# The Relocation Effect of a Major League Franchise on Residential Property Values*

## Quantifying the Intangible (Dis-) Benefits Generated by the Departure of the NFL's Rams Franchise from St. Louis to Los Angeles

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February 23, 2024

**Abstract**

We exploit the relocation of the NFL's Rams franchise as a natural experiment to estimate the effect of residential proximity to sports amenities using hedonic regression models. For a sample of single-family homes transacted within St. Louis between 2012-2019, we reveal that the relocation has provoked a significant relative price depreciation of housing values within a three-mile impact area. Subsequent distance ring analyses show that the effect expands up to four miles and declines in a non-linear distance-decaying pattern from the former host stadium. Estimates of the local welfare loss suggest that the intangible benefits emanated by a major league franchise may be large enough to justify generous public subsidies for the construction or maintenance of professional sports facilities.

**Key Words**: Hedonic Regression; Property Values; Spatial Externalities; Sports; NFL; St. Louis

*I would like to thank Pierre-Philippe Combes, Oliver Gürtler, Raoul van Maarseveen, Dominik Wied, Michele Fioretti, Guillaume Chapelle, and Gerrit Quaremba for helpful comments and suggestions. An earlier version of this paper had originally been written and published under the same title within the framework of the Public Policy Master Thesis Series at SciencesPo Paris' School of Public Affairs.

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# 1 Introduction

Between 1991 and 2005, 64 new arenas and stadiums were constructed in the US across the four major leagues: NFL (Football), NBA (Basketball), NHL (Ice Hockey), and MLB (Baseball) (Zimbalist (2010)). This national construction boom was catalyzed by larger major league expansions, and driven by municipalities desires of becoming major league host cities, ubiquitously considered a pivotal status criteria distinguishing top-tier cities. Albeit, there still prevails an excess demand for major league teams, resulting in intense inter-city competitions among large municipalities in the US,[1] similar to the bidding "wars" surrounding major industrial plants (Greenstone et al. (2010), Slattery (2023)). Aiming to lure in a franchise, public entities often provide massive public subsidies of several hundred millions of dollars for the construction, renovation, or maintenance of professional sports facilities. Similarly, cities that are already hosting a major league team, commonly encounter relocation threats leveraged by franchises to bolster their bargaining power and secure larger subsidies (Humphreys and Zhou (2015)).

In this context, stadium proponents typically argue that sports facilities generate considerable economic spillover effects within local economies, for example in terms of income revenue streams and employment opportunities. However, a plethora of ex-post evaluation studies comes to the unanimous conclusion that the direct, i.e. tangible, economic impact of sports facilities is at best non-significant as a result of crowding-out and substitution effects (e.g. see Baade and Dye (1988), Noll and Zimbalist (1997), Coates (2007) for early surveys on the subject). Intriguingly, despite the overwhelming evidence of the economic impotence of sports facilities, public funding for stadium projects has increased in magnitude, as stadium costs constantly evolve in light of new sophisticated stadium features. In total, an outstanding sum of \$33bn in public funds have been provided over the past fifty years for stadium projects (Bradbury et al. (2022)). Not only does this sum reflect immense opportunity costs, it also raises distributional concerns. As Alexander and Kern (2004) contend, the true winners of such subsidies may be above all team owners because team values tend to skyrocket upon moving to a new facility.[2] Moreover, Humphreys (2019) predicts that history is likely to repeat itself and that the next decade will presumably bring up a new construction boom, as several stadiums and arenas are considered outdated by today's standards. In this regard, the public financing of future stadium projects is a question of central importance for policymakers, taxpayers, and team owners alike.

While the literature demonstratively emphasizes the lack of a direct economic rationale justifying public subsidization, it may however be that hosting a major league franchise leads to market failure in terms of substantial positive externalities, that are intangible, i.e. non-pecuniary, amenity benefits. If sufficiently large, such amenity benefits might justify generous public subsidies for sports facilities. Concretely, sports facilities as urban amenities provide numerous perennial consumption opportunities to local residents (Glaeser et al. (2001), Brueckner et al. (1999)), not only in terms of the hosted sports- and non-sports events, i.e. concerts and conventions, but equally in terms of

[1] There also exist intra-city competitions between central cities and suburbs for the concrete location choice of stadiums (Nunn and Rosentraub (1997)).

[2] For instance, Click (2016) reports that the value of the Rams has doubled shortly after moving to the larger Los Angeles market.

their sports-related surrounding environment of shops, bars, and restaurants (Abbiasov and Sedov (2023)), tailored to enhance the overall fan experience. Moreover, well-designed sports facilities that neatly blend in the urban fabric may serve as important urban landmarks and catalysts driving and consolidating urban development, in particular in deserted downtown areas (Chapin (2004), Bachelor (1998), Holm (2019)). In this vein, Rosentraub (2006) argues that public investments in the sports sector, aimed at revitalizing or fostering the city core, act as important signals and enhance a city's overall appeal. Consequently, they implicitly alleviate urban flight of citizens and firms.

Rosentraub's argument tacitly suggests that professional sports conveys considerable amenity benefits to residents. Among the most prominent positive externalities associated with the presence of professional sports teams are an overall higher quality of life (e.g. Carlino and Coulson (2004)), enhanced social cohesion and community identity (e.g Johnson et al. (2012)), as well as a feeling of civic pride (e.g. Porsche and Maennig (2008)). However, ex ante, the net amenity effect is ambiguous as sports has been reported to also convey negative externalities, primarily related to spatial congestion. For instance, sporting events have been linked to increased traffic congestion (e.g. Humphreys and Pyun (2018)), elevated noise levels (e.g. Ahlfeldt and Kavetsos (2014)), air pollution (e.g. Locke (2019)), disease spread (e.g. Stoecker et al. (2016)), and heightened criminal activity, prompting higher police spending (e.g. Kalist and Lee (2016), Pyun et al. (2023)). Ultimately, the sign of the total effect reveals which side predominates.

Against this background, this paper explores the intangible (dis-)benefits generated by a major league sports franchise. Concretely, we exploit the relocation of the NFL's Rams franchise in 2016 from St. Louis, Missouri, to Los Angeles, California, as a natural experiment allowing to assess the foregone amenity benefits induced by the teams' departure. St. Louis provides insofar a unique and promising case study as the city constitutes typical characteristics of a Rust-belt city and has been on a general economic and population decline for more than 70 years (Metzger et al. (2018)). In an effort to countervail this long-term trend, St. Louis political and economic leaders have incrementally embraced a sports-led urban development strategy since the early 1990's, whereby sports facilities play a crucial role in promoting entertainment and tourism, and revitalizing the city core's urban landscape as imposing urban landmarks (Hurt (2021)). In this vein, despite its relatively low population size of about 330,000, the city hosted three major league franchises until the departure of the Rams in 2016: the Rams (NFL), the Cardinals (MLB), & the Blues (NHL).[3] Besides, Hurt (2021) underscores the synergies existing between sports and the St. Louis community and emphasizes that the city is a sports-fanatic city. Similarly, ESPN has designated St. Louis as "the ultimate sports city",[4] and Wagoner (2019) speaks of a "philanthropic void left behind by the Rams", and mentions a general drop in social morale accompanied by strong resentment from citizens and public official towards the Rams organization after their departure.

In light of the importance that professional sports plays for the city and its residents, we hypothesize that the Rams generated substantial intangible benefits and consequently that the departure of the franchise has induced a considerable local welfare loss. To approximate the social costs of

[3]Since March 2023, St. Louis hosts again three major league teams and is home to the MLS (soccer) franchise St. Louis City SC, which plays in a newly constructed stadium inaugurated in 2022.

[4]C.f. ExploreStLouis.com

the relocation, we examine the externalities generated by the Rams through the lens of the local housing market. Residential property prices serve insofar as fruitful ground for empirical analyses as they reflect the value of a bundle of structural housing attributes and neighborhood characteristics including local public goods (Tiebout (1956), Rosen (1974)). Accordingly, the externalities generated by a sports team and sports facility should be capitalized in local property values within a certain distance to the stadium. Simply put, if the presence of the Rams induced considerable quality-of-life benefits, the effect of the relocation should be expressed in a relative price discount of properties close to the Edward Jones Dome, the stadium in which the Rams played from 1995-2015.[5]

Furthermore, we postulate that the relocation of the Rams can be considered as a natural experiment, since until the filing for relocation on January 4th, 2016, and the ratification by the NFL a few days later, on January 12th, 2016, the Rams ownership has repeatedly publicly declared their intention to remain in St. Louis. Consequently, the franchise engaged in negotiations with the City of St. Louis and the NFL, first regarding upgrades to the Edward Jones Dome, and later on the construction of a new state-of-the-art venue whose financing plan was unveiled and ratified by city officials in late December 2015, only a few days before the Rams eventually decided to leave the city (Click (2016)). Conceptually, we exploit the departure as an exogenous shock and compare the changes in transaction prices of single-family homes located in vicinity to the stadium to those of properties with similar features but located farther away, for the period of 2012-2019. Specifically, we use a difference-in-differences methodology and embed distance rings within hedonic regression models to estimate the relative change in the valuation of residential proximity to the facility.

We find that the relocation is associated with a relative price depreciation of single-family homes of about 7.5% within a three-mile distance from the Edward Jones Dome. In addition, positive externalities are found to be most pronounced in direct vicinity to the facility and expand in a distance-decaying fashion up to four miles. Finally, an approximation of the net social costs of the Rams' departure reveals a substantial relative decline in housing values amounting to up to $520 million, expressed in 2023 prices. Essentially, this sum is roughly comparable to the funds initially provided for the construction of the stadium, which was about $550 million. Therefore, our case study provides evidence that major league franchises can produce sufficiently large intangible benefits to justify the public subsidization of sports facilities. This may be especially relevant in contexts of distressed markets and deserted city cores, where sports teams can take on a central role as catalysts of urban revitalization.

[5] The stadium was recognized under this name for the majority of the Rams' tenure in St. Louis. Yet, it's worth noting that its original designation was the *Trans World Dome*, and following the departure of the Rams, it was once again renamed to its current name, *The Dome at America's Center*.

# 2 Related Literature

The economists' toolkit provides three empirical approaches to unveil the intangible benefits associated with sports amenities. Firstly, the contingent valuation method (CVM) relies on surveys in which participants are directly asked about their willingness-to-pay (WTP) for keeping a specific franchise in town. Within their comprehensive review, Bradbury et al. (2022) conclude that the overall findings of the CVM examinations indicate considerable non-use values in terms of quality of life and civic pride benefits. However, these values are often small in magnitude relative to facility costs. Nonetheless, the method is often criticized for its lack of credibility due to the hypothetical nature of the relocation scenarios it presents. In a related instance to St. Louis, Fenn and Crooker (2009) address this concern and examine the credible relocation threat faced by the Vikings (NFL) in Minnesota if the city did not provide them with a new stadium. The authors estimate an aggregate WTP of $700 million, which would be sufficiently large to cover the costs of a new home ground.

Secondly, voting behavior in referendums may offer more accurate assessments of the anticipated benefits of new stadiums as voters face immediate real outcomes. Additionally, referendums allow to uncover spatial patterns in support levels related to proximity to the facility. Overall, while the literature generally suggests electoral support for sports facilities, evidence on the spatial distribution of support levels is somewhat discordant. On the one hand, Dehring et al. (2012) find that support for a new stadium for the Cowboys (NFL) in Dallas was positively associated with expected increases in property values, aligning with the homevoter hypothesis by Fischel (2001). Similarly, Coates and Humphreys (2006) observe a positive association between proximity to the stadium and the WTP for the renovation of a facility in Green Bay. On the other hand, Ahlfeldt and Maennig (2012) and Horn et al. (2015) observe NIMBY (Not In My Backyard) behavior during referendums in Munich and Seattle respectively, indicating that while there was general support for the new facilities, residents living close to the proposed sites exhibited the lowest levels of support.

Thirdly, this paper follows the footsteps of a relatively rich and predominantly hedonic literature exploring the effects of sports facilities and teams on local housing markets via cross-city comparisons or local case studies. While the vast majority of these papers examine the associated amenity benefits through housing prices and land values (Tu (2005), Ahlfeldt and Maennig (2009), Ahlfeldt and Maennig (2010), Feng and Humphreys (2012), Ahlfeldt and Kavetsos (2014), Feng and Humphreys (2018)), the question has also been studied from various other perspectives, including, tax assessment values (Propheter (2021), Bradbury (2022)), monthly rents (Carlino and Coulson (2004), Agha and Coates (2015)), as well as mortgage applications (Huang and Humphreys (2014)). The majority of these papers operate in either American or European contexts and emphasize that sports facilities emanate significant positive spatial externalities, concentrated a few miles around a respective facility and typically diminishing nonlinearly with distance. Concerning the prior literature investigating housing prices, estimates of the average relative housing value appreciation typically range between 5% to 15%. However, some papers also report negative (Dehring et al. (2007)) or null (Kiel et al. (2010), Bradbury (2022)) findings. Notably, these findings are not confined solely to the opening of a new facility, as several papers document that binding or credible announcements evoke comparable market reactions (Dehring et al. (2007), Kavetsos (2012), Keeler et al. (2021), Neto and Whetstone (2022)).

Overall, while several papers report substantial local welfare effects, the prior literature still provides inconclusive evidence as to what extent the total benefits stand in relation to the generous public subsidization. In this regard, Bradbury et al. (2022) draw a rather skeptical conclusion. Nevertheless, it should be noted that several papers at the upper end of the spectrum also report substantially significant effects, such as total increases in the housing stock value reaching up to £1.3bn following the announcement of the London Olympics (Kavetsos (2012)).

Generally though, while rich in essence, the prior literature has hitherto laid few emphasis on the underlying urban and economic mechanisms driving both direction and magnitude of the impact of sports amenities on local housing markets. In this light, this paper aims to better carve out the urban and economic context in which the Rams operated and to contextualize the findings to provide complementary evidence on the interplay of sports facilities and their idiosyncratic urban environments. Specifically, we enrich our set of covariates with urban and geographical characteristics, such as historical designation, floodzones, or proximity to parks, that have been vastly ignored within prior hedonic studies on sports amenities, despite their well-documented impact on housing markets. In addition, we exploit a unique geospatial dataset to obtain information on the urban composition of St. Louis. In this context, the integration of the Edward Jones Dome within downtown and its adjacent surroundings, predominantly composed of commercial and industrial parcels, enables us to implicitly examine arguments suggesting that sports facilities generate larger spatial externalities and enhance location desirability the most when seamlessly integrated into urban areas (Rosentraub (2009), Ahlfeldt and Maennig (2009)). This supports the notion that parking lots may hinder the realization of positive amenity benefits (Nelson (2001)). Intriguingly though, Propheter (2021) mirrors this logic by positing that the *"island-like"* design of Dodgers Stadium in Los Angeles might act as a buffer, separating residential living quarters also from sports-related congestion externalities.[6] Equally, the Dome's surrounding area in St. Louis may yield a comparable effect.
Further, by nature of the location of most major league teams, prior studies primarily examine the effect of sports facilities in large metropolitan market areas. However, Agha and Coates (2015) find that the impact of minor league teams on rents is largest in mid-sized cities like St. Louis, whereas it is less pronounced in larger, potentially more saturated markets. Hence, St. Louis' economic framework and reliance on the sports industry promises new evidence on this matter.

Ultimately, while the prior literature almost exclusively leverages stadium constructions and team arrivals, surprisingly little is known about the impact of team departures on the local housing market. To our knowledge, this paper constitutes the first empirical assessment of the effect of the departure of an NFL franchise on residential property values. Prior, only one paper by Humphreys and Nowak (2017) has analyzed the relocation of two NBA franchises from Seattle and Charlotte. The authors find that residential property values respectively appreciated about 6-7% & 7.5-14% within a one- and two-mile impact area after the relocation, suggesting that the franchises constituted considerable urban disamenities in the local market. However, an NFL franchise may have a differing impact because the NFL is by far the most important league, both in terms of revenue and popularity, and

[6] This reasoning aligns with the observation that support levels for a new stadium in Seattle were highest in areas within commutable distance to the proposed site, close enough to conveniently experience amenity benefits but far enough away to avoid negative congestion externalities (Horn et al. (2015)). Bradbury et al. (2022) refer to the notion of a *"Goldilocks Zone"*.

congestion effects may be substantially smaller as an average season consists of only eight home matches, as opposed to over forty games played per NBA, MLB, & NHL home season.
In addition, we are able to disentangle the team- from the facility effect due to the continuous use of the Edward Jones Dome as a venue for concerts and conventions throughout the sample period. This case study thus also contributes to a scarce literature, consisting of only two papers investigating pure team effects. First, Joshi et al. (2020) examine the effect of the promotion of an MLS (Soccer) franchise in Seattle in 2009 and observe a depreciation of property values within two miles from the stadium of 5-15%. Second, Chikish et al. (2019) study three consecutive sports-related shocks in Oklahoma: the opening of a new stadium in 2002, the unexpected arrival of an NBA franchise playing in the stadium from 2005-2007, and the eventual relocation of another permanent NBA franchise to Oklahoma. The authors find positive impacts on local property values after all three events. However, when replicating the estimations based on a repeated-sales sample, only the positive stadium effect remains significant. The authors conclude that facilities alone play a considerable role as urban amenities, contributing not only through hosting non-sports-related events but also by shaping the surrounding environment, such as bars and shops.

Finally, to the author's knowledge, no paper has yet examined the impact of sports teams on the residential real-estate market in St. Louis. While previous papers suggest that the sports industry has a significant impact on St. Louis, which is found to be positive in the realm of hotel occupancy rates (Stephenson (2021)), null with respect to employment effects in the construction sector (Miller (2002)), and negative in the context of crime (Mares and Blackburn (2019)), the total expected impact of the sports-led urban revitalization strategy on property values remains ambiguous a priori. This paper aims to partially close this research gap.

