MSA
Candlestick Park	MLB/NFL	Giants/49ers	San Francisco–Oakland–San Jose, CA CMSA
Kingdome#	MLB/NFL	Mariners/Seahawks	Seattle–Tacoma, WA CMSA
Metrodome	MLB/NFL/NBA	Twins/Vikings/T-wolves	Minneapolis–St. Paul, MN–WI MSA
Tropicana Field*	MLB/NHL	Devil Rays/Lightning	Tampa–St. Petersburg–Clearwater, FL MSA

tion represents a compromise between the MSA level data used by Carlino and Coulson (2004) and Kiel et al. (2010), and the micro-level data used by Tu (2005), Dehring, et al (2007) and Ahlfeld and Maennig (2010), Kiel et al. (2010) and Ahlfeldt and Kavetsos (2011). Census block groups are collections of census blocks containing between 600 and 3000 people. They are the smallest unit of analysis in publicly available Census data that contain both demographic and economic characteristics and geographical descriptors that will allow us to correct for spatial dependence. Data at more aggregated levels, like counties or MSAs would obscure the spatial effects, while publicly available Census micro data do not contain detailed geographic descriptors. The main limitation of block group data is that the block group median or average values do not fully reflect the underlying distributions of property values in the micro data. But we feel that the benefits of using data at the block-group level, in terms of providing data from a large number of metropolitan areas across the country and a large number of sports facilities, outweighs the limitations.

We use block group level data from the 1990 and 2000 Censuses. Unfortunately, we cannot pool these data because the geographical boundaries of the block groups changed from 1990 to 2000. Thus for any particular 1990 Census block group, there does not exist an exact corresponding block group in the 2000 Census. Because of this lack of correspondence, we estimate separate models for the 1990 and 2000 Censuses.

Our data contain all of the stadiums and arenas in use in the NFL, NBA, NHL, and MLB in the 1990 and/or 2000 Census. This comprehensive set of sports facilities yields a large data set containing 126 individual sports facilities in 45 MSAs. Tables 1A, 1B and 1C show the facilities included in the sample, the MSAs, and the teams that play in them.[4]

Table 2 contains summary statistics for the key variables appearing in Eq. (3), the spatial hedonic model. The sample contains 28,500 block groups in 1990 and 30,346 block groups in 2000. The dependent variable is the median value of all owner occupied housing units in each block group. The average of these block group medians in the sample was \$116,131 in 1990 and \$162,228 in 2000. For the housing structure attributes, the mean value of percent of owner occupied units with complete kitchen facilities and with plumbing facilities is close to 100% for both periods. Most of the sports facility sites in the sample contained multiple facilities.

[4] For 1990, we only include those facilities built before 1990 and not demolished by 1990. The stadiums with * were built after 1990 and therefore not included in the 1990 sample but in the 2000 sample. For the 2000 sample, we only include those built before (including) 2000 and not demolished by 2000. The stadiums with # were demolished by 2000 and therefore not included in the 2000 sample but are still in the 1990 sample.

Table 1B
Facilities in sample, NBA and NBA/NHL.