# 3 The Rams Relocation History

After losing the Cardinals (NFL) to Arizona in 1987, St. Louis was without a football team for almost a decade.[7] Aiming to fill this void, the City of St. Louis, St. Louis County, and the state of Missouri, joined forces and jointly provided $258 million for the construction of the Edward Jones Dome in 1995. To entice the Rams away from the more lucrative Los Angeles market, the franchise was offered an exceptionally favorable lease contract lasting thirty years. This lease included an 'escape-hatch' clause, allowing the Rams to unilaterally terminate the agreement without penalty if, by March 1, 2005, or March 1, 2015, respectively, the stadium failed to rank among the top 25% of NFL stadiums. While the stadium already fell short of meeting the benchmark by 2005, the franchise chose to stay after agreeing to $30 million worth of renovations. This decision signified not only their intent to stay in St. Louis but also their commitment to honoring their contractual obligations until at least 2015. Nevertheless, in the years leading up to 2015, it became apparent that the Edward Jones Dome would require a significant overhaul. This need raised the possibility of the Rams invoking their contract clause and departing from St. Louis. In response, city officials and Rams owner Stan Kroenke, a Missouri native who openly expressed his intent to seek a mutually agreeable solution, initiated negotiations in 2012. Their objective was to secure a long-term future for the Rams in St. Louis.[8] Though, as no mutual agreement could be found,[9] two events particularly fueled speculations about a return of the Rams to Los Angeles:

(i) On January 31, 2014, it was publicly disclosed that Kroenke had acquired land in Inglewood, California. This information was communicated to the NFL, in accordance with the league's regulations mandating franchise owners to report their involvement in the Los Angeles market.[10] Nevertheless, NFL Commissioner Goodell publicly stated that there had been no communication of intent to construct a stadium on the purchased land. He emphasized the NFL's stringent relocation policy, highlighting the significant practical and financial obstacles any relocation would face.[11] In addition, the parcel itself was too small for an entire stadium complex, and considering Kroenke's background as a real estate businessman, land acquisitions are not uncommon for him. Thus, it can be plausibly assumed that the purchase of land should not have triggered any anticipatory market reaction in St. Louis. Further, in December 2014, the Rams announced their decision not to exercise their right to relocate, confirming the intention to stay in St. Louis for the forthcoming season.[12]

(ii) On January 5, 2015, Rams owner Kroenke revealed intentions to construct an 80,000-seat sta-

[7] If not stated otherwise, the information presented in this section stem primarily from Click (2016), who offers an excellent account of the complete trajectory of football in St. Louis.

[8] C.f. Stltoday.com[1].

[9] Eventually, both sides' views diverged significantly. In January 2013, an arbitration tribunal ruled that fulfilling the contract required the Rams' proposed $700 million renovations. Due to the city's limited financial capacity of $124 million, the city initially rejected the proposal. Instead, they set on new negotiation rounds, knowing that a departure before March 2015 was contractually impossible.

[10] C.f. Wagoner (2014).

[11] In retrospect, this turned out to be a false statement, and it recently leaked out that more concrete talks had already taken place behind the scenes between Kroenke and the NFL (Huguelet et al. (2022)).

[12] An essential factor was the NFL's clear directive to teams, stating that no relocations would be permitted in 2015, with any potential moves postponed until at least 2016.

dium in Inglewood, projected for completion in 2018.[13] In regard of his ownership status, the Rams were obviously seen as a hot candidate to play in the new stadium. However, it should also be mentioned that two other NFL franchises, the Chargers and Raiders, who were in a similar situation and equally expressed dissatisfaction about their host facilities, positioned themselves for a move to Los Angeles. Moreover, as mentioned earlier, the practice of leveraging relocation threats to elicit larger public contributions for a new stadium or for considerable renovations of the current home ground, is a common practice in the American franchise system.[14]
Effectively, a mere four days later, the tacit threat of relocation seems to have proven fruitful as Missouri Governor Jay Nixon promptly established a stadium task-force, mandated to develop a concept for a new billion-dollar stadium, located a bit closer to the waterfront and equipped with a series of sophisticated features which would have made it one of the most modern stadiums in the NFL.[15] The plans were ultimately unveiled to the NFL during a conference on the future of the St. Louis franchise in October 2015, which was described by city officials as highly productive and insightful and led to the approval of the new stadium plans by various city committees in early December. Subsequently, these approved plans were submitted to the NFL in late December 2015. Despite these efforts, on January 4, 2016, the Rams submitted a relocation application to the NFL, coinciding with applications from the Chargers and Raiders. Alongside their application, the Rams' owners issued a statement declaring the city's proposed new stadium plans unacceptable. Only a few days later on January 9, the NFL also rejected the new stadium plans and labeled them as "unsatisfactory". Eventually, on January 12, the NFL approved the relocation of the Rams and Chargers who were supposed to share the new stadium in Inglewood upon completion.
Following the relocation, several public officials expressed disappointment and outrage at the NFL's decision and accused the league of dishonesty, claiming that it had promised St. Louis a good chance of keeping the franchise. Consequently, the City of St. Louis, St. Louis County, and the Regional Convention and Sports Complex authority filed a $1bn compensation lawsuit against the NFL. Finally, the case was settled at the end of 2021, with total damage payments of $820 million agreed upon.

Against this backdrop, we postulate that the likelihood of the Rams either staying or departing from St. Louis was equally plausible, in view of the ongoing negotiations involving the NFL, Rams, and the City of St. Louis, the concurrent developments across the three cities, the emergence of the billion-dollar stadium proposal, and the common practice of franchises exerting pressure on local governments for higher benefits or concessions. Moreover, there existed the credible possibility that the Chargers or Raiders could instantly replace the Rams in St. Louis should they win the "race" for the LA market.[16] Hence, we contend that leveraging the relocation as a natural experiment within our identification strategy is justified.

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[13] C.f. Farmer and Vincent (2015).

[14] For example, Los Angeles did not host any NFL franchise from 1995-2016, despite its large market size. During this time, 17 franchises threatened to relocate to Los Angeles, which allowed them to secure higher levels of public funding in exchange for staying in town (Hanau (2016)).

[15] C.f. Stltoday.com[2].

[16] Effectively, recent trials on relocation-related damages have exposed previously hidden documents revealing that the NFL had already considered moving either franchise to St. Louis back in 2014 (Gullo (2022)).

# 4 Methodology

From a theoretical point of view, the price of a property can be decomposed and reflects the aggregate value of inherent structural attributes, i.e. the number of bathrooms, as well as the idiosyncratic locational context, i.e. neighborhood characteristics. In this regard, Tiebout (1956) has theorized the existence of an implicit market for neighborhoods, in which local public services act as market goods for which consumers have a WTP, as these services bring benefits to local residents (Oates (1969)). In a similar vein, any intangible (dis-) benefits associated with sports teams and sports facilities should be equally capitalized in local property values and reflect consumers' aggregate WTP for these amenities.
However, in reality, there exists no direct market for singular housing attributes and neighborhood characteristics. Fortunately, within his seminal paper, Rosen (1974) bypasses this issue and formalizes a model of hedonic prices that can be specified as follows:

$$p = f(H, N, M, U) \tag{1}$$

whereby the price of a property $p$, is a function of the property's structural housing attributes $H$, neighborhood characteristics $N$, market features $M$, as well as urban amenities $U$. While typically, $N$ is said to be a vector incorporating $U$, we explicitly specify $U$ as its proper vector of urban characteristics to make explicit that urban amenities, such as sports facilities, have a distinct impact on property prices.
This hedonic price function can be readily embedded within regression models by regressing the price of a property on its value-shaping attributes. This allows to assign an implicit marginal price to each singular attribute as the average difference in transaction prices between otherwise similar properties differing in only one or a few distinct features. By this logic, comparing property values in proximity to the stadium with similar properties located farther away enables to reveal the spatial externality generated by hosting a major league franchise and to quantify the internalized value of residential proximity to the stadium.

Notwithstanding, while the theoretical framework of hedonic regressions is clear-cut, several empirical issues arise in practice, as Tu (2005) constates. In short, Rosen's and subsequent theoretical works on hedonic models provide relatively little guidance on the choice of variables and functional form of the model. Ultimately, model specification remains at the researcher's discretion and should be guided by both theoretical principles and context-specific considerations.
In terms of functional form, hedonic models typically adopt one of three specifications: a) a simple linear model; b) a semi-log model; or c) a log-log specification. There is no evident theoretical justification for the superiority of either model and all three bring about advantages and caveats respectively (C.f. Feng and Humphreys (2018)). Hence, we follow the vast majority of the literature and specify a semi-log model which has two major advantages. First, the range of housing prices is often very large and possibly heavily influenced by outliers. In this regard, log-transforming the dependent variable helps to dampen the weight of prices at the lower and upper ends of the distribution, resulting in a less skewed and more normal distribution.[17] Second, the coefficients of

[17] In a similar vein, we also log-transform the parcel size and floor size of a building. Figures of the respective transformations are provided in the Online Appendix.

the semi-log model are easily interpretable as semi-elasticities, which is insofar relevant as it allows the implicit marginal prices to vary across properties of different price categories, whereas the linear model is more strict and assumes a constant effect.[18]
In terms of variable selection, the analyst is facing a tradeoff between including as many control variables as possible to prevent omitted variable bias (OVB), and avoiding the inclusion of highly correlated covariates often stemming from structural dependencies among above all neighborhood characteristics, to prevent multicollinearity.[19] We discuss both of these concerns in the Appendix and argue that our model is correctly specified.

Another common concern that arises with hedonic modeling is endogeneity (C.f. Bayoh et al. (2004)). Specifically, one might suspect that the relocation of the Rams is ultimately provoked by abruptly or incrementally deteriorating economic conditions in the downtown area where the stadium is located, which would be likely to also induce a price depreciation of residential properties. In this case, one would mistakenly attribute the observable decline in property values to the relocation, whereas the causal chain is actually reversed. Responding to this concern, while the fact that St. Louis incorporates several facets of a quintessential Rust Belt City having been on a long term economic and demographic decline for about 70 years (Metzger et al. (2018)) has certainly contributed to the Rams general willingness to relocate to a larger market, it is essential to note that this continuous decline is primarily observable in the very long run and the economic situation over the sample period was relatively stable and characterized by an absence of any other major economic shock.[20]
Additionally, it is shown in the Appendix that the inclusion or removal of potentially endogenous regressors does not alter the results, which leads us to argue that endogeneity should be less of a concern.

Further, as outlined in the prior section, we posit that the Rams' departure can be exploited as a natural experiment, since until the eventual date of approval by the NFL, the relocation of the Rams was as equally likely as their remainder in St. Louis. Consequently, the relocation-induced exogenous variation of housing prices invites to embed the hedonic pricing model within a quasi-experimental difference-in-differences framework. Thereby, we adopt the methodology proposed by Ahlfeldt and Kavetsos (2012) and pool housing price data into space-time cells. This approach enables us to divide the sample into a pre-and post-treatment period and compare the relative price evolution within a treatment area, defined based on prior findings as a three-mile radius ring around the stadium, with a control area consisting of properties located farther away. An inherent appeal of the difference-in-differences method is that it cancels out unobserved group fixed effects as well as time trends. Though, for the sake of causal inference, it is required to strongly assume that the treatment and control group embody reasonable counterparts, meaning that, in the absence of treatment, they would have followed the same trend. Typically, this assumption is considered plausible if the groups

[18]The linear model is advantageous in that one can directly interpret the coefficients as marginal price estimates of attributes. Nonetheless, the semi-log model may still be preferable in the context of housing. While it can be assumed that an additional unit of, for example, another bathroom has approximately the same percentage effect, it seems doubtful to assume whether is has the same marginal value for two houses sold for completely different prices (C.f. Keeler et al. (2021)).

[19]Albeit, in practice, variable selection is almost always limited by data availability

[20]If anything, one might emphasize that the economic conditions were steadily ameliorating within St. Louis Metro-Area since 2011 in terms of the GDP per capita.

follow fairly identical pre-trends.

In this context, simply visualizing the pre-trends of both groups can already reveal obvious violations of the common trend assumption. Figure 1 plots these trends and shows that both groups followed a fairly similar trajectory until the occurrence of the treatment in January 2016, and there are no obvious violations, i.e. reversed trends, of the common trend assumption. In addition, one can clearly see that the relocation has induced a considerable exogenous shock within the impact area, but also that average (log-) transaction prices quickly recovered a year later but flattened out over the following years. In contrast, one can see a relatively constant increase of the average (log-) housing price within the control area throughout the sample period. Nonetheless, one may want to note that the pre-trends are not perfectly parallel, with housing prices appearing to increase slightly more in the impact area relative to the control area in 2013, although this difference in magnitude is relatively small.

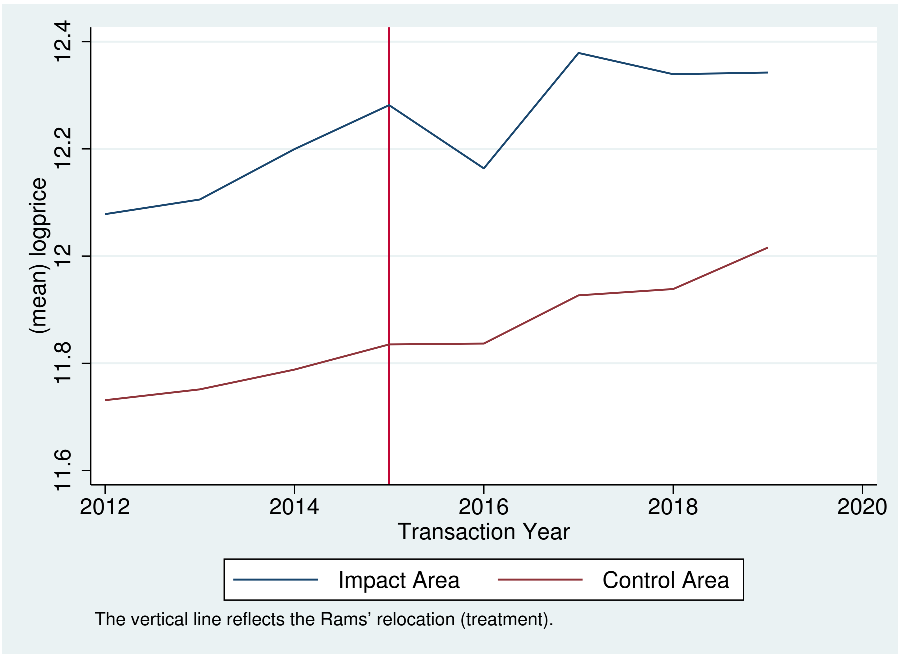



Figure 1: Parallel Trend Plot

In this context, as is common practice, we also estimate a leads- and lags regression model and find that none of the leads is statistically significant on any of the conventional levels, consolidating the credibility of the common trend assumption. The results are presented in the Appendix. Moreover, in light of numerous recent publications in the difference-in-differences literature highlighting inherent concerns and flaws of the methodology (Roth et al. (2023)), we additionally employ novel diagnosis tools (Roth (2022)) and conduct sensitivity analysis (Rambachan and Roth (2023)) to further assess the robustness of the parallel trend assumption. In short, we argue that a realization of a counterfactual trend is implausible, and if anything, it would lead to an underestimation of the true effect. Likewise, even if parallel trends should not hold exactly, we show that our conclusions are generally robust up to violations of parallel trends that are a quarter as large as the maximal observed pre-treatment coefficient. The results are portrayed in further detail in the Appendix.

Against this methodological background, partly following Kavetsos (2012) & Ahlfeldt and Kavetsos (2014), we first estimate the following difference-in-differences model, which we refer to as our base model:

$$\begin{aligned}\ln p_{i,t} =& \beta_0 + \delta_1 * \text{Post}_t + \delta_2 * \text{Impact}_i + \delta_3 * \text{Post}_t \times \text{Impact}_i \\ &+ \sum_{j=1}^{m} \beta_j x_{j,i,t} + \sum_t \kappa_t y_t + \sum_l \theta_l m_l + \sum_q \psi_q c_q + \epsilon_{i,t}\end{aligned} \tag{2}$$

whereby the natural logarithm of the price $p$ of property $i$ sold at time $t$ is regressed on the difference-in-differences specification in the first line, and a number of covariates and fixed effects in the second line. Concretely, $x_{j,i,t}$ is a vector including time-invariant structural housing attributes, as well as time-varying neighborhood characteristics, market features, and urban characteristics associated with property $i$'s location at the point of transaction $t$. The $\beta_j$ coefficients approximately reflect the percentage effect of a one unit change in $x_j$.[21] Additionally, we include time-fixed effects by year $y_t$, and by month $m_t$, to control for annual price variations and seasonality in housing prices (Ngai and Tenreyro (2014)), as well as local fixed effects $c_q$,[22] to account for base differences in neighborhood values.[23] Lastly, $\epsilon_{i,t}$ is the error term.

With respect to the difference-in-differences estimates, $\text{Post}_t$ is a dummy taking the value one when a property was sold in the post-relocation period, and $\text{Impact}_i$ is a dummy for properties transacted within the three-mile treatment area. Accordingly, $\text{Post}_t \times \text{Impact}_i$ is the interaction term for properties transacted post-relocation within the vicinity of the stadium. The main coefficient of interest, $\delta_3$, is the difference-in-differences estimator. It can be interpreted as the difference between changes in average (log-) transaction prices within the impact area before and after the relocation, relative to those changes in the control area:

$$\delta_3 = \left(\overline{\ln(P_{t=1,\,\text{Impact}=1})} - \overline{\ln(P_{t=0,\,\text{Impact}=1})}\right) - \left(\overline{\ln(P_{t=1,\,\text{Impact}=0})} - \overline{\ln(P_{t=0,\,\text{Impact}=0})}\right)$$

In a second step, we further redefine the base model and split the treatment and control area into mutually exclusive distance rings to examine whether the treatment effect is distributed heterogeneously across space, as suggested by several previous studies. The adjusted ring model looks as follows:

[21]For discrete and continuous coefficients, the precise percentage effect of a $\Delta$-unit change in coefficient $\beta_j$ is equal to $\exp(\beta_j * \Delta - 1) * 100$, which likewise gives the percentage effect for dummies in case of which $\Delta = 1$ (Halvorsen and Palmquist (1980)).

[22]We specify local fixed effects at the census tract level, as neighborhood fixed effects introduced multicollinearity into the model. As demonstrated in the Online Appendix, both specifications lead to the same conclusions.

[23]While the fixed effects should vastly capture the effect of spatial autocorrelation of housing prices due to shared local public goods, i.e. neighborhood effects (C.f. Feng and Humphreys (2018)), a minor limitation of this paper is that we are unable to control for absolute spatial spillover effects, defined as the impact of adjacent property sales on housing values (Can (1992)). Future research may want to address this issue by including spatial autoregressive lags or errors within the model (Anselin and Bera (1998)).

$$
\begin{aligned}
\ln p_{i,t} =& \beta_0 + \beta_1 * \text{Post}_t + \sum_r \gamma_r^N * R_{i,r}^N + \sum_r \delta_r^N * \text{Post}_t \times R_{i,r}^N \\
&+ \sum_{j=2}^{m} \beta_j x_{j,i,t} + \sum_t \kappa_t y_t + \sum_l \theta_l m_l + \sum_q \psi_q c_q + \epsilon_{i,t}
\end{aligned} \tag{3}
$$

The main coefficients of interest are the $\delta_r$'s, which denote the difference-in-differences estimates for properties located within ring $r$. The model is estimated twice. $N = a$ corresponds to the specification with one-mile distance rings, while $N = b$ indicates the specification with half-mile distance rings. In both cases, the outermost distance ring serves as the reference or control area. For the one-mile specification, the control area corresponds to the 7-8 mile ring. As it is widely argued that sports-related amenity benefits are highly concentrated within the immediate vicinity of a facility, for specification $b$, we follow Neto and Whetstone (2022) and initially only include half-mile distance rings within a 5-mile radius. This implies that the control area is composed of all houses located farther away. Subsequently, based on our findings, we further zoom in and discard all properties located farther than five miles away from the stadium, using the 4.5-5 mile ring as the control area.

## 4.1 Model Specification

Table 1 provides a comprehensive account of the variables used in our main analysis. While we primarily focus on typical housing attributes and neighborhood characteristics requiring little methodological explanation, there are some variables we would like to briefly comment on. For instance, given St. Louis' stark housing market segregation along racial lines, as further elaborated on in the Appendix, and the significant degree of urban blight in certain areas, we control for the share of the Black population and the share of vacant housing per neighborhood.

Additionally, we include crime levels as a noteworthy covariate, as crime constitutes a direct source of externality known to considerably impact residential property prices (e.g. Buck et al. (1991), Lynch and Rasmussen (2001), & Tita et al. (2006)). Moreover, the negative association between crime and professional sports has been well-documented in diverse contexts and from several perspectives (e.g. Card and Dahl (2011), Kalist and Lee (2016), Marie (2016)). In particular, Mares and Blackburn (2019) also observe this negative association surrounding major league matches in St. Louis. However, in a framework similar to this paper, Pyun and Hall (2019) exploit the relocation of the NFL's *Lions* franchise from Pontiac to Detroit as a natural experiment but do not observe significant changes in local crime rates in Pontiac after the relocation. Also, while sports-related crime damages may be substantial in magnitude, their share of total crime levels in St. Louis is likely to be small, given the city's consistently high rates of violent and property crimes among major US cities (C.f. Fieldstadt (2020)). Controlling for local crime rates is thus indispensable in our eyes. Most importantly, as we find that controlling for crime does not significantly alter the findings, we maintain its inclusion as we do not consider it as the underlying driver of our results.

Moreover, our unique geospatial data set allows us to account for St. Louis' distinct geographical location and rich historic background, still evident in today's housing market. St. Louis served as

a designated *gateway to the west* during the 19th-century westward expansion of the US. Consequently, much of the housing stock is relatively old, and a significant portion of the city has been historically designated as either local, certified local, or national historic districts, as portrayed in Figure 2. These historically designated neighborhoods are characterized by stringent regulations, where every alteration of a building's exterior or structural features requires a special permit.
Against this background, the survey by Mason (2005) suggests a general consensus in the empirical literature: historical designation significantly appreciates property values.[24] Hence, we include dummies for the three historic districts to account for this potential price premium. Additionally, they serve as important proxies for unobserved external building features characteristic of a certain building period. Thus, their inclusion can be regarded as an approximate remedy to the Age-Period-Cohort Problem (APC) common in hedonic modeling. This problem arises from the dilemma that the simultaneous inclusion of a building's age, transaction year, and construction year, would introduce perfect multicollinearity into the model. Therefore, one variable, typically the latter one, must be omitted. However, this omission may lead to biased estimates (Yiu and Cheung (2022)) in the presence of vintage-/cohort effects (Hall (1971), Randolph (1988)), that is the demand for particular housing characteristics typical of a certain building cohort. Closely related is the phenomenon of age-induced heteroskedasticity of the error term (Goodman and Thibodeau (1995)), occurring when housing values depreciate non-linearly with age (Cannaday and Sunderman (1986)). The dummies for historical designated properties may cater to both concerns.[25]

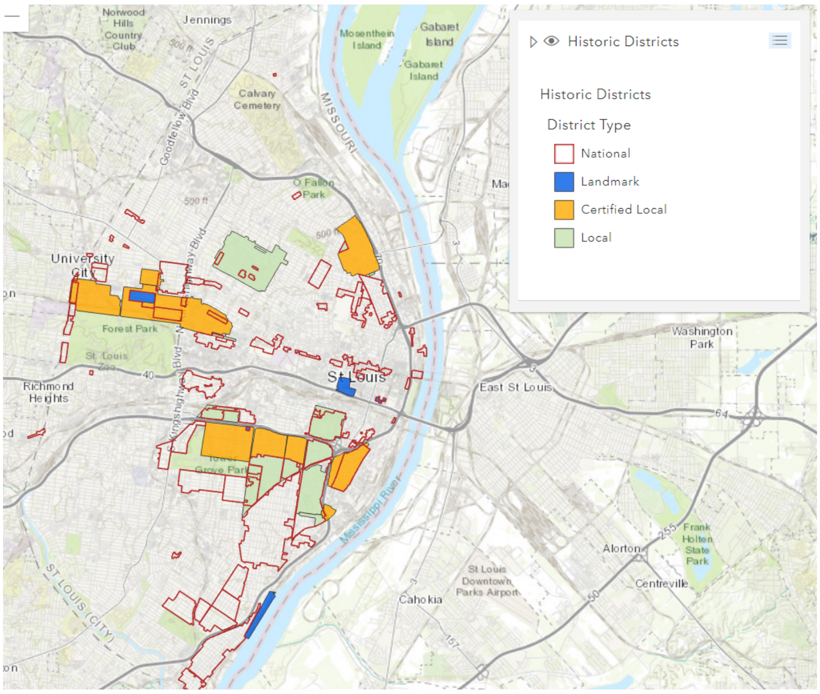
Likewise, we also include dummies for properties within Preservation Review Areas and those under the Housing Conservation Program. Preservationist and conservationist efforts are central targets within the city's Strategic Land Use Plan. Properties in Preservation Review Areas require city approval before any proposed demolition can proceed. This measure aims to stabilize neighborhoods and reduce the impact of abandoned housing and vacant land on adjacent property values (C.f. Griswold and Norris (2007), Han (2014)). Similarly, houses participating in the Housing Conservation Program must meet specific qualitative building standards. Hence, these properties may, on average, be in better condition, and the housing conservation dummy should capture associated differences in home values.
Additionally, a dummy is constructed for single-family homes located within Enterprise Zones. These are urban areas designed to attract new investment and businesses, often offering favorable conditions such as tax abatement. If commercial or industrial land use in these zones generates substantial negative externalities for nearby residential properties, we might expect to see a reduction in the prices of single-family homes located within Enterprise Zones.

Further, St. Louis exhibits a distinct geography. Situated at the confluence of the two largest rivers in the US, the Mississippi and the Missouri, and lacking surrounding mountains for shielding, the

[24] Various explanations have been proposed for this price premium. For example, Ford (1989) argues that historical listing serves as an insurance mechanism, ensuring continuity of neighborhood character. Gordon and Stowe (2014) contend that historical designation reduces informational asymmetry and generates spatial spillovers onto adjacent neighborhoods. Meanwhile, Rypkema (2002) emphasizes the inherent value of designated properties.

[25] A discussion on age-induced heteroskedasticity is presented as a small digression in the Online Appendix.

Figure 2: Map of the Local and National Historic Districts in St. Louis




Source: www.stlouis-mo.gov

city is exposed to severe weather conditions, including heavy flooding.[26] Several papers have shown that the risk of flooding and associated reparation costs are absorbed in residential housing prices, expressed in average price discounts of up to 7.5% in the US (Daniel et al. (2009)). In turn, residing close to a river often provides recreational amenity benefits, which could lead to appreciations of properties located along the waterfront (Eves (2002)). As shown in Figure 10 in the Appendix, the Federal Emergency Management Administration (FEMA) identifies two floodplains in St. Louis. The 100-year floodplain is officially defined as land that has a one percent chance of being equaled or exceeded each year, whereas the 500-year floodplain is statistically flooded once in 500 years. We include dummies for either plain.

Finally, as our last urban control, we account for the WTP for proximity to urban parks by regressing on a property's distance to the closest (major) urban park or green space. Similar to sports facilities, urban parks constitute local public goods in the Tieboutian sense, and their use is primarily defined by accessibility in terms of residential proximity. Hence, we claim that citizens may be willing to pay a premium for residing close to parks.[27] Notwithstanding, the inclusion of the covariate may be controversial if one believes that the valuation of residential proximity to sports facilities and urban spaces manifests a complementary or substitutional relationship.[28]

[26] C.f. Newamerica.com

[27] More et al. (1988) review several papers providing evidence for distance-decaying effects, similar to what is posited regarding sports amenities.

[28] Results presented in the Online Appendix show consistent findings, regardless of the inclusion of the covariate. We regard this as preliminary evidence that there does not seem to exist an evident endogenous relationship among the WTP for residing close to the stadium and the WTP for residing close to urban parks.

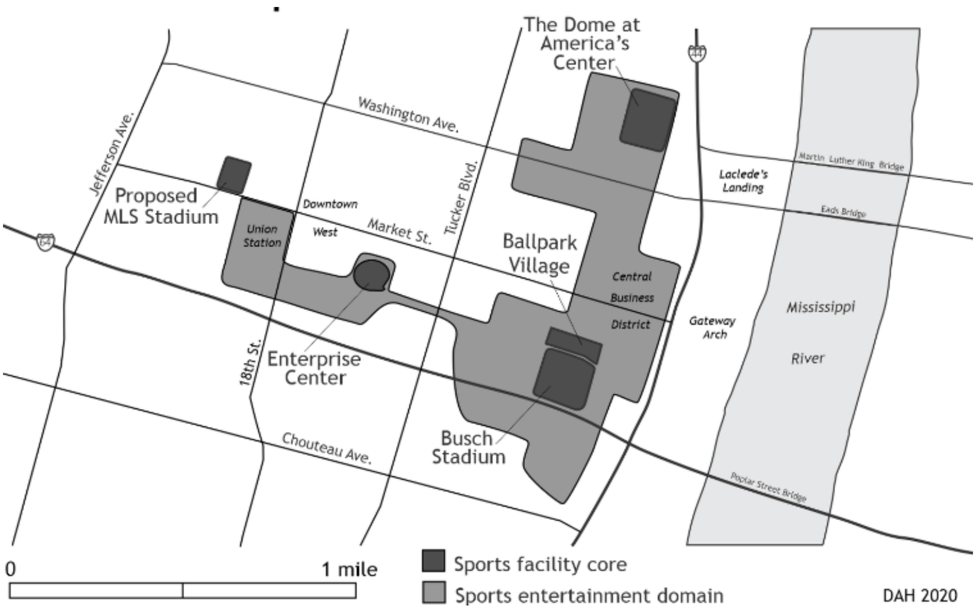
What is more, we place particular emphasis on the relevance of additionally including controls for local market and population characteristics in our case. Generally, the identification of proximity effects requires the team/facility-effect to be separated from other location-related confounding factors that simultaneously influence property values. Due to the integration of the stadium within downtown St. Louis, it is crucial to capture potential spillovers generated by the downtown area. In this light, we isolate the proximity effect of residing close to the stadium in two ways.
First, we incorporate market controls, considering the number of three types of commercial establishments: 1) Accommodation and Food Services, 2) Retail Trade Establishments, and 3) Finance and Insurance Companies. Particularly the latter type serves as a proxy for distance to the downtown area, specifically the central business district (CBD), where the majority of finance and insurance companies are typically located. Additionally, Abbiasov and Sedov (2023) demonstrate that the rate of visits to retail stores, and even more so, food and accommodation establishments, situated in the vicinity of a stadium, is positively associated with NFL home game attendance. Therefore, controlling for these types of establishments may also capture the effect of potential changes in property values induced by a negative demand shock for sports-related industries following the relocation.[29]
Second, standard urban economic theory, in form of the *Monocentric-City-Model* (C.f. Alonso (1964); Muth (1985); Fujita (1989)), suggests that the land and subsequently house price gradient decline with distance to the CBD, where many jobs are located. Additionally, population density is simultaneously determined and typically highest closest to the CBD, as consumers value both proximity to work as well as living close to urban amenities offered by downtown areas. Thus, as part of our neighborhood characteristics, we control for changes in population density by neighborhood. This not only serves as a proxy for proximity to the CBD but also allows to account for spatial heterogeneity resulting from zoning ordinances, natural barriers, or imperfections in the local housing market (C.f. Buck et al. (1991)).

However, the integration of the Edward Jones Dome into a designated sports-and entertainment district, which also includes the *Enterprise Center* (a multipurpose-arena home to the St. Louis Blues, NHL) and *Busch Stadium* (an open-air baseball stadium hosting the St. Louis Cardinals, MLB), presents an additional empirical challenge for isolating the proximity effect. The three major league stadia are situated just a few hundred meters away from each other, as displayed in Figure 3. To ensure the unbiasedness of the difference-in-differences estimate, it is hence indispensable to equally control for proximity to the other two stadia. Similarly, the relocation of the Rams might have elicited a decrease in WTP for proximity to the other two stadia, potentially due to foregone spatial synergies leveraged by the presence of three major league teams, rather than two. Furthermore, considerable changes in the spatial externalities generated by the other two teams, occurring over the course of the sample period, could interfere with our identification strategy and result in spurious regression estimates. Fortunately, both the Blues and the Cardinals have played continuously within their stadiums throughout the time frame under investigation.

Nevertheless, in 2017, the Blues initiated a privately financed three-year, $150 million renovation plan for the Enterprise Center. The plan included incremental infrastructural upgrades in terms of

[29]Similar to the covariate for crime, we contend that in view of the results presented below, relocation-induced changes in the commercial landscape are likewise not the main drivers underlying the relative price depreciation of housing values in the impact area.

Figure 3: St. Louis - Sports Entertainment District



Source: Hurt (2021)

improved heating, lighting, and seating, as well as enhanced fan amenities in terms of a beer garden, a kids zone, and augmented fan gathering spaces (Hurt (2021)). While these improvements undoubtedly enhanced the consumption experience, it raises questions about whether these renovation works generated additional spatial externalities comparable in magnitude to the effects of constructing a completely new stadium or the arrival/departure of a team. Moreover, the facility upgrades do not constitute a typical market shock, as neither the team nor the stadium were considerably affected in their functional form, and these upgrades occurred gradually. Thus, we posit that the renovation of the Enterprise Center should not interfere with our identification strategy.[30]

Albeit, there were two potentially confounding sports-related events whose impact on property values might be more pronounced. First, against all odds, the Blues crowned themselves the Stanley Cup winners at the end of the 2018/2019 season. Despite having the worst record of any NHL team in January 2019, the franchise barely reached the playoffs and unexpectedly won the league following a series of consecutive tight matches (Augustyn (2023)). If the Blues' unanticipated success story has evoked significant spatial externalities, such as increased civic pride or social cohesion among supporters,[31] or, in the negative sense, increased congestion, resulting, for instance, from fan gatherings, those externalities should be capitalized into residential property values and could bias the results if left unaccounted for.

In a similar vein, regarding the Cardinals, the franchise is mandated to create *Ballpark Village*, an entertainment and business district directly adjacent to Busch stadium, as part of a package deal for

[30]If anything, one would expect a price appreciation of surrounding property values following the renovations, in which case the negative effect of the Rams' relocation would be underestimated.

[31]Effectively, Wagoner (2019) reports that the win of the Stanley Cup has resurrected the collective morale in St. Louis and given momentum to urban renewal efforts.

partial public subsidies for the construction of the stadium in 2006. The project is split into three phases, with the first phase, *Ballpark Village I*, opening in March 2014. It consists of a 120,000 square feet structural complex offering ample space for offices, retail stores, restaurants & bars, as well as the Cardinals Hall of Fame and Museum (Click (2014)). The second phase, *Ballpark Village II*, was predominantly inaugurated in 2020 and therefore does not pose any explicit concern for our identification strategy. Nevertheless, it might be that the additional consumption benefits offered by Ballpark Village I are somewhat capitalized within local property values. This is particularly crucial in view of reported displacement effects following the inauguration of the fist phase, expressed in multiple closures of downtown restaurants and bars, highlighting the popularity of Ballpark village and its substitutional effect on the local economy (Hurt (2021)).