Facility name	Sport	Team	MSA/CMSA
Charlotte Coliseum	NBA	Hornets	Charlotte–Gastonia–Rock Hill, NC–SC MSA
Quicken Loans Arena*	NBA	Cavaliers	Cleveland–Akron–Lorain, OH CMSA
Richfield Coliseum#	NBA	Cavaliers	Cleveland–Akron–Lorain, OH CMSA
McNichols Sports Arena#	NBA	Nuggets	Denver–Boulder, CO CMSA
Cobo Arena	NBA	Pistons	Detroit–Ann Arbor, MI CMSA
The Palace of Auburn Hills	NBA	Pistons	Detroit–Ann Arbor, MI CMSA
Oakland Arena	NBA	Warriors	San Francisco–Oakland–San Jose, CA CMSA
The CompaqCenter	NBA	Rockets	Houston–Galveston–Brazoria, TX CMSA
Conseco Fieldhouse*	NBA	Pacers	Indianapolis, IN MSA
Market Square Arena	NBA	Pacers	Indianapolis, IN MSA
The Los Angeles Sports Arena	NBA	Clippers	Los Angeles–Anaheim–Riverside, CA CMSA
Memphis Pyramid*	NBA	Grizzlies	Memphis, TN-MS-AR MSA
American Airlines Arena*	NBA	Heat	Miami–Fort Lauderdale, FL CMSA
The Bradley Center	NBA	Bucks	Milwaukee–Racine, WI CMSA
Target Center	NBA	Timberwolves	Minneapolis–St. Paul, MN–WI MSA
New Orleans Arena*	NBA	Hornets	New Orleans, LA MSA
TD Waterhouse Centre	NBA	Magic	Orlando, FL MSA
Rose Graden*	NBA	Trailblazers	Portland–Vancouver, OR–WA CMSA
The Memorial Coliseum	NBA	Trailblazers	Portland–Vancouver, OR–WA CMSA
The Arco Arena	NBA	Kings	Sacramento, CA MSA
Alamodome*	NBA	Spurs	San Antonio, TX MSA
HemisFair Arena#	NBA	Spurs	San Antonio, TX MSA
Key Arena	NBA	Supersonics	Seattle–Tacoma, WA CMSA
DeltaCenter*	NBA	Jazz	Salt Lake City–Ogden, UT MSA
Spectrum	NBA/NHL	76ers/Flyers	Philadelphia CMSA
The Omni#	NBA/NHL	Hawks /Flames	Atlanta, GA MSA
Philips Arena*	NBA/NHL	Hawks/ Thrashers	Atlanta, GA MSA
TD Banknorth Garden*	NBA/NHL	Celtics/Bruins	Boston–Lawrence–Salem, MA-NH CMSA
The Boston Garden#	NBA/NHL	Celtics/Bruins	Boston–Lawrence–Salem, MA-NH CMSA
United Center*	NBA/NHL	Bulls/ Blackhawks	Chicago–Gary–Lake County, IL–IN–WI CMSA
Chicago Stadium#	NBA/NHL	Bulls/Blackhawks	Chicago–Gary–Lake County, IL–IN–WI CMSA
Reunion Arena	NBA/NHL	Mavericks/Stars	Dallas–Fort Worth, TX CMSA
Pepsi Center*	NBA/NHL	Nuggets/ Avalanche	Denver–Boulder, CO CMSA
Staples Center*	NBA/NHL	Lakers/Clippers/ Kings	Los Angeles–Anaheim–Riverside, CA CMSA
Great Western Forum	NBA/NHL	Lakers/Kings	Los Angeles–Anaheim–Riverside, CA CMSA
The Miami Arena	NBA/NHL	Heat/Panthers	Miami–Fort Lauderdale, FL CMSA
Milwaukee Arena	NBA	Bucks	Milwaukee–Racine, WI CMSA
Continental Airlines Arena	NBA/NHL	Nets/ Devils	New York CMSA
Madison Square Garden	NBA/NHL	Knicks/Rangers	New York CMSA
First Union Center*	NBA/NHL	76ers/ Flyers	Philadelphia CMSA
America West Arena*	NBA/NHL	Suns/Coyotes	Phoenix, AZ MSA
Verizon Center*	NBA/NHL	Bullets/ Capitals	Washington, DC-MD-VA MSA
Capital Center	NBA/NHL	Wizards/Capitals	Washington, DC-MD-VA MSA

One of the major issues in the hedonic housing literature is the selection of control variables to explain observed variation in housing values. The literature contains two broad categories of explanatory variables: characteristics of the housing units, including lot size and structural characteristics; and characteristics of the neighborhood, including socio-economic characteristics such as racial composition and median household income, and public amenities such as schools and parks. The latter category is the focus of many hedonic studies and has been extended to include crime, air quality, water quality, and other environmental amenities.[5] Ideally, the empirical model should control for as many housing unit specific and neighborhood specific characteristics as possible, but sometimes data availability is a major determinant of the selection of explanatory variables.

We use explanatory variables, grouped into three categories: housing structure attributes, neighborhood characteristics, and sports facility related characteristics. The first category contains percent of owner occupied housing units with structure detached, average number of bedrooms in owner occupied housing units, average number of vehicles owned by owner occupied housing units, and median age of owner occupied housing units. Most of these housing attributes are examined in the standard hedonic housing literature but the selection of these housing attributes is influenced by data availability.

The second category, neighborhood characteristics, seems to be unmotivated in the hedonic literature. These variables are often included in an *ad hoc* fashion, with little theoretical justification foundation and empirical motivation. Following the existing literature and some theoretical considerations, our choices in the second category include median block group household income, distance from the block group to the central business district (CBD),[6] percent of population 25 years old and over with high school or equivalent degrees, percent of population 25 years old and over with bachelor's degrees, percent of population that is black, and percent of Hispanic population. In addition we include a vector of city specific dummy variables to capture

[5] See Boyle and Kiel (2001) for a full review of house price hedonic studies. But some studies did not include any neighborhood characteristics at all (Basu & Thibodeau, 1998; Can, 1992).

[6] All the distance variables are calculated from centroid to centroid of the block groups. For example, distance to the CBD is calculated from the centroid of each block group to the centroid of CBD block groups. Distance to the sports facility is calculated from the centroid of each block group to the block group where the facility is located.

Table 1C
Facilities in sample, NFL and NHL.

Facility Name	Sport	Team	MSA/CMSA
Sun Devil Stadium	NFL	Cardinals	Phoenix, AZ MSA
Georgia Dome*	NFL	Falcons	Atlanta, GA MSA
M&T Bank Stadium	NFL	Ravens	Baltimore, MD MSA
Ralph Wilson Stadium	NFL	Bills	Buffalo–Niagara Falls, NY CMSA
Ericsson Stadium*	NFL	Panthers	Charlotte–Gastonia–Rock Hill, NC-SC MSA
Soldier Field	NFL	Bears	Chicago–Gary–Lake County, IL-IN-WI CMSA
Paul Brown Stadium*	NFL	Bengals	Cincinnati–Hamilton, OH-KY-IN CMSA
Cleveland Browns Stadium*	NFL	Browns	Cleveland–Akron–Lorain, OH CMSA
Texas Stadium	NFL	Cowboys	Dallas–Fort Worth, TX CMSA
Pontiac Silverdome	NFL	Lions	Detroit–Ann Arbor, MI CMSA
Lambeau Field	NFL	Packers	Green Bay, WI MSA
RCA Dome	NFL	Colts	Indianapolis, IN MSA
ALLTEL Stadium	NFL	Jaguars	Jacksonville, FL MSA
Arrowhead Stadium	NFL	Chiefs	Kansas City, MO-KS MSA
LA Coliseum	NFL	Raiders	Los Angeles–Anaheim–Riverside, CA CMSA
Gillette Stadium	NFL	Patriots	Providence–Pawtucket–Fall River, RI-MA CMSA
Louisiana Superdome	NFL	Saints	New Orleans, LA MSA
Giants Stadium	NFL	Giants	New York CMSA
RFK Memorial Stadium	NFL	Redskins	Washington, DC-MD-VA MSA
Edward Jones Dome*	NFL	Rams	St. Louis, MO-IL MSA
Tampa Stadium#	NFL	Buccaneers	Tampa–St. Petersburg–Clearwater, FL MSA
Raymond James Stadium*	NFL	Buccaneers	Tampa–St. Petersburg–Clearwater, FL MSA
Adelphia Coliseum*	NFL	Titans	Nashville, TN MSA
FedEx Field*	NFL	Redskins	Washington, DC-MD-VA MSA
Buffalo Memorial Auditorium	NHL	Sabres	Buffalo–Niagara Falls, NY CMSA
HSBC Arena*	NHL	Sabres	Buffalo–Niagara Falls, NY CMSA
Greensboro Coliseum	NHL	Hurricanes	Greensboro–Winston–Salem, NC MSA
Raleigh Sports Arena*	NHL	Hurricane	Raleigh–Durham–Chapel Hill, NC MSA
Nationwide Arena*	NHL	Blue Jackets	Columbus, OH MSA
Joe Louis Arena	NHL	Red Wings	Detroit–Ann Arbor, MI CMSA
Bank Atlantic Center*	NHL	Panthers	Miami–Fort Lauderdale-, FL MSA
Hartford Civic Center	NHL	Whalers	Hartford–West Hartford–East Hartford, CT MSA
Arrowhead Pond*	NHL	Mighty Ducks	Los Angeles–Anaheim–Riverside, CA CMSA
Metropolitan Sports Center#	NHL	North Stars	Minneapolis–St. Paul–Bloomington, MN-WI MSA
Xcel Energy Center*	NHL	Wild	Minneapolis–St. Paul, MN-WI MSA
Gaylord Center*	NHL	Predators	Nashville, TN MSA
Nassau Coliseum	NHL	Islanders	New York CMSA
Civic Arena	NHL	Penguins	Pittsburgh–Beaver Valley, PA CMSA
San Jose Arena*	NHL	Sharks	San Francisco–Oakland–San Jose, CA CMSA
Savvis Center*	NHL	Blues	St. Louis, MO-IL MSA
St. Louis Arena#	NHL	Blues	St. Louis, MO-IL MSA
St.Pete Times Forum*	NHL	Lightning	Tampa–St. Petersburg–Clearwater, FL MSA

other unobserved heterogeneity in the area which will also influence housing values, for example environmental amenities such as weather or access to a sea shore.