Against this backdrop, we test for the robustness of our findings by replicating our analysis on a shortened pre-and post-treatment period, excluding potentially spurious transactions from the sample. For brevity, we present only the results for the whole sample period in the main body, while the adjusted regression outputs for the shortened sample periods are presented in the Appendix.[32] In short, the findings align with the general conclusions and imply that neither the Blues' heroic triumph nor the new Ballpark entertainment district, lead to considerable estimation bias.

As a final methodological note, it is not-uncommon in empirical practice to encounter a non-spherical variance-covariance matrix of the errors, leading to biased standard errors and potentially misleading inferences. In particular, within-group correlation is a well-documented concern when working with micro-level data in difference-in-differences frameworks (Moulton (1986), Moulton (1990), & Bertrand et al. (2004)). Additionally, Breusch-Pagan tests (Breusch and Pagan (1980)) indicate heteroskedasticity in the error terms within our models.
In this context, we align with prior literature, which equally employs two remedies to address non-spherical errors: reporting standard heteroskedasticity-robust standard errors (Eicker (1967), Huber (1967), & White (1980)), or additionally clustering standard errors by group. Within our preferred model specification, we rely on standard robust errors in Stata, due to their conservatism and their ability to address the more general case of heteroskedasticity of an unknown source, exhibiting a "flexibility" advantage. Likewise, following the reasoning of Tita et al. (2006), one may argue that, since we are examining only one city context, and geographical clusters (i.e. census tracts) are subject to the same urban laws and economic policies, additionally clustering the errors may not necessarily improve the precision of the errors due to a lack of substantial heterogeneity.[33]
Notwithstanding, we also present the results with cluster-robust errors, which provide a more comprehensive correction when the variance-covariance matrix is block-diagonal, implying correlation within but not among geographical clusters. In our context, it may be advisable to additionally cluster standard errors for experimental design reasons, given that the assignment mechanism for the treatment is naturally spatially clustered around the stadium (Abadie et al. (2017)). While local

[32] Simultaneously, shortening the pre-and post-sample period enables us to exclude the possibility that the findings are influenced by potentially confounding construction projects within the impact area, occurring during the sample period, such as the renovation of Union Station in 2014 or the makeover of the iconic Gateway Arch Museum, re-inaugurated in July 2018.

[33] In fact, Abadie et al. (2023) demonstrate that in some scenarios standard robust errors may constitute a more accurate adjustment when there is no clear rationale for clustering.

fixed effects are likely to capture most of the variance in local housing prices associated with spatial dependence, cluster-robust errors might account for the remaining random spatial shocks in the error term. However, clustering remains somewhat of an empirical puzzle, and there is, for example, no straightforward theoretical answer on which geographical scale-level the error terms would need to be clustered (Abadie et al. (2023)).[34] Therefore, within our alternative model specifications, we cluster our errors on the census tract, neighborhood, and ward level, respectively.[35] Ultimately, irrespective of the error specification, we find that the variations in significance levels are relatively minor, suggesting that the model is justly fitted (King and Roberts (2015)).

[34] For instance, an unanswered question remains whether standard errors should be clustered on the same scale as fixed effects.

[35] We consider the cluster sizes to be sufficiently large for classical estimation procedures: there are 99 census-tracts, 72 neighborhoods, and 28 wards in our data.

Table 1: Variable Definitions

| Variable | Description |
|---|---|
| *Dependent Variable* | |
| logPrice | The natural logarithm of the recorded transaction price in $ |
| *Target Variables* | |
| Impact | Dummy for properties within 3-mile distance to the Edward Jones Dome (1 = Yes) |
| Post | Dummy for the post-relocation period (1 = Yes) |
| ImpactxPost | Interaction term of Impact and Post |
| *Housing Characteristics* | |
| logfloorsize | The natural logarithm of the floor size in square feet |
| logparcelsize | The natural logarithm of the parcel area in square feet |
| Age | The age of a property at the time of transaction |
| Frame | Dummy for houses with a frame facade (1 = Yes) |
| Stone | Dummy for houses with a stone facade (1 = Yes) |
| Brick | Dummy for houses with a brick facade (1 = Yes) |
| Stories | Number of stories |
| Garages | Number of garages |
| Carports | Number of carports |
| Attic | Dummy for houses having an attic (1 = Yes) |
| *Demographic Characteristics* | |
| PopDensity | Total population$/100$ per km$^2$, neighborhood level |
| Crime | Total crimes per 1000 people$/10$, neighborhood level |
| Black | Share of the Black population, neighborhood level |
| Vacancy | Share of vacant housing, neighborhood level |
| Youth | Share of the population under 18, neighborhood level |
| MedianIncome | Median household income in $1000 (inflation-adjusted), zip-code level |
| *Market Characteristics* | |
| AccFood | Number of accommodation & food services$/10$, zip-code level |
| Finance | Number of finance & insurance establishments$/10$, zip-code level |
| Retail | Number of retail trade establishments$/10$, zip-code level |
| *Urban Characteristics* | |
| DistancePark | Distance in miles to the closest park |
| Local | Dummy for local historic designation (1 = Yes) |
| National | Dummy for national historic designation (1 = Yes) |
| CertifiedLocal | Dummy for certified local historic designation (1 = Yes) |
| Conservation | Dummy for properties under the Housing Conservation Program (1 = Yes) |
| Preservation | Dummy for properties within a Preservation Review Area (1 = Yes) |
| Enterprise | Dummy for properties within an Enterprise Zone (1 = Yes) |
| Flood100 | Dummy for properties within a Flood100 zone (1 = Yes) |
| Flood500 | Dummy for properties within a Flood500 zone (1 = Yes) |
| DistanceBusch | Distance in miles to the Busch Stadium (MLB) |
| DistanceEC | Distance in miles to the Enterprise Center (NHL) |

# 5 Data

## 5.1 Sample Selection & Distance Calculation

St. Louis City's Planning & Urban Design Agency manages a publicly accessible data-portal called *Geo St. Louis*, which provides geospatial parcel data on the City of St. Louis, including a comprehensive record of parcel sales from 1977 to 2019. Each transaction comes with a report exhibiting factual information on the precise location, characteristics, i.e. building attributes, legal history, and transaction history of any parcel. With the help of web-scraping techniques in Python, we first scraped all recorded transactions occurring between January 1, 2012, and December 31, 2019 ($n = 43,818$). This data was then merged with information on a parcels' location and, when available, information on building attributes. The sample period was intentionally selected to encompass a balanced pre- and post-treatment phase, approximately four years each, surrounding the relocation application and ratification on January 4, 2016, and December 12, 2016, respectively. This duration is considered adequately long for discerning capitalization effects, relocation-induced population dynamics, and changes in neighborhood features at both large and minor scales. Simultaneously, the sample period is sufficiently short to mitigate potential bias from nearby urban development projects.[36]

Furthermore, as the parcel data is restricted to the City of St. Louis, the sample area is conceptually predetermined by the city fringe, which was established in 1876 and has remained unchanged ever since (Metzger et al. (2018)). This consistency is advantageous, as it allows for comparison of the treatment effect across properties situated within a fairly homogeneous context of long-term economic and urban policies. However, as shown in Figure 4, the Edward Jones Dome is situated at the eastern edge of the city near the Mississippi River, which serves as a natural state line between St. Louis, Missouri, and East St. Louis, Illinois. Therefore, one natural data limitation is that our three-mile treatment area intersects the city border and overlaps into East St. Louis, as shown in Figure 5, whereas we are only able to analyze properties which were transacted within St. Louis.
In this context, we rely on address information from the parcel records to determine each property's coordinates via Google's geocoding API. Next, we computed the geodesic distance of each property from the Edward Jones Dome using Geopy's freely available API in Python. In the process, 34 single-family homes were discarded from the sample, as their address information appeared outdated.

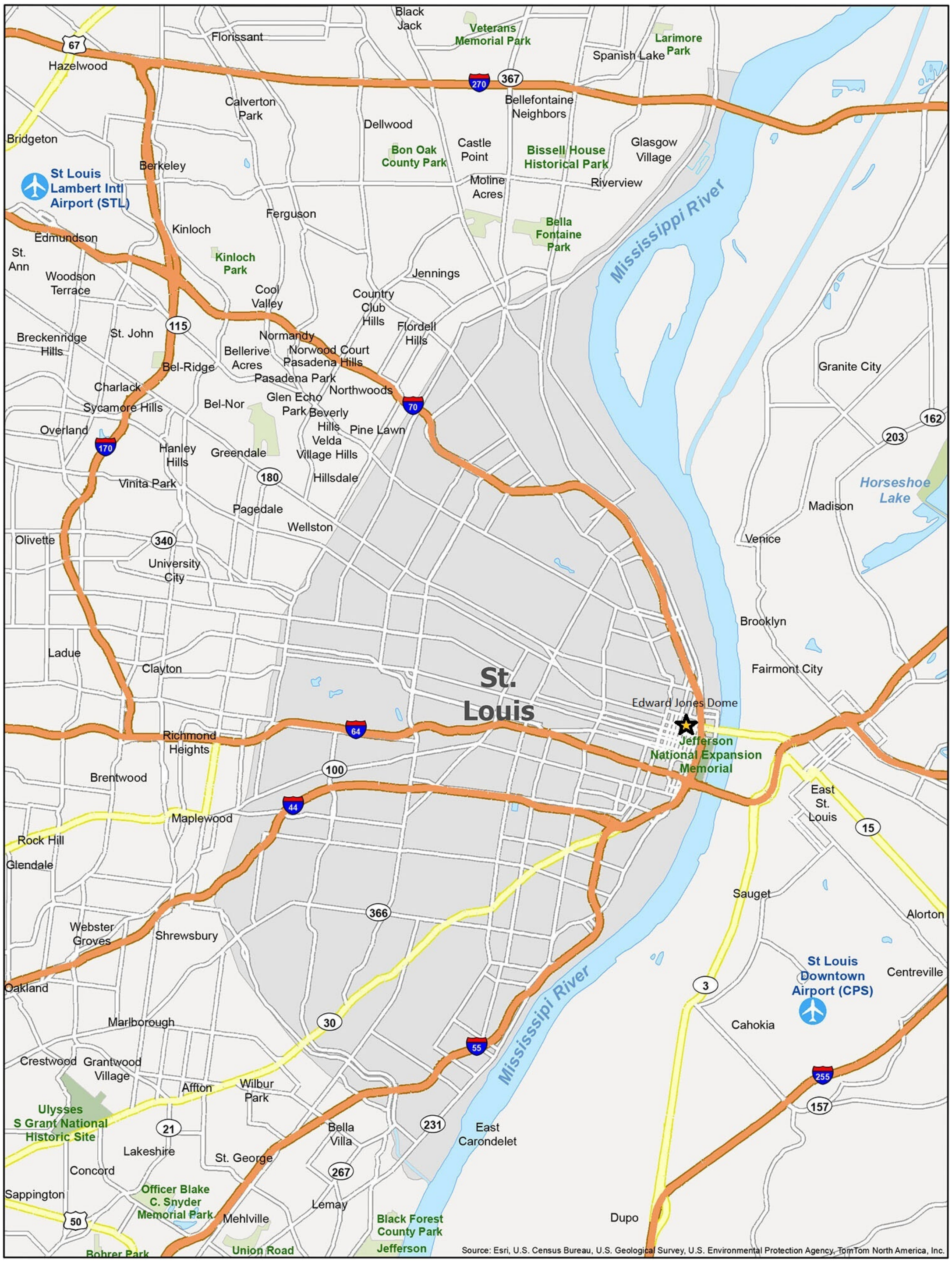
## 5.2 Data Cleansing & Selection of Covariates

### Housing Types & Structural Housing Attributes

As we are only interested in residential housing sales, we first filtered the transaction records and assigned each transaction to one of three categories, primarily based on information on the assessor use and building type: 1) Residential, 2) Mixed-Residential, i.e. apartments above stores or restaurants, or 3) Commercial/Industrial/Other parcels. The vast majority of transactions are residential sales, which make up 93.14% ($n = 40,842$) of the data, followed by commercial, industrial, or miscellaneous parcels totaling about 6,2 % ($n = 2697$), and lastly mixed-residential parcel sales only

[36]While the end date of 2019 aligns with the availability of parcel sale data, it is also contextually relevant because it precedes the arrival of the minor-league BattleHawks (XFL) franchise playing in the Edward Jones Dome since February 2020.

Figure 4: St. Louis - City Map




Source: gisgeography.com

accounting for 0.71% ($n = 313$) of the data. Ultimately, we only kept residential parcel sales.

The retrieved building information reflects a snapshot in time of primarily time-invariant structural housing attributes, namely, the parcel size, floor size, exterior facade (e.g. brick, stone, or frame wall), number of stories, number of carports, number of garages, building year, and information on whether houses have attics. Unfortunately, information on whether buildings have central air conditioning or heating systems, as well as the number of full-and half-bathrooms, could not be used, as the variation in outcomes was too few and the data was categorically incomplete. Moreover, it must be remarked that a substantial number of building records exhibits zero- or missing values across the selected structural housing attributes. Faced with the trade-off of either reducing the number of independent variables to increase the sample size and include as many observations as possible, or discarding observations with missing or zero values and controlling for as many housing attributes as possible to increase the precision of the estimates and to prevent OVB (C.f. Agha and Coates (2015)), we opted for the latter approach. This decision aligns with the widely reported observation that structural housing attributes alone account for the vast majority of variation in housing prices. Additionally, our final sample size, as shown below, remains adequately high.[37]
Besides, we conducted additional data cleansing to address the issue of a small number of parcels that are shared by multiple buildings registered under the same address. Distinguishing the specific value of each individual property in these cases was challenging, so we only included sales of unique parcels in our sample. In addition, we removed a few observations of properties that were sold before they were constructed.

Furthermore, in line with most prior studies, we restrict our analysis to single-family residential homes only. Given that 78.35% ($n = 31,972$) of all residential sales within the sample period are single-family homes, this selection provides an ample sample size for our hedonic regressions. Table 2 contains summary information on the consecutive distance rings and shows that, with exception of the immediate one-mile area surrounding the stadium, all rings are reasonably populated.[38] To enhance and ensure comparability, we follow Neto and Whetstone (2022) and group the first four half-mile rings together in our second estimation of Equation 3 ($N = b$). We designate this joint two-mile ring as *Target2*.

In this context, it is also noteworthy that data limitations leave few alternatives to the selection of single-family homes. Some hedonic papers opt to analyze apartment buildings or condominiums instead of single-family homes. In general, there is again no clear theoretical guideline dictating the superiority of either choice over the other. While, on the one hand, one might assume homogeneous treatment effects across all building types, implying that the spatial externality would be equally capitalized into all residential property prices, on the other hand, spatial heterogeneity resulting from

[37]Yet, it needs to be noted that this choice is made deliberately at the expense of potential selectivity bias in the data. Coates et al. (2006) argue that missing or zero values might not occur randomly but predominantly in lower-priced properties. However, given the substantial share of incomplete records, we posit that the severity of selectivity bias should not be comparable to that of an OVB, which might potentially arise if several structural housing attributes were excluded.

[38]For the sake of clarity, we refer to the one-mile rings as *Impact*-rings, while the half-mile rings are coined *Target*-rings.

zoning ordinances, among other factors, might lead to detecting heterogeneous effects conditional on building types. In this respect, due to the integration of the Edward Jones Dome into downtown, it would have been desirable to also examine the price evolution of apartment complexes or condominiums, as it can be assumed that their share increases proportionally to population density and thus increases with proximity to the city core. Unfortunately, the retrieved data only contains information on transactions of entire parcels, meaning that we lack information on the sale of individual apartments and only observe occasional sales of whole apartment complexes. Apart from the fact that the sample size would be insufficient, we also lack substantial information on building characteristics of multiple-family residential buildings and hence would not be able to include them within our hedonic regression models.

Table 2: Summary Statistics - Ring Variables (N=12695)

| | Observations | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| *Base Model* | | | | | |
| Impact | 1,146 | 0.0903 | 0.29 | 0.00 | 1.00 |
| Post | 7,842 | 0.6177 | 0.49 | 0.00 | 1.00 |
| ImpactxPost | 686 | 0.0540 | 0.23 | 0.00 | 1.00 |
| *One-Mile Rings* | | | | | |
| Impact1 | 13 | 0.0010 | 0.03 | 0.00 | 1.00 |
| Impact2 | 314 | 0.0247 | 0.16 | 0.00 | 1.00 |
| Impact3 | 819 | 0.0645 | 0.25 | 0.00 | 1.00 |
| Impact4 | 1,329 | 0.1047 | 0.31 | 0.00 | 1.00 |
| Impact5 | 1,293 | 0.1019 | 0.30 | 0.00 | 1.00 |
| Impact6 | 3,219 | 0.2536 | 0.44 | 0.00 | 1.00 |
| Impact7 | 4,433 | 0.3492 | 0.48 | 0.00 | 1.00 |
| Impact8 | 1,275 | 0.1004 | 0.30 | 0.00 | 1.00 |
| *Half-Mile Rings* | | | | | |
| Target2 | 327 | 0.0258 | 0.16 | 0.00 | 1.00 |
| Target0_5 | 9 | 0.0007 | 0.03 | 0.00 | 1.00 |
| Target1 | 4 | 0.0003 | 0.02 | 0.00 | 1.00 |
| Target1_5 | 41 | 0.0032 | 0.06 | 0.00 | 1.00 |
| Target2_0 | 273 | 0.0215 | 0.15 | 0.00 | 1.00 |
| Target2_5 | 317 | 0.0250 | 0.16 | 0.00 | 1.00 |
| Target3 | 502 | 0.0395 | 0.19 | 0.00 | 1.00 |
| Target3_5 | 653 | 0.0514 | 0.22 | 0.00 | 1.00 |
| Target4 | 676 | 0.0532 | 0.22 | 0.00 | 1.00 |
| Target4_5 | 623 | 0.0491 | 0.22 | 0.00 | 1.00 |
| Target5 | 670 | 0.0528 | 0.22 | 0.00 | 1.00 |

Notwithstanding, in comparison to previous papers, one eminent asset of the data is that each parcel transaction is neatly classified by sales type, enabling us to seamlessly exclude non-arms length transactions from the data. In short, it is decided to only include transactions classified as *"Valid"* sales within the sample, because they constitute the majority of single-family home sales over the sample period ($n = 13,872$; 43.39%) and promise to be the least biased and most "pure" market transactions. Other sale types, classified, for example, as "Gift", "Not Open", or "Related Party", were evidently discarded as the sales price is likely to be non-representative of the true market value of the corresponding properties. Similarly, we also exclude foreclosures and investor sales from the sample as the recorded transaction price is likely to be downward biased as a result of the circumstances surrounding the transaction.

Further, consistent with prior literature, we limit our analysis to transactions over $30,000. This cutoff value is conservative and well-below half the median value of the valid single-family home transactions in the sample, which is $145,000. Lower-priced properties were excluded as they are more likely to have unobserved qualitative deficiencies or significant mortgage debt, which could introduce bias. However, as the St. Louis housing market is deeply segregated and some areas experience severe distress and urban blight (Tighe and Ganning (2015)), the exclusion of property transactions below the cutoff value of $30,000 could be worrisome and likewise lead to bias, particularly if it evokes a structural change in the spatial composition of either the specified treatment or control area. To address this potential concern, we replicate our models using a sample without a lower price bound and find that the results are unaffected.[39] This robustness check is presented in the Appendix.

Eventually, the final sample comprises a total of $n = 12,695$ observations. Table 3 provides a comprehensive summary of the data. Based on the sample, the average single-family home sells for $178,497, with a floor size of 1,360 square feet and a parcel size of 5,028 square feet. The average home is approximately 86 years old at the time of the sale, with one and a half stories, brick walls, one garage but no carport, and no attic.

Table 3: Summary Statistics (N=12695)

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| *Dependent Variable* | | | | |
| Price | 178,497.16 | 129,243.01 | 30,000.00 | 2,050,000.00 |
| *Housing Characteristics* | | | | |
| Floorsize | 1,360.31 | 723.43 | 384.00 | 12,988.00 |
| Parcelsize | 5,028.46 | 3,048.53 | 745.00 | 106,327.00 |
| Age | 86.10 | 27.12 | 0.00 | 183.00 |
| Frame | 0.26 | 0.44 | 0.00 | 1.00 |
| Stone | 0.00 | 0.05 | 0.00 | 1.00 |
| Brick | 0.74 | 0.44 | 0.00 | 1.00 |
| Stories | 1.43 | 0.53 | 1.00 | 3.00 |
| Garages | 0.64 | 0.49 | 0.00 | 2.00 |

[39] We also replicate our analysis on behalf of a "ghetto" sample, and discuss the impact of spatial inequality in light of St. Louis' stark housing segregation.

| | | | | |
|---|---|---|---|---|
| Carports | 0.14 | 0.51 | 0.00 | 2.00 |
| Attic | 0.24 | 0.43 | 0.00 | 1.00 |
| *Demographic Characteristics* | | | | |
| PopDensity | 28.37 | 8.26 | 0.71 | 48.73 |
| Crime | 5.12 | 2.52 | 2.04 | 45.83 |
| Black | 0.19 | 0.19 | 0.03 | 0.97 |
| Vacancy | 0.11 | 0.05 | 0.07 | 0.39 |
| Youth | 0.17 | 0.04 | 0.06 | 0.39 |
| MedianIncome | 46.87 | 9.58 | 13.28 | 106.21 |
| *Market Characteristics* | | | | |
| AccFood | 6.75 | 1.76 | 0.60 | 12.00 |
| Finance | 2.54 | 1.92 | 0.30 | 29.20 |
| Retail | 6.81 | 1.85 | 1.00 | 16.80 |
| *Urban Characteristics* | | | | |
| DistancePark | 0.82 | 0.39 | 0.02 | 4.08 |
| Local | 0.07 | 0.26 | 0.00 | 1.00 |
| National | 0.20 | 0.40 | 0.00 | 1.00 |
| CertifiedLocal | 0.08 | 0.28 | 0.00 | 1.00 |
| Conservation | 1.00 | 0.06 | 0.00 | 1.00 |
| Preservation | 0.95 | 0.22 | 0.00 | 1.00 |
| Enterprise | 0.14 | 0.35 | 0.00 | 1.00 |
| Flood100 | 0.01 | 0.09 | 0.00 | 1.00 |
| Flood500 | 0.01 | 0.10 | 0.00 | 1.00 |
| DistanceBusch | 4.90 | 1.46 | 0.54 | 8.50 |
| DistanceEC | 4.63 | 1.45 | 0.64 | 8.21 |

### Neighborhood and Market Characteristics

With respect to our neighborhood controls, we retrieve data from two primary sources. First, we obtain socio-demographic information from the 2010 and 2020 US Census, available on the neighborhood level.[40] As a second source, the US Census Bureau's annual American Community Survey (ACS) provides additional socio-demographic information, from which we retrieve the median income on the zip-code level.[41] Aiming to better depict variation in local neighborhood characteristics, we construct annual weighted averages, assuming a fairly linear trend in the evolution of socio-demographic compositions of neighborhoods.

Further, as mentioned earlier, we consider it crucial to include population density as a covariate. To this end, we match the annual population numbers per neighborhood from the Census Data with information on the size of each neighborhood retrieved from Wikipedia. We adjust the scale so that a one-unit increase represents the percentage effect of a 100-person population increase, enhancing

[40] C.f. StLouis-Mo.Gov.

[41] Unfortunately, small deviations in reported census tracts prevent us from neatly merging the data and from controlling on a smaller geographical scale level than the zip-code or neighborhood level.

the readability of the coefficient. Similarly, we apply a transformation to the coefficient of crime so that the coefficient reflects the approximate percentage effect of an increase in ten total crimes per 1000 residents. The underlying crime statistics are obtained from the St. Louis Metropolitan Police Department.

Lastly, as outlined in the previous section, we control for local market characteristics via the number of retail trade establishments, accommodation and food services, as well as finance and insurance companies. The data is obtained from the US Census Bureau's annual County Business Patterns (CBP) survey and available on the zip-code level. To enhance interpretability, we rescale the numbers so that the corresponding $\beta_j$ coefficient respectively indicates the approximate percentage effect of ten additional establishments.

**Urban Characteristics**

Finally, our vector of covariates contains several dummy variables providing information on the urban setting of transacted single-family homes. Thereby, data on historical designation, housing preservation and conservation, enterprise zones, and floodplains is directly obtained from the parcel records retrieved from Geo St. Louis.

Regarding the proximity to parks covariate, the City of St. Louis reports a total of 108 parks within the city boundaries. Using qualitative criteria, in particular in terms of size, location, and popularity, we have identified the 17 most relevant urban parks in St. Louis.[42] This selection is based on the somewhat strong assumption that only parks exceeding a certain size generate substantial and discernible amenity benefits, and that the impact of parks is approximately homogeneous, regardless of differences in attributes.

[42] A list of these selected parks is provided in the Online Appendix.

# 6 Empirical Results

## 6.1 Results of the Base Model

Table 4: Regression Estimates of the Base Model

| | (1)<br>Model 1 | (2)<br>Model 2 | (3)<br>Model 3 | (4)<br>Model 4 |
|---|---|---|---|---|
| *Target Variables* | | | | |
| Impact | 0.3269*** | 0.1785*** | 0.1046*** | 0.1444*** |
| | (0.028) | (0.036) | (0.036) | (0.036) |
| Post | 0.1923*** | 0.3684*** | 0.3324*** | 0.3205*** |
| | (0.008) | (0.018) | (0.022) | (0.022) |
| ImpactxPost | -0.0785** | -0.0595*** | -0.0730*** | -0.0752*** |
| | (0.031) | (0.022) | (0.021) | (0.021) |
| *Housing Characteristics* | | | | |
| logFloorsize | 0.5303*** | 0.4819*** | 0.4682*** | 0.4508*** |
| | (0.018) | (0.015) | (0.015) | (0.015) |
| logParcelsize | 0.1564*** | 0.1995*** | 0.1998*** | 0.1904*** |
| | (0.013) | (0.010) | (0.010) | (0.009) |
| Age | -0.0034*** | -0.0034*** | -0.0036*** | -0.0036*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Frame | -0.1741*** | -0.1288*** | -0.1293*** | -0.1153*** |
| | (0.009) | (0.008) | (0.008) | (0.008) |
| Stone | 0.1550* | 0.1047* | 0.0971* | 0.1055* |
| | (0.083) | (0.057) | (0.057) | (0.055) |
| Stories | 0.2819*** | 0.2538*** | 0.2509*** | 0.2476*** |
| | (0.014) | (0.011) | (0.010) | (0.010) |
| Garages | 0.1475*** | 0.0942*** | 0.0905*** | 0.0886*** |
| | (0.008) | (0.006) | (0.006) | (0.006) |
| Carports | 0.0337*** | 0.0161*** | 0.0167*** | 0.0170*** |
| | (0.008) | (0.006) | (0.006) | (0.006) |
| Attic | 0.1752*** | 0.1595*** | 0.1573*** | 0.1518*** |
| | (0.009) | (0.007) | (0.007) | (0.006) |
| *Demographic Characteristics* | | | | |
| PopDensity | | | -0.0021*** | -0.0014* |

| | | |
|---|---|---|
| | (0.001) | (0.001) |
| Crime | -0.0138*** | -0.0120*** |
| | (0.004) | (0.004) |
| Black | -0.7703*** | -0.3539*** |
| | (0.069) | (0.082) |
| Vacancy | -0.4542** | -1.1322*** |
| | (0.232) | (0.250) |
| Youth | 0.6144** | 0.4385* |
| | (0.271) | (0.251) |
| MedianIncome | 0.0011 | 0.0019* |
| | (0.001) | (0.001) |
| *Market Characteristics* | | |
| AccFood | 0.0061 | 0.0076 |
| | (0.005) | (0.005) |
| Finance | -0.0006 | 0.0058* |
| | (0.003) | (0.004) |
| Retail | -0.0118*** | -0.0145*** |
| | (0.004) | (0.004) |
| *Urban Characteristics* | | |
| DistancePark | | -0.2002*** |
| | | (0.015) |
| Local | | 0.1180*** |
| | | (0.037) |
| National | | 0.0848*** |
| | | (0.017) |
| CertifiedLocal | | 0.2478*** |
| | | (0.034) |
| Conservation | | 0.1945* |
| | | (0.101) |
| Preservation | | 0.1091*** |
| | | (0.026) |
| Enterprise | | -0.0018 |
| | | (0.014) |
| Flood100 | | -0.0636** |

| | | | | |
|---|---|---|---|---|
| | | | | (0.031) |
| Flood500 | | | | 0.0013 |
| | | | | (0.024) |
| DistanceBusch | 0.8483*** | 0.6235*** | 0.2850*** | 0.0097 |
| | (0.034) | (0.107) | (0.106) | (0.111) |
| DistanceEC | -0.7986*** | -0.5424*** | -0.2795** | 0.0065 |
| | (0.033) | (0.110) | (0.109) | (0.113) |
| Constant | 6.0160*** | 5.6912*** | 6.3939*** | 6.3883*** |
| | (0.127) | (0.123) | (0.148) | (0.174) |
| Census Tract FE | No | Yes | Yes | Yes |
| Year FE | No | Yes | Yes | Yes |
| Month FE | No | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.5224 | 0.7401 | 0.7499 | 0.7571 |
| Observations | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4 presents the estimation results of Equation 2. The columns represent four different specifications of the base model. Column (1) shows the results when only controlling for structural housing attributes and proximity to the other two stadiums. The adjusted $R^2$ increases from 0.5224 in Model 1 to 0.7401 in Model 2 with the addition of fixed effects. Columns (3) and (4) add neighborhood and market characteristics, as well as urban controls, respectively. This slightly increases the goodness of fit, with the largest adjusted $R^2$ value of 0.7571 observed in Model 4. Additionally, our analysis reveals consistent qualitative findings across the four specifications. There are no substantial differences in terms of direction, magnitude, and statistical significance among the independent variables. These results suggest that the inclusion of additional covariates enhances the precision of the estimates and aids in isolating the treatment effect, which is why we consider Model 4 as our preferred model. In the following, we provide a brief overview of the findings for the covariates, before delving into the estimates of our target variables.

In general, most covariates are highly significant, and nearly all exhibit the expected sign. Regarding the estimates for housing attributes, the data suggests that, on average, larger parcels and buildings unsurprisingly sell for higher prices, while housing values tend to depreciate with age. Further, we discern that garages, carports, and attics, tend to elevate the value of single-family homes in the sample. Finally, compared to houses with brick walls, those constructed with stone command a premium, whereas houses with frame walls tend to sell at a discount.

Regarding the socio-demographic neighborhood features, we discern that single-family homes located in neighborhoods with a higher proportion of black residents tend to have lower transaction prices. This finding was expected in light of housing segregation in St. Louis and the phenomenon of white flight (Oliveri (2015)). Additionally, the model suggests that higher crime and vacancy rates are associated with lower transaction values. Conversely, single-family homes located in more affluent areas, as proxied by the annual median income per zip-code, sold on average for a higher price. However, it is worth noting that the coefficient is relatively small in magnitude and only significant at the ten percent level.

Potentially less evident are the findings for the share of youth residents and the population density per neighborhood, both of which are only significant at the ten percent level. Concerning the prior, we find that prices for single-family homes are higher in neighborhoods with a relatively larger share of young residents. To put differently, as Youth implicitly serves as a proxy for the presence of families, one possible explanation for the price premium might be that families select into neighborhoods with family-friendly characteristics, such as school quality, safety, and noise levels.
The negative sign of the coefficient for population density is somewhat unexpected, considering the theoretical prediction of the Monocentric-City Model. However, it should be noted that the null of non-significance is only rejected at the ten percent level, and the point estimate is relatively low in magnitude. This estimate might reflect the vast diversity of neighborhoods in St. Louis in terms of size and population. Moreover, while the negative sign seems to contradict urban economic theory,[43] the findings are not entirely implausible. For instance, our analysis focuses on single-family homes, and it may be that property owners prefer less crowded and less congested areas, which tend to be higher priced.

Looking at the coefficients for the market controls, we observe that the number of retail trade establishments per zip code is highly significant and negatively associated with single-family home values. The coefficient potentially reflects negative congestion spillovers from lower-hierarchical land use, i.e. commercial and industrial usage, to residential properties. Additionally, we find that the number of finance and insurance companies is positively associated with higher transaction prices. This is insofar expected as the coefficient proxies for proximity to the CBD, with a larger number of finance and insurance establishments suggesting residential proximity to employment centers and urban amenities. Finally, the point estimate for accommodation and food services per zip code is statistically insignificant. Notwithstanding, previous research has provided evidence that the impact of sports facilities on the economic performance of sports-related industries, such as restaurants and bars, is highly localized (C.f. Abbiasov and Sedov (2023)) and controlling at the zip-code level might not adequately capture local trends in establishment numbers.[44]

As for the urban controls, residential proximity to parks is significantly valued and capitalized in higher prices. The negative sign of the coefficient suggests that residing an additional mile away

[43]Nonetheless, it should be noted that the overall findings align closely with urban economic theory in general, and the Monocentric-City Model in particular. More specifically, it is described in further detail below that the price-gradient of single-family homes in our sample increases inversely in distance to the CBD, as the model suggests. Thus, it seems highly likely that density patterns do not perfectly align with proximity to the city core.

[44]Moreover, Table 15 shows that the coefficient has a relatively large variance inflation factor (VIF), which might also explain its insignificance.

from the closest urban park or green space lowers the value of a single-family home by about 18.14%,[45] which aligns with the literature (Crompton (2005)). Furthermore, the analysis reveals that single-family homes located on the 100-year floodplain sell on average for a price discount of about 6.16%,[46] consistent with prior research (Mason (2005)). In contrast, the 500-year floodplain does not appear to have a significant impact on single-family home prices.
What is more, the distance controls for the other two stadiums are both positive but insignificant. However, this insignificance likely results from an almost perfect correlation of the coefficients given the stadiums' adjacency, as shown in the Appendix. It is worth noting that multicollinearity among these control variables does not impair their function as control variables, as we further check that the exclusion or inclusion into the set of covariates does not visibly impact the findings.
With respect to the remaining urban control dummies, we find that Enterprise Zones are not associated with price reductions of single-family homes, contradicting our initial assumption of potential negative spillovers. Finally, a thorough discussion of the findings for the urban controls dummies concerning historical designation, preservation, and conservation, is provided as a small digression in the Online Appendix. In short, all coefficients are significant and positive, as expected. Furthermore, the magnitude of the point estimates accords with those of prior research.

Finally, concerning our target variables, the analysis reveals that all three difference-in-differences coefficients are statistically significant at the highest level and have the expected sign. First, the dummy for the impact area has a positive sign and suggests that over the pooled sample period, single-family homes transacted within three-mile distance to the stadium sold for about 15.53% more, relative to properties exhibiting similar characteristics but located farther away. This price appreciation is expected and might be considered as a general premium for positive spillovers generated by the downtown area. Second, the post-relocation dummy is also positive, possibly reflecting a general long-term recovery of St. Louis' housing market following the economic crisis that started in 2008.

Ultimately, the difference-in-differences estimate reflecting the treatment effect of the Rams' departure is negative and reveals that the relocation has led to a relative decrease in single-family home values in vicinity to the stadium. The point estimate suggests that post-relocation, single-family homes located within three-miles to the Edward Jones Dome sold for a substantial discount of 7.52% relative to properties with similar characteristics transacted within the control area. These findings confirm our hypothesis that the Rams generated substantial amenity benefits capitalized into local residential property values. Likewise, from a more general point of view, we exploit the relocation as a natural experiment allowing us to disentangle the team- from the facility effect. In this vein, our results are striking, as they suggest that a major league franchise can generate large positive externalities, in contrast to previous negative findings in different settings. We discuss these contrasting findings in the Concluding Discussion.