Median household income is usually included in hedonic models to capture neighborhood characteristics. Alternatively, some studies include the percentage of the population below the poverty line (Beron, Hanson, Murdoch, and Thayer, 2004) or median family income (Palmquist, 1984) to control for these characteristics. The distance to the Central Business District (CBD), an area of high land valuation characterized by a high concentration of retail businesses, service businesses, offices, theaters, and hotels, and by a very high traffic flow (http://www.census.gov/geo/www/cbd.html), may also affect residential location choices because it reflects accessibility to the work place. It is important to control for accessibility to the CBD by including some accessibility variables in the hedonic housing price model (Freeman, 1979). Usually distance to the CBD or some other locational measures such as distance to major freeways is used to measure the accessibility effects.[7] Educational attainment variables, such as percentage of population with high school degree or bachelor's degree, are expected to have some effect on property values. While these two variables seldom appear in the hedonic literature (Bowen, Mikelbank, and Prestegaard (2001)),[8] they are often studied in regional growth literature (Carlino & Mills, 1987; Clark & Murphy, 1996). The educational attainment percentage in this study is not viewed to reflect school quality. It represents partially the quality of life. Quality of life, usually referring a series of environmental amenities and public services, will affect housing values. So percentage of high school graduates and bachelors is hypothesized to influence the housing values through influencing the quality of life in the neighborhood. It is expected that the higher the percentage of population with lower education, the lower the housing values in the neighborhood, and the higher the percentage of population with higher education, the higher the housing values in the neighborhood. This is because, in general, workers with a high school degree will have blue collar jobs while workers with a college degree will have

[7] The distance from housing units to the CBD (DIST_CBD) is excluded in the final model estimation though it is important for housing values. We excluded it because of collinearity between it and the distance to the sports facility when the sports facility is located in the CBD. If the facility is located in the CBD, then these two distances are equivalent. Since the effect from the distance variable from housing units to the facility is the focus of the paper, DIST_CBD is dropped from the model.

[8] Some studies use the school district average assessment (Beron *et al.*, 2004) or school district dummies (Dale, Murdoch, Thayer, & Waddell, 1999) to control for the effects of school quality on housing values.

Table 2
Summary statistics.

Variable	1990 Mean	1990 Std dev	2000 Mean	2000 Std dev
Median value, owner occupied units	116131	98506	162228	138499
Multiple stadiums indicator	0.51	0.50	0.71	0.45
Multiple use stadium indicator	0.60	0.49	0.59	0.49
NFL	0.11	0.31	0.14	0.35
MLB	0.26	0.44	0.25	0.43
NBA	0.50	0.50	0.30	0.46
CBD indicator	0.29	0.46	0.33	0.47
Stadium age	22.85	18.80	16.56	21.34
Renovated stadium	0.09	0.29	0.12	0.33
Percent in block group with College degree	0.13	0.11	0.15	0.12
Percent of block group African American	0.26	0.36	0.26	0.34
Percent of block group Hispanic	0.14	0.23	0.20	0.26
Average number of rooms	5.13	1.14	4.99	1.25
Percent detached owner occupied units	0.67	0.35	0.63	0.36
Percent of housing units with Propane heat	0.68	0.29	0.65	0.27
Average# of bedrooms	2.84	0.52	2.74	0.60
Average number of vehicles	1.57	0.51	1.55	0.52
Median household income	30286	16989	42271	23937
Median house age	39.27	12.07	48.55	14.30

white collar jobs. So the percentage of population with a high school degree will have a negative effect on the housing value while the percentage of population with bachelor's degree will have a positive effect. The percent of the population that is African-American is also often included in hedonic models and is expected to have a negative effect on property values (Bowen et al., 2001).