Against this background, as discussed in Section 4, we estimate our model across various error specifications. Table 5 summarizes the regression output for the main variables of interest, while the complete regression output is available in Table 30 in the Online Appendix. Column (1) presents the

[45] $(\exp(-0.2002 * 1) - 1) * 100 = -18.1433$.
[46] $(\exp(-0.0636) - 1) * 100 = -6.16197$.

results of our preferred model with robust standard errors, while column (2) depicts the estimates using OLS errors for comparability. Columns (3) through (5) display the estimation results with clustered standard errors.

Table 5: Regression Estimates Across Different Error Specifications - Base Model

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Impact | 0.144*** | 0.144*** | 0.144* | 0.144* | 0.144* |
| | (0.036) | (0.028) | (0.080) | (0.084) | (0.084) |
| Post | 0.320*** | 0.320*** | 0.320*** | 0.320*** | 0.320*** |
| | (0.022) | (0.021) | (0.032) | (0.033) | (0.033) |
| ImpactxPost | -0.0752*** | -0.0752*** | -0.0752*** | -0.0752*** | -0.0752*** |
| | (0.021) | (0.019) | (0.028) | (0.023) | (0.023) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7571 | 0.7571 | 0.7571 | 0.7571 | 0.7571 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
The full regression results can be found in the Appendix.
Standard errors are depicted in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The results are aligned. Irrespective of the error specification used, the main coefficient of interest, ImpactxPost, remains significant at the highest level. This indicates a consistent and robust observed price discount associated with the departure of the Rams. Additionally, the post-relocation dummy is likewise significant at the highest levels across all specifications, whereas the Impact dummy is only significant at the ten percent level when clustering the error term. Although we observe minor changes in the significance of some individual covariates with different error specifications, these variations are negligible, and the overall significance of the covariates appears reasonable.

## 6.2 Results of the Distance Ring Models

### One-Mile Distance Rings

Continuing our investigation into the foregone amenity benefits linked to the relocation, we aim to examine whether the treatment effect is heterogeneously dispersed across space and if so, which pattern it exhibits. For this purpose, we first estimate Equation 3 for the specification with one-mile distance rings, whereby the outermost ring, Impact8, serves as the reference category. Table 6 summarizes the results. As before, we also report regression estimates for the different error specifications, and the full regression output is provided in Table 31 in the Online Appendix.

Table 6: Regression Estimates Across Different Error Specifications - One-Mile Distance Rings

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.322*** | 0.322*** | 0.322*** | 0.322*** | 0.322*** |
| | (0.027) | (0.026) | (0.043) | (0.043) | (0.041) |
| Impact1 | 0.870*** | 0.870*** | 0.870*** | 0.870*** | 0.870*** |
| | (0.196) | (0.197) | (0.247) | (0.236) | (0.305) |
| Impact2 | 0.244*** | 0.244*** | 0.244 | 0.244 | 0.244 |
| | (0.080) | (0.072) | (0.191) | (0.162) | (0.165) |
| Impact3 | 0.199*** | 0.199*** | 0.199 | 0.199 | 0.199 |
| | (0.064) | (0.056) | (0.161) | (0.150) | (0.141) |
| Impact4 | 0.097* | 0.097** | 0.097 | 0.097 | 0.097 |
| | (0.053) | (0.048) | (0.128) | (0.124) | (0.113) |
| Impact5 | -0.064* | -0.064* | -0.064 | -0.064 | -0.064 |
| | (0.039) | (0.037) | (0.101) | (0.102) | (0.098) |
| Impact6 | -0.049* | -0.049* | -0.049 | -0.049 | -0.049 |
| | (0.025) | (0.025) | (0.068) | (0.068) | (0.061) |
| Impact7 | 0.023 | 0.023 | 0.023 | 0.023 | 0.023 |
| | (0.019) | (0.019) | (0.051) | (0.050) | (0.046) |
| Impact1xPost | -0.380*** | -0.380** | -0.380*** | -0.380*** | -0.380*** |
| | (0.109) | (0.166) | (0.094) | (0.093) | (0.126) |
| Impact2xPost | -0.105*** | -0.105*** | -0.105** | -0.105*** | -0.105*** |
| | (0.038) | (0.038) | (0.040) | (0.037) | (0.031) |
| Impact3xPost | -0.069** | -0.069*** | -0.069* | -0.069** | -0.069* |
| | (0.028) | (0.027) | (0.040) | (0.026) | (0.036) |
| Impact4xPost | -0.050* | -0.050** | -0.050 | -0.050 | -0.050 |
| | (0.026) | (0.024) | (0.036) | (0.044) | (0.039) |
| Impact5xPost | -0.005 | -0.005 | -0.005 | -0.005 | -0.005 |
| | (0.025) | (0.024) | (0.035) | (0.030) | (0.030) |
| Impact6xPost | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |
| | (0.019) | (0.020) | (0.024) | (0.026) | (0.021) |

| | | | | | |
|---|---|---|---|---|---|
| Impact7xPost | -0.022 | -0.022 | -0.022 | -0.022 | -0.022 |
| | (0.017) | (0.019) | (0.023) | (0.025) | (0.021) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7583 | 0.7583 | 0.7583 | 0.7583 | 0.7583 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

Reference is the outermost distance ring Impact8.

The full regression results can be found in the Appendix.

Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Regarding the pooled ring dummies, the estimates suggest that the values of single-family homes tend to be higher the closer a property is located to the stadium and thus to downtown. Notably, the sample indicates that the price gradient follows a distance decaying pattern. Simply put, the estimated relative price differences among adjacent distance rings are considerably large for the first distance rings but become less pronounced for rings located farther away. Besides, while we find significant coefficients for distances up to seven miles in our preferred model, it is worth noting that we observe a significant switch in sign at the five-mile mark. This might be interpreted as suggesting that the aggregated positive spillovers generated by the city's core appear to extend up to five miles. Notwithstanding, while the OLS error model yields nearly identical levels of significance, clustering the error term renders all distance rings except the first one statistically insignificant.

Looking at the estimates for the main coefficients of interest, the results indicate significant price depreciation rates for distances up to three or four miles, depending on the model specification. Importantly, our ring analysis also reveals a distance-decaying structure, implying that the spatial externalities generated by the franchise are heterogeneously dispersed across space and largest in the immediate vicinity of the stadium. In terms of magnitude, we find a substantial relative price depreciation ranging from 38% in the first ring to 5% in the four-mile ring.
In terms of significance, the coefficients of the first two rings are statistically significant at the highest level across all specifications, but we discern some loss of significance of the third ring and a total loss of significance of the fourth ring when clustering the error term. Overall, the results are nevertheless fairly consistent, and we observe distance-decaying price discounts reaching up to three or four miles from the stadium. These results also reinforce our selection of a three-mile treatment area, which was originally specified in an ad-hoc manner based on prior findings.

**Half-Mile Distance Rings**

The one-mile ring model suggests that the general spillover effects of the city core seem to extend up to five miles. Hence, we intensify our ring analysis and focus on a five-mile radius around the stadium, with all property transactions outside this area forming the control group. This adjustment is also made as amenity benefits are typically highly localized, and the eight-mile ring may not provide an ideal control area. Additionally, since the one-mile rings are relatively wide, the target area is further divided into half-mile distance rings to more precisely map out the heterogeneity of the treatment effect across space.

Notwithstanding, the use of half-mile distance rings must not necessarily be better, as it reduces sample size per ring. In fact, Table 2 shows, that the first four rings around the stadium are sparsely populated due to zoning ordinances and commercial and industrial land use in the broader downtown area. To address this issue, we initially group these rings together following the approach of Neto and Whetstone (2022). The estimation results are displayed in Table 7.

Table 7: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.314*** | 0.314*** | 0.314*** | 0.314*** | 0.314*** |
| | (0.024) | (0.021) | (0.036) | (0.037) | (0.036) |
| Target2 | 0.415*** | 0.415*** | 0.415** | 0.415*** | 0.415*** |
| | (0.098) | (0.080) | (0.204) | (0.135) | (0.153) |
| Target2_5 | 0.349*** | 0.349*** | 0.349** | 0.349*** | 0.349** |
| | (0.083) | (0.069) | (0.172) | (0.108) | (0.138) |
| Target3 | 0.393*** | 0.393*** | 0.393** | 0.393*** | 0.393*** |
| | (0.072) | (0.060) | (0.170) | (0.125) | (0.131) |
| Target3_5 | 0.286*** | 0.286*** | 0.286** | 0.286*** | 0.286*** |
| | (0.062) | (0.052) | (0.126) | (0.080) | (0.099) |
| Target4 | 0.219*** | 0.219*** | 0.219* | 0.219*** | 0.219** |
| | (0.050) | (0.043) | (0.117) | (0.079) | (0.092) |
| Target4_5 | 0.068* | 0.068** | 0.068 | 0.068 | 0.068 |
| | (0.040) | (0.034) | (0.086) | (0.061) | (0.076) |
| Target5 | -0.027 | -0.027 | -0.027 | -0.027 | -0.027 |
| | (0.030) | (0.026) | (0.080) | (0.085) | (0.085) |
| Target2xPost | -0.111*** | -0.111*** | -0.111*** | -0.111*** | -0.111*** |
| | (0.035) | (0.034) | (0.033) | (0.030) | (0.023) |
| Target2_5xPost | -0.057 | -0.057* | -0.057 | -0.057* | -0.057 |
| | (0.039) | (0.035) | (0.042) | (0.030) | (0.042) |
| Target3xPost | -0.073** | -0.073*** | -0.073* | -0.073* | -0.073* |
| | (0.032) | (0.027) | (0.043) | (0.041) | (0.042) |

| | | | | | |
|---|---|---|---|---|---|
| Target3_5xPost | -0.071** | -0.071*** | -0.071** | -0.071 | -0.071* |
| | (0.032) | (0.025) | (0.035) | (0.050) | (0.040) |
| Target4xPost | -0.027 | -0.027 | -0.027 | -0.027 | -0.027 |
| | (0.028) | (0.024) | (0.047) | (0.051) | (0.044) |
| Target4_5xPost | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 |
| | (0.029) | (0.025) | (0.039) | (0.031) | (0.034) |
| Target5xPost | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.028) | (0.024) | (0.038) | (0.029) | (0.037) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7580 | 0.7580 | 0.7580 | 0.7580 | 0.7580 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
Reference are properties located outside of a 5 mile radius ring around the stadium.
The full regression results can be found in the Appendix.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Regarding the pooled target area dummies, we observe significant positive estimates for all rings up to a distance of four and a half miles, indicating a less pronounced yet still present distance-decaying pattern. The significance levels remain fairly consistent across the alternative error specifications. Concerning the interaction terms, significant effects are found up to three and a half miles. While a distance-decaying structure persists, the relative differences diminish in magnitude, ranging from 11.1% for the grouped two-mile ring to 7.1% for the three to three and a half-mile ring. As expected, it seems that the very large effect of the first mile ring is somewhat dampened and absorbed by grouping the first two miles together. Overall, while the individual significance levels of the difference-in-differences estimates vary slightly more across the different specifications, this is expected due to the aforementioned limitations in sample size per ring.

Finally, we zoom in further and also estimate the model using half-mile rings for the first two miles. In addition, we restrict the sample to a five-mile radius around the facility, with the reference area being the five-mile ring, as it constitutes the closest insignificant ring in the previous estimation. The results are presented in Table 8. Due to the reduced sample size ($n = 3768$) and the low transaction numbers in the first half-mile rings, the results need to be interpreted with some caution.
While negative and significant treatment effects can still be observed up to three and a half miles from the Edward Jones Dome, the significance levels of individual rings differ considerably across the models. For instance, significant coefficients are found for the first four rings when clustering the error term, but only for the first and fourth rings when using robust standard errors. Conversely, no significance beyond the two-mile mark is observed when the error term is clustered at any of

the three levels, but significant findings are observed up to three and a half miles within the robust model. These differences in significance are likely related to the lower sample size, but overall, the findings are consistent with the previous results.

Lastly, a significant advantage of the estimated model is its ability to illustrate the convexity of the treatment effect across space. In terms of magnitude, the relocation-induced price discount is estimated to range between 34.3% and 6.5%, depending on the distance to the facility.

Table 8: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 5 Mile Radius

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.331*** | 0.331*** | 0.331*** | 0.331*** | 0.331*** |
| | (0.050) | (0.048) | (0.053) | (0.046) | (0.053) |
| Target0_5 | 0.169 | 0.169 | 0.169 | 0.169 | 0.169 |
| | (0.167) | (0.432) | (0.175) | (0.125) | (0.178) |
| Target1 | 0.752*** | 0.752** | 0.752*** | 0.752*** | 0.752* |
| | (0.212) | (0.297) | (0.198) | (0.213) | (0.381) |
| Target1_5 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 |
| | (0.134) | (0.141) | (0.180) | (0.105) | (0.181) |
| Target2_0 | 0.110 | 0.110 | 0.110 | 0.110 | 0.110 |
| | (0.116) | (0.111) | (0.159) | (0.083) | (0.151) |
| Target2_5 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 |
| | (0.094) | (0.090) | (0.125) | (0.077) | (0.122) |
| Target3 | 0.219*** | 0.219*** | 0.219* | 0.219* | 0.219** |
| | (0.075) | (0.072) | (0.124) | (0.106) | (0.094) |
| Target3_5 | 0.166*** | 0.166*** | 0.166** | 0.166* | 0.166** |
| | (0.061) | (0.058) | (0.079) | (0.082) | (0.068) |
| Target4 | 0.074* | 0.074* | 0.074 | 0.074 | 0.074 |
| | (0.041) | (0.040) | (0.055) | (0.047) | (0.053) |
| Target0_5xPost | -0.343*** | -0.343 | -0.343*** | -0.343*** | -0.343*** |
| | (0.119) | (0.247) | (0.059) | (0.059) | (0.050) |
| Target1xPost | -0.190 | -0.190 | -0.190** | -0.190* | -0.190* |
| | (0.130) | (0.338) | (0.078) | (0.106) | (0.095) |
| Target1_5xPost | -0.112 | -0.112 | -0.112** | -0.112* | -0.112** |
| | (0.092) | (0.111) | (0.046) | (0.056) | (0.053) |
| Target2_0xPost | -0.075* | -0.075 | -0.075 | -0.075** | -0.075* |

| | | | | | |
|---|---|---|---|---|---|
| | (0.044) | (0.049) | (0.052) | (0.032) | (0.038) |
| Target2_5xPost | -0.041 | -0.041 | -0.041 | -0.041 | -0.041 |
| | (0.042) | (0.045) | (0.046) | (0.041) | (0.044) |
| Target3xPost | -0.065* | -0.065* | -0.065 | -0.065 | -0.065 |
| | (0.037) | (0.037) | (0.055) | (0.055) | (0.049) |
| Target3_5xPost | -0.069* | -0.069* | -0.069 | -0.069 | -0.069 |
| | (0.039) | (0.035) | (0.050) | (0.061) | (0.050) |
| Target4xPost | -0.025 | -0.025 | -0.025 | -0.025 | -0.025 |
| | (0.035) | (0.034) | (0.053) | (0.044) | (0.043) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7857 | 0.7857 | 0.7857 | 0.7857 | 0.7857 |
| Observations | 3768 | 3768 | 3768 | 3768 | 3768 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
Reference are properties located 4-5 miles from the stadium.
The full regression results can be found in the Appendix.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## 6.3 Estimating the Aggregated Social Costs of the Relocation

Our analysis provides substantial evidence that a major league sports franchise can indeed yield considerable positive externalities. Specifically, our estimates suggest a capitalization rate of about 7.5% within a three-mile radius from the stadium. However, this finding is somewhat challenging to assess for researchers and policymakers alike. Therefore, the question of the justification for the public subsidization of sports facilities requires contextualizing the findings. In this spirit, we approximate the local social welfare loss induced by the relocation and compare it to the total public spending on the stadium. In short, we demonstrate that the relocation has caused a significant loss in value of the total housing stock in St. Louis, which is comparable in magnitude to the total public subsidies spent and supports the general case of stadium proponents. Though, due to limitations in the data, it was required to make some strong assumptions, which is why we caution to interpret the results with some care.

Conceptually, we estimate the aggregate local welfare loss by approximating the value of the housing stock within the impact area in 2015, the year prior to the relocation, and depreciating it at the rate of the observed price discount. First, we approximate the number of total housing units per neighborhood in 2015 using the average of the 2010 and 2020 Census data. Second, we make the light assumption that the market is functioning efficiently and that the observed transaction prices are representative of the distribution of housing values of the latent housing stock. In this regard, we determine the median sales price of properties transacted within the impact area in 2015, which we find to be \$229,500 in our sample. However, this value is naturally elevated due to the sample selection and data cleansing, so we consider it an upper price bound. For our lower price bound, we use the median sales price of all residential buildings transacted in 2015 within the impact area, which amounts to \$166,625. Thereby, we include valid sales, but also foreclosures, investor sales, and unverified valid sales, which typically sell at a discount relative to valid sales.