The last category is sports facility related variables. It includes the distance from the census block group centroid to the closest sports facility, an indicator for the presence of multiple facilities in the city, the age of the sports facility, a renovation dummy to indicate whether the facility was renovated before 2000, and a multiple usage indicator variable to identify facilities with multiple teams playing in them. The distance to the stadium captures the spatial economic effects of sports facilities. The multiple-usage indicator is based on the presence of teams in the four professional sports leagues and does not include hosting concerts or other non-sports events. As discussed in the literature review, the economic impact of sports facilities may differ when the facility is located in the center of a city compared to a suburban area. To control for this difference, we constructed a CBD indicator that is equal to one when the sports facility is located in the CBD of a city. This CBD indicator is based on the definition of Census Business Districts from the 1982 Census of Retail Trade. The problem with using the 1982 CBD definition with 1990 and 2000 census data is that there might be more census block groups which should be defined as in the CBD in both the 1990 and 2000 census data than in the 1982 census data. But this is the most recent definition of CBDs available. The Census Bureau discontinued the CBD program after the 1982 Census of Retail Trade.

The number of block groups varies among MSAs, so the number of observations in a MSA is as large as 16,576 in the New York MSA or as small as 178 in the Green Bay MSA. The average MSA has 2738 block groups. It is not necessary to pool all the observations from all 37 MSAs for this cross-sectional analysis because the impacts from sports facilities are not expected to spill over the entire MSA or even the entire county. From our empirical analysis, the effects are not significant when the facility is 4 or more miles away.[9] After all facility block groups are identified, we extracted data from block groups within a radius of 5 miles of the centroid of the block group containing the facility.

Results

Table 3 shows the results from estimating the hedonic housing price model, Eq. (7), with spatial lags based on the "rook" spatial weights matrix, using data from the 1990 and 2000 Censuses.[10] Table 3 contains estimated parameters with *P*-values shown below. The empirical model also included MSA-specific intercept terms in order to control for unobservable MSA-specific housing market characteristics. These parameter estimates are not reported, but most were significant. Since the hedonic housing price literature contains a variety of functional forms, and theory provides no clear guidance on functional form in this instance, we report results based on two functional forms: linear, and log-log models. The linear form forces the effect of distance from a sports facility to be constant, while the log–log form allows this effect to vary systematically with distance.

The spatial lag parameter is positive and significant in all model specifications, indicating that spatial dependence is important in these data. Recall that failure to account for this dependence can lead to biased and inconsistent estimates when using the OLS estimator.

The key parameter of interest on this table is the estimated effect of distance from a sports facility on the median value of owner occupied housing units in a block group. The sign of this parameter is negative in three of the four model specifications and not statistically different from

[9] Tu (2005) showed similar results that the impact is not significant after 3 miles.
[10] The model specification testing and literature using spatial hedonic model (Kim, Phipps, & Anselin, 2003) suggest that spatial lag instead of spatial error model is more likely to be appropriate in capturing the spillover effects on housing values with rook contiguity spatial weights matrix.

Table 3
Estimates from hedonic spatial lag model, Eq. (7).

Variable	1990 Linear	Census Log–log	2000 Linear	Census Log–log
Spatial lag	0.303	0.038	0.385	0.0001
	0.001	0.001	0.001	0.001
Distance to facility	−570	0.004	−793	−0.008
	0.001	0.221	0.008	0.001
Multiple facilities	−6369	0.012	15098	0.099
	0.001	0.116	0.001	0.001
Multi-use facility	6385	0.037	−4562	0.020
	0.001	0.001	0.003	0.014
NFL	−10781	0.024	−28202	−0.251
	0.001	0.099	0.001	0.001
MLB	1994	0.082	17609	−0.043
	0.122	0.001	0.001	0.001
NBA	−4352	0.068	4321	−0.044
	0.001	0.001	0.018	0.001
CBD indicator	14636	−0.060	23847	0.006
	0.001	0.001	0.001	0.509
Stadium age	264	0.001	121	0.002
	0.001	0.001	0.001	0.001
Renovated facility	−15415	−0.005	14756	0.187
	0.001	0.671	0.001	0.001
%College degree	76369	1.747	6474	1.375
	0.001	0.001	0.357	0.001
% Black	−14858	−0.363	−3760	−0.354
	0.001	0.001	0.055	0.001
% Hispanic	−50427	−0.354	−26072	−0.209
	0.001	0.001	0.001	0.001
Average# of rooms	−14397	−0.084	−22701	−0.062
	0.001	0.001	0.001	0.001
Average# bedrooms	17904	0.171	47522	0.262
	0.001	0.001	0.001	0.001
% Detached homes	−16070	−0.078	−28291	−0.029
	0.001	0.001	0.001	0.006
% With propane heat	−997	−0.078	−6915	−0.139
	0.572	0.001	0.017	0.001
Average# of vehicles	−7817	0.072	−17613	0.064
	0.001	0.001	0.001	0.001
Median Household Inc.	1.953	0.352	2.555	0.312
	0.001	0.001	0.001	0.001
Median house age	407	−0.002	655	0.0008
	0.001	0.001	0.001	0.001
N	28472	28472	30297	30297
R^2	0.787	0.825	0.702	0.742

Parameter estimates and *P*-values shown on table.

zero in the third. We focus on the results from the linear models in our discussion, as both are statistically significant.

The results indicate that proximity to a sports facility has a positive effect on the value of owner occupied housing for the linear model using 1990 Census data and for the linear and log-log models using 2000 Census data. The negative sign on the distance parameter implies that median owner occupied property values decline as the block groups get farther from the sports facility. The parameter on the distance variable in the log-log model using 2000 data can be interpreted as the elasticity of changes in property values with respect to changes in distance. The size of this parameter indicates that property values decline by 0.8% for each one percent increase in distance from the sports facility.

Note that these parameter estimates reflect statistical association, and do not reflect a causal relationship. If new sports facilities tend to locate in areas with higher residential property values, then this parameter will substantially over-estimate the actual relationship between the presence of a sports facility and residential property values. However, urban planners and decision makers may not have significant discretion in locating new sports facilities. The footprint of a new sports facility is quite large; even NBA/NHL arenas can require a footprint of 15 to 50 acres.[11] In many metropolitan areas, locating a parcel of land large enough to place a new sports facility on is a difficult process. In addition, a suitable parcel of land must have access to roads and other transportation infrastructure. These requirements restrict the number of potential sites for a new sports facility in a metropolitan area. In addition, if significant land acquisition must take place to prepare a site, then total costs would be lower if a new facility was located in an area with low property values.

These results indicate that sports facilities generate positive spillover effects on the local economy, and that these spillover effects are capitalized into the value of owner occupied residential housing. The positive and statistically significant sign on the stadium age variable supports the idea of positive spillovers, as this parameter suggests the longer a sports facility has been at a given location, the greater the increase in median housing values near the facility. These results differ from the results in Kiel et al. (2010), who also analyze the relationship between housing values and sports facilities. However, Kiel et al. only examine proximity to NFL stadiums in the 1990s and do not control for spatial dependence. We examine proximity to NFL, NBA, NHL and MLB facilities and correct for spatial dependence, which may explain the difference.

The other parameters in the model are precisely estimated and generally have the expected signs. The housing unit characteristics parameter estimates indicate that houses with more bedrooms have higher median value and that block groups with detached homes have lower median values. The neighborhood characteristics suggest that the larger the fraction of the population in the block group with a college education, the higher the property values in the block group, and the larger the minority population in the block group, the lower the median housing value in the block group. Median housing values also rise with median household income and housing age.

Discussion and conclusions

In this paper, we investigate the effect of spatial proximity to a sports facility on housing values using cross-sectional data from the 1990 and 2000 Censuses at the block group level. Using a standard hedonic housing price model with two alternative functional forms, the results show that the distance to a sports facility has a significant and positive effect on housing values and the effect is distance decaying. The effects from other housing structure attributes, such as average number of bedrooms, etc. and neighborhood characteristics, such as median household income and black population percentage etc. are significant and consistent with the hedonic housing literature. Since we use data from a large number of metropolitan areas containing professional sports facilities from four different sports, our results indicate that evidence from case studies can be generalized to other settings.

[11] For example the footprint of the Pepsi Center Arena in Denver was 45 acres and the footprint of Lincoln Financial Field was 15 acres.

Table 4
Increase in aggregate occupied property value, 2000 census results.