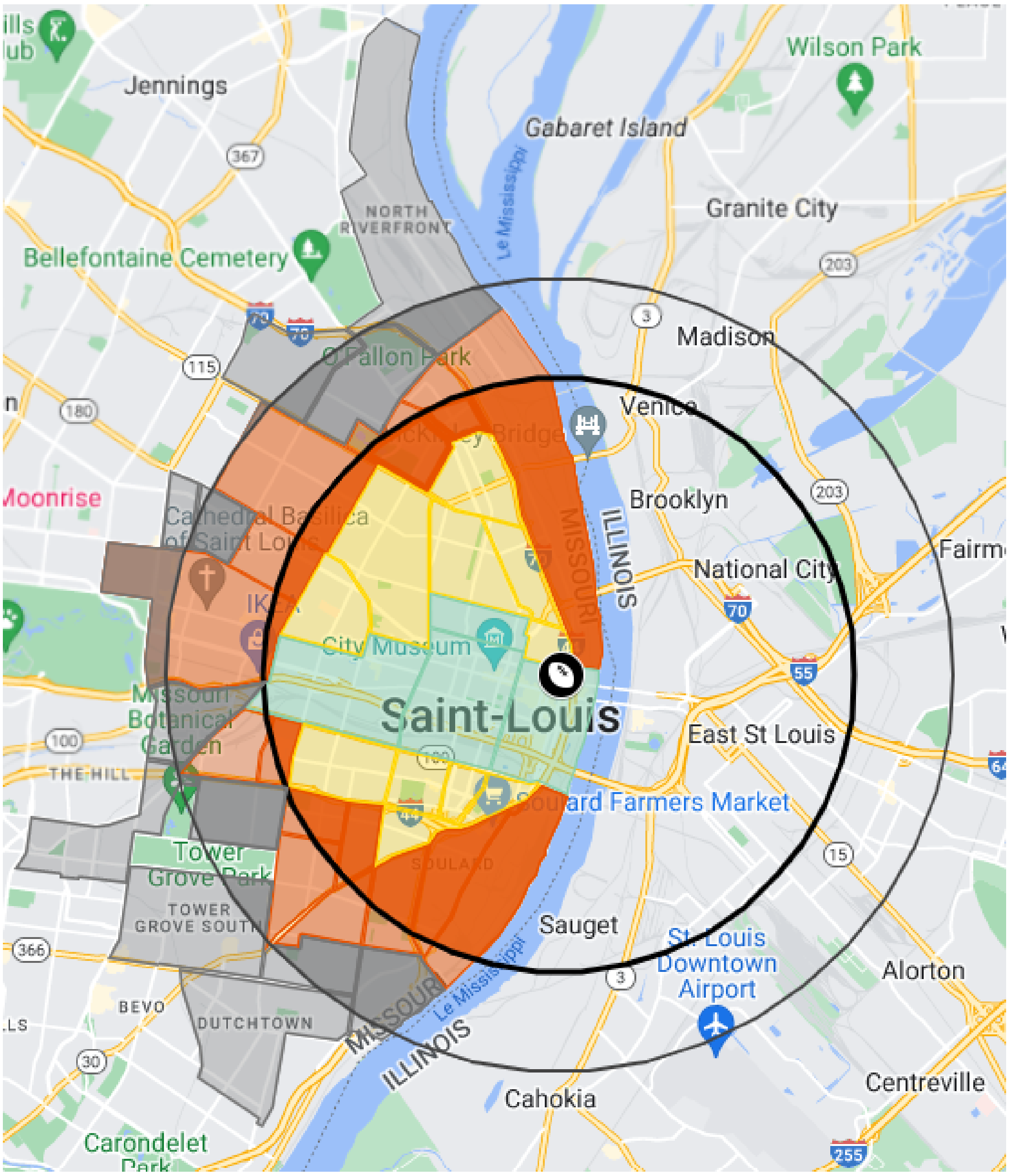
Our hedonic price regressions reveal significant discounts expanding about three to four miles from the stadium. However, neighborhood boundaries are shaped in somewhat arbitrary patterns across space. In this respect, Figure 5 shows that while some neighborhoods (in yellow) are fully enclosed, others (in red) intersect the three-mile impact area, delineated by the inner thick ring. For these intersecting areas, we assume an approximately equal dispersion of housing units across space. In this vein, with the help of Google My Maps, we compute the share of each neighborhood falling into the impact area, allowing us to estimate the total number of housing units ($n_3 = 35,551$) within a three-mile radius of the Edward Jones Dome. The estimated social costs based on the three-mile area can be considered as a rather conservative estimate, as the one-mile ring model suggested that the impact of the relocation may also be observed in properties located up to four miles away from the stadium. To also provide an extended estimate, we likewise estimate the local welfare loss based on a four-mile impact area ($n_4 = 52,856$), following the same steps as for the three-mile area.[47]

In this context, it is essential to note that the number of housing units is almost always larger than the size of the housing stock, due to some dwellings being shared by multiple units. Similarly, the median price per housing unit is typically not equivalent to the median price per dwelling. As we only have information on the number of housing units, while our price information is based on sales of entire dwellings, we need to approximate the per-unit price of properties by building type. Specifically, we make the strong assumption that, on average, the per-unit value of a shared residential building roughly corresponds to the total sales price divided by the number of units. Additionally, we estimate the share of each residential building type within the impact area based on their transactional share over the entire sample period. Thereby, it is implicitly assumed that the observed transaction shares per building type reasonably reflect their share in the latent residential housing stock. In this context, we focus on six building types which together account for 94.75% of all transactions: single-family units, duplexes, triplexes, quadplexes, five-family units, and multiple-family residential buildings.

Unfortunately, we cannot apply this approach to six neighborhoods within the three-mile impact area due to either no or only a few residential housing transactions occurring over the sample period. Specifically, this means we lack sufficient information to make assumptions about the composition of the building stock within these neighborhoods. Two neighborhoods - Kosciusko and Botanical Heights - are simply excluded from the analysis. Kosciusko is primarily an industrial neighborhood with only 5 housing units recorded in 2020 according to the Census, while Botanical Heights has only 1.4% of its area falling within the three-mile area. Nevertheless, the remaining four neighborhoods - Downtown, Downtown West, Midtown, and Carr Square - account for a considerable share of about

[47] The upper price bound of the four-mile impact area in 2015 matches the three-mile value of \$229,500, while the lower bound of \$145,000 is smaller, as expected given the expanded area.

Figure 5: St. Louis - Impact Area




Own depiction created with Google's *My Maps* tool and *KML Circle Generator*.
Color Legend: a) Red: Neighborhoods intersecting the three-mile impact area; b) Yellow: Neighborhoods fully enclosed; c) Green: Downtown, Downtown West, Midtown and Carr Square; d) Grey: Neighborhoods intersecting the four-mile ring.

one third ($n = 10,535$) of all housing units within the impact area in 2015. One evident reason for the low number of observations within these neighborhoods has to do with the fact that Geo St. Louis records only parcel sales, which means, as elaborated earlier, that we do not observe sales of individual apartments and condominiums, but only sales of entire apartment complexes. Figure 5 illustrates that these neighborhoods, distinguished in green, are largely part of St. Louis' CBD and entertainment district, which is why it seems plausible to assume that the predominant building type in theses areas is apartment buildings. Moreover, the city's core is primarily characterized by commercial and industrial land use, as displayed in Figure 11, consistent with previous reports by Hurt (2021) and Mares and Blackburn (2019). Although the number of parcel sales is low, our data tells a similar story: out of 128 recorded parcel sales, 90.63% constitute commercial or industrial sales, with only five transactions involving multiple-family residential buildings across the four concerned neighborhoods.

Against this background, it appears highly likely that the building stock within the four neighborhoods does not follow the same pattern as the remaining neighborhoods. Therefore, we approximate the building composition based on information on the housing stock within Downtown Nashville, assuming that the downtown areas of both cities are roughly comparable in size and composition.[48] According to a report by Dickson (2020), there were 9,511 residential housing units in Downtown, Nashville, out of which 69% were rental apartment units, 28% condominiums, and only 3% were family homes with up to four units. We consider these numbers to be plausible proxies for St. Louis as well. Notwithstanding, one prevailing and unsolvable issue is that we do not have any information on the median sales price of residential buildings within the concerned neighborhoods. Therefore, we must make the strong assumption that the median sales prices is approximately similar to the observed median price in 2015 of the other neighborhoods within the impact area. Given the proximity to the CBD, it is possible that the true median price might be higher and reflective of amenity and consumption benefits.

Ultimately, we approximate the number of units per building type located within the impact area, both for the observed and non-observed neighborhoods. The total number is obtained by simply summing the two estimates together. Eventually, the approximate total social costs induced by the relocation can then be calculated as follows:

$$C_{i,k} = \sum_j b_{j,i,t=2015} * w_j * \bar{p}_{k,i,t=2015} \times \delta_i \tag{4}$$

where $b_{j,i}$ denotes the number of total building units per building type $j \in [1, 6]$ and impact area $i \in [1 = \text{3-mile}, 2 = \text{4-mile}]$. $\bar{p}$ reflects the lower ($k = l$) and upper ($k = u$) median price in 2015 for buildings transacted within impact area $i$. Finally, $w_j$ is a vector of weights allowing to adjust for the number of units per building type, whereby $w_j = \{1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}, \frac{1}{16}\}$. For example, a duplex is weighted by the factor $\frac{1}{2}$ to account for the fact that two building units correspond to one singular dwelling. As for multiple-family buildings, we chose a weight of 16 which corresponds to the average number of apartments in multiple-family buildings sold over the sample period. Lastly, $\delta_i$ stands for

[48] While it was generally difficult to find data on the composition of downtown areas limiting our selection, we consider Nashville the best available approximation as it is a mid-sized city somewhat similar in size and popularity to St. Louis and is also home to an NFL franchise.

the estimated depreciation rates of 7.52% ($i = 3$) and 6.73% ($i = 4$).

Based on the three-mile specification, we obtain a lower inflation-adjusted estimate of $254,720,530 and an upper estimate of $350,837,879.[49] Regarding the four-mile specification, the inflation-adjusted price range is estimated to be $329,012,021 - $520,746,612. The results underscore the substantial reduction in the value of the local housing stock resulting from the departure of the Rams. Conversely, the findings also suggest that the local welfare gains generated by an NFL franchise may justify public subsidies for stadium projects. Nonetheless, it is worth noting that the upper estimate of the price range is still moderately below the present value of the $258 million in governmental bonds paid in 1995 for the stadium construction (Click (2016)), which is equivalent to $552,724,409 in 2023 prices. Additionally, it needs to be considered that the total public expenses for the stadium were substantially larger, as the bond debt and maintenance costs were paid off over a 30-year time span, during which the City and County both paid $6 million annually, while the state of Missouri contributed $12 million per year. In total, this amounts to repayments worth $720 million, according to Reuters (Respaut (2016)).
Nevertheless, the annual debt payments were largely offset by the direct tax revenue streams generated by the matches of the Rams. In this regard, Reuters reports an annual income of $12.4 million for the state of Missouri and $4.2 million for the City of St. Louis, while the income of St. Louis County is not documented. Therefore, the outstanding bond debt of $144 million ($180,498,735 in 2023 prices) at the time of relocation might be a better indicator for the total net expenses, as this sum was not offset by income revenue from home matches anymore. Finally, an important piece of the financing history of the stadium is its end, as in 2021, St. Louis agreed with the Rams on a relocation settlement worth a substantial sum of $820 million in damage payments (Raskin (2022)). This settlement implicitly reveals an imperfect proxy for the aggregated foregone revenue stream that the Rams would have generated had they stayed another ten years in St. Louis and fulfilled their original contract.

Overall, the public subsidies provided for the stadium seem to be fairly justified in view of the large direct and indirect economic benefits that the Rams generated in the market. Nevertheless, it needs to be taken into account that the Edward Jones Dome was built in 1995 and is outdated by today's standards. Nowadays, many new stadiums are technologically state-of the art multi-purpose facilities whose costs often exceed the billion dollar mark. For example, the new stadium of the Rams in Los Angeles cost more than $4bn in total, though it must be noted that the facility was entirely privately financed. In the case of St. Louis, in late December 2015, the city board unveiled last-minute plans for a new stadium in hopes of preventing the Rams' relocation to Los Angeles or attracting another franchise to St. Louis. The total costs of the proposed stadium were projected to be up to $985 million, with plans including a public contribution of $405 million (Hunn (2015)). In view of the estimated social costs induced by the Rams' departure, such a public subsidy would have been fairly justified to keep the franchise in St. Louis. However, a public commitment to cover the entire construction costs, as was the case for the Edward Jones Dome, would have likely not resulted in net positive benefits.

[49] The inflation-adjusted prices were computed with the US Inflation Calculator.

Finally, in light of constantly rising construction costs and increasingly sophisticated stadium features, one yet unanswered empirical question remains to what extent the generated amenity benefits depend on stadium characteristics. Prior work by Ahlfeldt and Kavetsos (2014) suggests that sports facilities can also convey positive externalities due to their exterior appearance, but no research has yet addressed the effects of technical or structural features of a stadium. If the additional spatial externalities associated with more sophisticated stadium features are observed to be relatively small compared to the additional costs of such features, public contributions for stadium projects should not be determined as a fixed percentage share of the total costs, as historically observed (Bradbury et al. (2022)), but rather assessed in terms of the expected positive magnitude effect of the new stadium. In light of increasing construction and maintenance costs, new blended-financing mechanisms promise to become a fruitful bedrock to explore for future public-private stadium projects (Hanau (2016)).

# 7 Concluding Discussion

This paper exploits the exogenous price shock induced by the relocation of the NFL's Rams franchise from St. Louis to Los Angeles in 2016. It provides evidence that the team generated considerable amenity benefits in the market, as we find a relative price depreciation of single-family homes within up to four-miles from the host stadium following the teams' departure. Hedonic regression estimates suggest that the relative price discount equals about 7.5% for properties located within a three-mile impact area. Subsequently, hedonic distance ring analyses reveal that the treatment effect is heterogeneously dispersed across space, and that the impact is most pronounced within the immediate vicinity of the stadium and decreases in a non-linear distance decaying pattern. Further, we estimate the cumulative social costs to lie within a relatively wide price range between $254-520 million, conditional on the size of the impact area. Lastly, we conduct several robustness checks in the Appendix. These checks demonstrate that the results are robust against alternative model specifications and data cleansing. Additionally, we rule out that potential anticipation effects, confounding events, or endogenous regressors significantly bias the estimates.
Taken together, the findings suggest that a major league franchise can create substantially large positive externalities, which may justify the public subsidization of sports facilities. It appears plausible that the findings are somewhat generalizable and indicative, especially for other mid-sized cities where sports plays an integral role in urban revitalization. Nevertheless, it seems likely that St. Louis is an outstanding example towards the upper end of the spectrum, and the results need to be evaluated in the context of local idiosyncrasies. In this regard, we contend that St. Louis' relatively unique urban composition, as well as its political and historical trajectory, may help explain why our analysis reveals substantially positive team effects, whereas prior research has found net negative externalities in other settings.

In this context, in terms of direction and magnitude, our results are generally consistent with prior research, primarily finding positive externalities associated with the announcement or inauguration of a new stadium. Relative to previous hedonic studies, our estimated price discount of 7.52% is fairly moderate and reflects an approximate average of prior findings. Similarly, our estimated local welfare loss is comparable in absolute value to prior estimates of the welfare gains associated with major league teams. For example, it is somewhat comparable to the estimated present discounted tax value of $254 million by Feng and Humphreys (2012),[50] and likewise similar to Agha and Coates (2015), who estimated the impact of minor league teams to be around $154-465 million (in 2023 prices), depending on population size. Nonetheless, the impact of the Rams' relocation is unsurprisingly smaller than the estimated £1.3 billion cumulative price increase observed in London's housing market following the official winning bid for the Olympic Games, as reported by Kavetsos (2012). More importantly though, Carlino and Coulson (2004) estimated the average welfare value of an NFL franchise to be about $186 million (in 2023 prices) for a city of the size of St. Louis. Our estimates suggest that the loss of welfare in St. Louis is considerably larger, emphasizing the importance of the Rams for the city.

Notwithstanding, our results stand in contrast to the findings by Humphreys and Nowak (2017) and

[50] Unfortunately, as we are not able to determine with certainty to which year the price estimate relates, we report the original estimate of the authors.

Joshi et al. (2020), who revealed that basketball and soccer franchises generated disamenities in Charlotte's and Seattle's housing markets, respectively. Similarly, contrary to Chikish et al. (2019), who did not find any additional team effect upon arrival of two NBA franchises in Oklahoma, we find a significant relocation effect despite the continuous use of the stadium for other non-sports related events, indicating the presence of pure team effects. There are a number of potential explanations for the contrasting findings.

Firstly, while the aforementioned papers predominantly study the impact associated with NBA teams, this paper analyzes the team effects associated with an NFL franchise. It is worth noting that there are considerable differences between the leagues, particularly regarding the number of games. While a typical NFL season consists of only about eight home matches, the average NBA home season exhibits more than 40 matches. In this respect, NBA games primarily attract local residents arriving shortly before the match begins, whereas football matches draw many fans from farther away who often stay for the weekend. This implies that game-related traffic is much more spread out over several days (C.f. Abbiasov and Sedov (2023)). Hence, it may be argued that congestion should be a larger issue surrounding NBA matches, which could partly explain the inverse sign of the observed effects. Additionally, football constitutes the most important sports in the US, both in terms of revenue and popularity. Therefore, hosting an NFL franchise likely conveys additional status value to a city.

Secondly, it may be that the facility's design and location play a non-negligible role in preventing congestion externalities in St. Louis. A typical argument brought forward among others by Rosentraub (2009) is that sports facilities create larger benefits the more they are integrated into urban areas. Similarly, Nelson (2001) argues that stadiums should not be surrounded by large parking lots as they would prevent the unfolding of positive spillovers. Mirroring this logic, we contend that the integration of the Edward Jones Dome into the CBD may have also contributed to mitigating congestion externalities affecting residential areas. Thereby, we implicitly follow the reasoning of Propheter (2021), who posits that a large parking lot around Dodgers Stadium potentially acts as a buffer to prevent nuisances such as noise and congestion. We argue that the primarily commercial and industrial land use around the Edward Jones Dome, as shown in Figure 11, may fulfill a similar function. As shown in Table 2, our sample consists of only 13 transactions occurring within a one-mile radius from the stadium. Therefore, it may be that most of the residential living quarters within the impact area are located close enough to conveniently experience the amenity benefits of the facility, but far enough away to not be exposed to strong congestion effects ((C.f. Horn et al. (2015), Bradbury et al. (2022)).[51] This reasoning aligns with Ahlfeldt and Maennig (2009) & Ahlfeldt and Maennig (2010), who argue that the emanation of positive externalities largely depends on policymakers' ability to limit congestion effects, especially by selecting an adequate location neatly integrating the facility into its surrounding neighborhood.[52]

[51]Hurt (2021) describes that the Dome is part of a large convention center which makes it somewhat physically isolated. Additionally, the author judges that the immediate surrounding is rather unexciting and "dead". In this vein, Hurt reports that fans have particularly complained about a bad environment lacking space for tailgating parties before matches. While this may be generally unpleasant for the overall fan experience, it could be at the benefit of local residents, as it is likely to minimize match-related nuisance.