Impact radius	Average increase	Median increase	Smallest increase	Largest increase
One mile	$19,500,000	$11,200,000	$1570,649	$103,000,000
Two miles	$102,000,000	$55,500,000	$14,600,000	$653,000,000
Three miles	$247,000,000	$153,000,000	$39,600,000	$1680,000,000
Four miles	$424,000,000	$277,000,000	$80,000,000	$3180,000,000

Our results confirm the findings contained in other case studies of the spatial economic impact of professional sports facilities (Ahlfeldt and Kavetsos, 2011; Tu, 2005). We find evidence consistent with the idea that professional sports facilities generate externalities, and that these effects are capitalized in residential property values and decline with distance. Our results are based on a large, comprehensive data set containing housing values located near a wide variety of sports facilities in many cities.

How large are the increases in property values, in aggregate, in cities with professional sports facilities? The results in column 3 of Table 3 suggest that moving a residential housing unit one mile closer to a sports facility would increase its value by $793. The total increase in housing values in a city would depend on the number of residences in the city and the proximity of these residences to the sports facility. In order to provide an estimate of the total value of the increase in housing values in a city attributable to a sports facility, we performed the following thought experiment/back of the envelope calculation: if every occupied housing unit within X miles of a sports facility in a city were moved to adjacent to the facility, by how much would housing values increase in that city?

Table 4 shows the results of this calculation, using data from the 2000 Census. The unit of observation is a metropolitan area; the housing density and location of the facility differs across metropolitan areas, leading to different values for the calculation. We have performed this calculation for four different impact areas: all occupied residences within one, two, three and four miles of the facility. Table 4 shows the average and median increase in total housing values, and the smallest and largest increases across the metropolitan areas in the sample. Note that in some metropolitan areas the increase in aggregate housing values is relatively small, and that a few very large metropolitan areas with high housing density skew the estimated average increase in aggregate housing values well above the median increase. The median increase in aggregate housing value is modest, ranging from $11.2 million in a one mile radius to $277 million in a four mile radius. Eleven new professional sports facilities were opened in the US in 2000 and 2001, a banner period for such openings. The average cost of these facilities was $316 million (and the median cost was $339 million), so the increase in aggregate housing values would only equal the cost of a facility in the largest cities.

However, cities collect property taxes annually, and the results on Table 4 are for permanent increases in property values. Assuming a 30 year useful life of each facility, a discount rate of 5%, and an average property tax of 1.38%, the present discounted value of the future property tax increases for the median total property value increase of $11.2 million is $10 million.[12] At the median for the four mile radius impact area, the present discounted value of the increased property taxes is $254 million. Again, it appears that the increase in residential property values generated by a new sports facility is less than the cost of building such a facility in all but the largest, most densely populated metropolitan areas.

We note that unlike the papers using data on individual house prices, this analysis uses data aggregated to the Census Block level. If the median house value in a census block does not reflect the distribution of housing prices in each Census Block, then the results here are weakened. However, we believe that the use of census block group data is an important bridge between research using data aggregated to the MSA level and case studies of a single location.

The results in this paper have important urban policy implications. The lack of evidence supporting the notion that professional sports teams generate tangible economic benefits in the local economy has called into question the economic rationale for the large subsidies provided by state and local governments for the construction and operation of sports facilities. However, the results presented here suggest that sports facilities generate important intangible spillover benefits in the local economy, and that these intangible benefits are capitalized into residential housing prices. The presence of these benefits, if large enough, could justify subsidies for sports facility construction and operation, since many local governments generate tax revenues from taxing property.

A considerable amount of work remains to be done in this line of research. The observed effect of proximity of a sports stadium on residential housing prices could work through the effect of these facilities on business location, and the effect of business location on residential properties. If many bars and restaurants open close to sports facilities, this will increase the demand for land in these areas and drive up existing property values. This issue can be addressed by expanding the data set to include neighborhood business characteristics. Decisions about the location of sports facilities in metropolitan areas may not be exogenous; urban planners may build new sports facilities in areas in need of economic development. If this is true, then the distance variable will be correlated with the equation error term in Eq. (7), and the results in the paper may be biased and inconsistent.

If sports facilities increase residential property values, then the cities that are host to professional sports teams may collect more property tax revenues than they would have absent these facilities. Clearly, this implication deserves further attention. Our empirical results can serve

[12] In 2007 the average property tax rate in the US was 1.38%; (http://www.nytimes.com/2007/04/10/business/11leonhardt-avgproptaxrates.html).

as the basis of a cost-benefit study comparing the value of sports facility subsidies to the additional property tax revenues generated by these facilities.

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