[52]We note that the question of the heterogeneity of housing market impacts due to different facility

Thirdly, the relatively large local welfare loss induced by the relocation likely correlates directly with St. Louis' distressed economic and demographic situation, along with the pivotal role sports plays in driving urban revitalization within the city core. Over the last century, St. Louis has lost much of its old glamour, with the sports industry serving as a beacon of hope, making residents somewhat agnostic about the city's challenges. Moreover, having three major league teams in a city the size of St. Louis is somewhat uncommon, potentially fostering particularly strong feelings of community identity and civic pride. In this vein, the departure of the Rams evoked a highly emotional response from both fans and public officials, underscoring the deep-seated societal and political significance of the team for the city. As mentioned earlier, Wagoner (2019) speaks of a "philanthropic void left behind by the Rams" and emphasizes how the departure has consolidated the synergies between the Blues and the Cardinals, who work ever closer together to fill the remaining void. Lastly, since February 2020, the minor league XFL franchise BattleHawks has been playing their home games in the Rams' old stadium, consistently drawing high attendance figures across the league (Barrabi (2020)), further highlighting the enduring bond between football in particular, and sports in general, and the St. Louis community.

Fourthly, closely related to the previous point, the Rams highlighted within their relocation application that St. Louis does not provide a sufficiently large market potential for the franchise to thrive in the long run. This perception may have decreased the attractiveness of the city for both residents and investors, serving as a negative signal. Additionally, as noted by Agha and Coates (2015), minor league sports teams can have a particularly strong impact in mid-sized cities like St. Louis. In this regard, one could argue that in larger and more saturated markets such as Seattle and Charlotte, the sports sector plays a rather marginal role, and teams could exacerbate congestion in already crowded areas.

Lastly, as is common for empirical works, we need to report a few caveats of this paper. For instance, regarding the model specification, we were unfortunately unable to obtain information on the proximity of single-family homes to transport infrastructures, and likewise, lack information on school quality. As further elaborated within the Appendix, we contend that we are, to some degree, accounting for school quality because it is likely to be highly correlated with several of our selected sociodemographic neighborhood covariates. However, we were unable to find a decent proxy for proximity to transport infrastructures. Nevertheless, we believe that any resulting OVB should be relatively minor, as we are not aware of significant changes in St. Louis' transport infrastructure following the Rams' departure.
Furthermore, another data-related limitation is that we were only able to acquire information on parcel sales and hence focused on single-family home transactions. Although the selection of single-family homes is common in the hedonic literature, it might have been desirable to also assess the robustness of the results for alternative residential building types. In particular, transactions of apartments and condominiums might have shed additional light on the impact of the relocation, especially on properties within very close proximity to the stadium, as those building types are typically more prevalent in downtown areas than single-family homes, as already elaborated earlier.

designs and locations promises an interesting puzzle for future research.

Consequently, we might have observed a different sign for these building types, and the overall results may suffer to some degree from selectivity bias.
Moreover, another potential source of bias might stem from time-invariant non-observed housing or location characteristics that are somewhat correlated with the treatment. In this vein, it would have been desirable to additionally run repeated sales regressions, either for the whole sample, as done by Chikish et al. (2019), or embedded within the model using a repeated-sales sample, as done by Humphreys and Nowak (2017), to address this bias. However, our sample does not contain enough repeated sales for either approach.

## 7.1 Policy Implications

The case of the relocation of the Rams is informative for policymakers from various angles. Firstly, the results suggest that sports facilities and sports teams can generate substantial intangible benefits significant enough to justify generous public subsidies from an economic standpoint. Secondly, in particular in non-saturated and distressed markets, a well-planned sports-led urban development strategy may serve as a crucial anchor for downtown revitalization. This is especially true because a major league sports team's presence can enhance the perceived attractiveness and credibility of a city, thereby sending a positive signal to businesses and residents.

While this paper suggests that sports subsidies can constitute a useful tool in the policymaker's toolbox, it should be noted that our analysis cannot determine whether public funds might be better invested in other sectors generating larger net benefits. Ultimately, this decision needs to be made based on local needs and the respective context. Additionally, the intangible impact of sports facilities is highly localized and should therefore also be assessed from a distributional perspective. In the past, public subsidies for sports facilities have often been accompanied by an increase in property tax rates across the whole city. This means that residents living far away from the stadium cross-subsidized residents living in the impact area who, in case of home-ownership, are usually better off due to a relative value increase of their property.

Further elaborating on distributional concerns, as mentioned previously, especially team owners tend to benefit from public subsidization seeing their team values skyrocketing after moving to a new stadium. Additionally, franchise owners wield considerable bargaining power over their host city, mainly through the threat of relocation. In this light, it seems desirable to increase corporate accountability and simultaneously toughen relocation regulations. Future public-private stadium projects may find promising opportunities in exploring new blended-financing mechanisms, such as the *sports communities model*,[53] which offer increased involvement from franchises, thereby increasing their "skin in the game".

[53] Under this model, the city provides public subsidies for a new stadium based on the expected tax revenue streams generated by an adjacent neighborhood that the franchise is responsible for developing and managing.

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# Appendix

The Appendix is organized as follows: Appendix A contains robustness checks concerning the parallel trend assumption and sample period selection. Appendix B offers additional robustness checks related to alternative model specifications and data cleansing approaches. Further, Appendix C includes supplementary figures referenced throughout the paper. Finally, we provide a rich Online Appendix containing additional material going beyond the scope of our main analysis. For instance, we present the results of a simple proximity model, which was omitted from the main text due to severe multicollinearity. Additionally, we elaborate on the role of historical designation and residential proximity to parks within the framework of brief digressions. Lastly, the Online Appendix encompasses all complete regression outputs alongside summary information on the additional variables used throughout the Appendix.

# Appendix A - Robustness Checks

## Testing for the Parallel Trend Assumption

### DiD with Leads and Lags

To further examine the credibility of the parallel trend assumption, we estimate a hedonic leads- and lags model to statistically examine potential deviations in pre-trends between treatment and control group. Based on Equation 2, the model is specified as follows:

$$\begin{aligned}\ln p_{i,t} =& \beta_0 + \beta_1 * \text{Impact}_i + \sum_{\tau=0}^{m} \delta_{-\tau} \text{Impact}_{i,\,2016-\tau} + \sum_{\tau=1}^{q} \delta_{+\tau} \text{Impact}_{i,\,2016+\tau} \\ &+ \sum_{j=1}^{J} \beta_i x_{j,i,t} + \sum_t \kappa_t y_t + \sum_l \theta_l m_l + \sum_k \psi_k c_k + \epsilon_{i,t}\end{aligned} \tag{5}$$

whereby the model incorporates $m = 4$ leads ($\delta_{-1}, \ldots, \delta_{-4}$) capturing the pre-treatment-, i.e. anticipatory effects, and $q = 4$ lags ($\delta_1, \ldots, \delta_4$) capturing the post-treatment effects. The other model components remain as defined before.

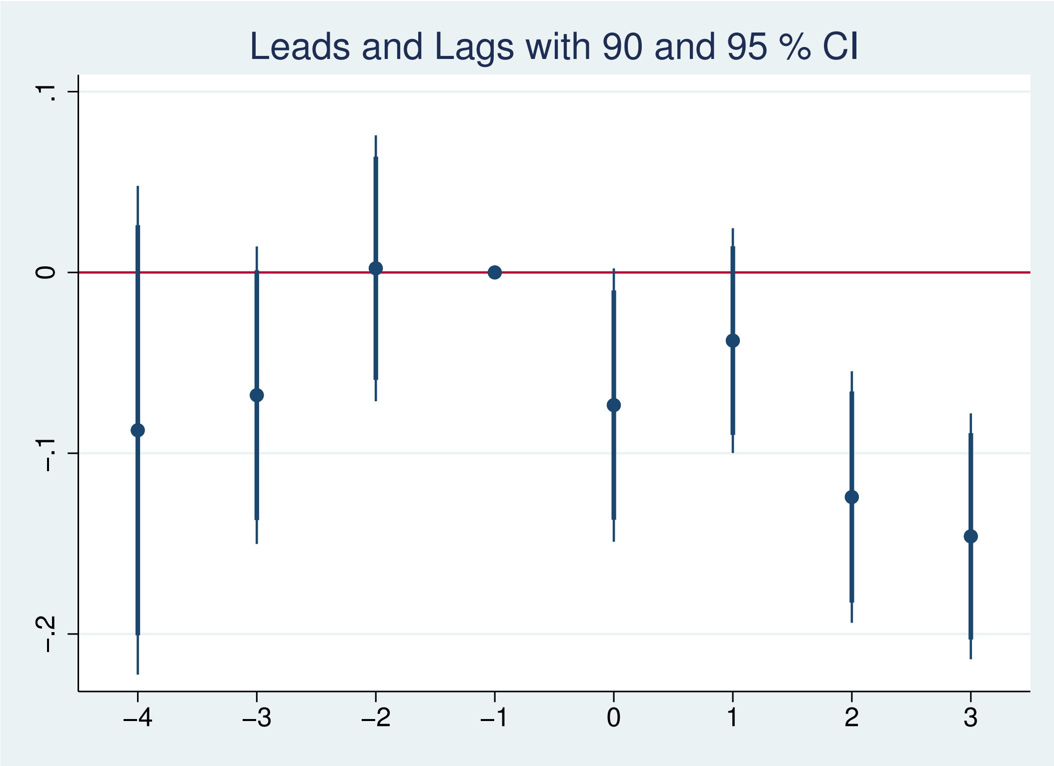
Table 9 displays the regression estimates of the leads and lags, whereby Impact2015, the year prior to the relocation, serves as reference. In our preferred model with robust standard errors (column 1) and the model with standard errors clustered on the neighborhood level (column 5), none of the leads is statistically different from zero. However, in columns (2) - (4), the coefficient for 2013 is marginally significant, potentially reflecting the light kink observed in Figure 1. Finally, with respect to the lags, the results suggest that the treatment effect becomes larger over time. Figure 6 illustrates this evolution by plotting the model coefficients.

Table 9: Regression Estimates of the Leads and Lags Model Across Different Error Specifications

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Impact | 0.162*** | 0.162*** | 0.162* | 0.162* | 0.162** |
| | (0.040) | (0.032) | (0.088) | (0.085) | (0.079) |
| Impact2012 | -0.087 | -0.087 | -0.087 | -0.087 | -0.087 |
| | (0.069) | (0.056) | (0.064) | (0.066) | (0.056) |
| Impact2013 | -0.068 | -0.068* | -0.068* | -0.068* | -0.068 |
| | (0.042) | (0.038) | (0.039) | (0.037) | (0.047) |
| Impact2014 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.038) | (0.035) | (0.040) | (0.023) | (0.033) |
| Impact2016 | -0.073* | -0.073** | -0.073 | -0.073** | -0.073* |
| | (0.039) | (0.034) | (0.046) | (0.035) | (0.042) |
| Impact2017 | -0.038 | -0.038 | -0.038 | -0.038 | -0.038 |
| | (0.032) | (0.031) | (0.044) | (0.027) | (0.036) |
| Impact2018 | -0.124*** | -0.124*** | -0.124** | -0.124*** | -0.124*** |
| | (0.035) | (0.031) | (0.051) | (0.033) | (0.045) |
| Impact2019 | -0.146*** | -0.146*** | -0.146*** | -0.146*** | -0.146*** |
| | (0.035) | (0.032) | (0.032) | (0.035) | (0.040) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7573 | 0.7573 | 0.7573 | 0.7573 | 0.7573 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
Reference is Impact2015.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 6: Coefplot - Model with Leads and Lags




In conclusion, the results consolidate our identification strategy and provide reasonable support to believe that, in the absence of the treatment, the treatment and control group would have followed the same trend. However, given the marginally significant coefficient of Impact2013 for specific error specifications, we additionally test for the robustness of our results by replicating our hedonic analyses for adjusted sample periods, i.e. excluding 2012 and 2013 from the sample.[54] The results are presented below. Likewise, within the next subsection, we follow the recommendations from Roth et al. (2023) and employ novel diagnosis tools and conduct sensitivity analysis to further assess the robustness and credibility of the parallel trend assumption.

### Pre-Trend Diagnosis and Sensitivity Analysis

First, Roth (2022) shows that conventional pre-trend tests in event-study designs may suffer from low power leading to an underdetection of pre-trends and consequently biased estimates. Hence, we employ the derived *pretrends* Stata package which provides tools for power calculations of pre-trend tests and allows to plot and assess possible violations of parallel trends for specified power levels. In this context, Figure 7 plots the linear trend for which we would have 80% power to detect it,[55] which has a slope of 0.0462.[56] Following the reasoning of Lovenheim and Willen (2018), we claim that an extrapolation of such a hypothesized pre-trend seems implausible for monotonicity reasons,

[54] None of the coefficients for 2014 is significant when re-estimating the leads-and lags model with a shortened sample period from 2014-2019. The results are available from the author.

[55] To put simply, in eight out of ten cases we would observe a significant pre-trend, but in two cases we would not.

[56] For the 50% level, the according slope would be 0.0301.

because none of the post-treatment confidence intervals includes the red line.[57] If anything, as the trend goes in the opposite direction, we would underestimate the true relocation effect and in reality, the departure of the Rams would have even been more detrimental than our estimates already suggest.

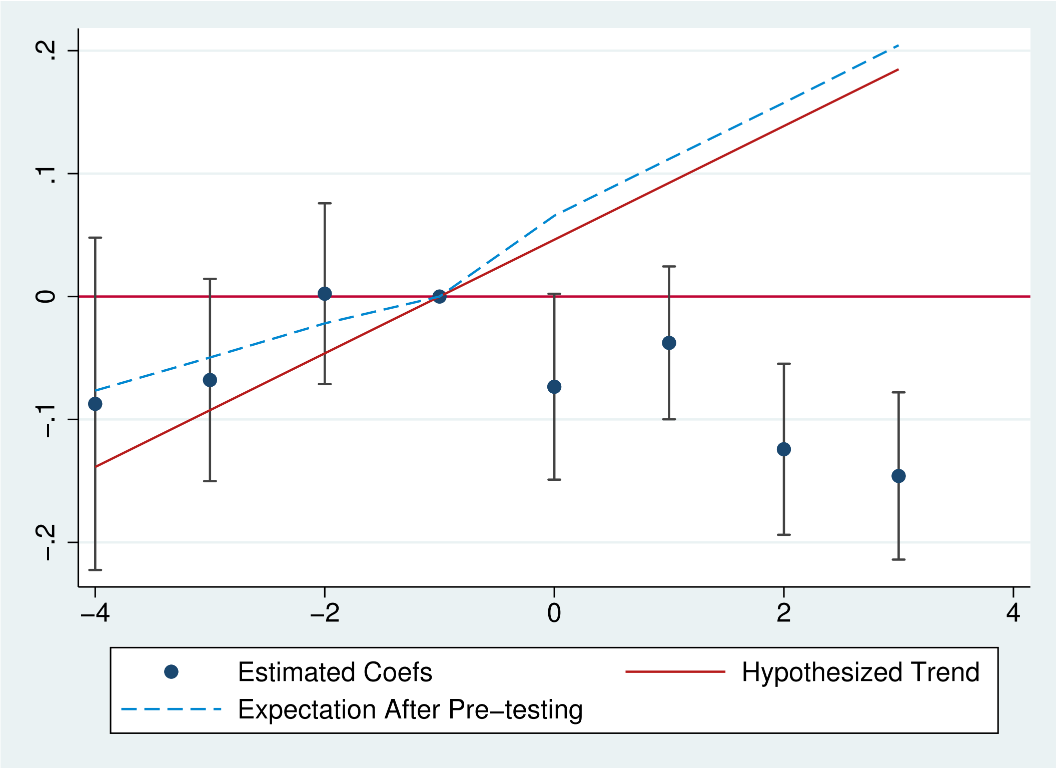



Figure 7: Linear Pre-Trend with 80% Power

Second, we can show that our significant result is robust even if the parallel trend assumption should not hold perfectly. Concretely, based on Rambachan and Roth (2023), the derived *honestdid* Stata package allows among other things to compute robust 95% confidence intervals for the average treatment effect imposing relative magnitude bounds on the post-treatment violation of parallel trends. Thereby, these bounds are determined in relation to the maximal pre-treatment deviation of parallel trends formalizing the intuition that the (observed) pre-treatment differences are informative about the (latent) counterfactual differences in trends. Accordingly, Figure 8 portrays such robust confidence intervals, whereby $\bar{M}$ indicates different degrees of restrictions imposed on the violation of parallel trends. We can see that the breakdown value is $\bar{M}^* = 0.25$, meaning that we would not overturn our significant result unless we believe that that the violation of parallel trends is in fact more than a quarter as big as the maximal differences in pre-trends.

[57]Though, the package also allows to calculate the likelihood ratio (LR), that is, the likelihood to observe the leads under the hypothesized linear trend relative to under parallel trends. Here, the LR is 3.323, meaning that it is about three times as likely to observe the pre-treatment coefficients under the hypothesized trend than under parallel trends. Yet, when replicating the diagnostic analysis with a shortened sample period, i.e. excluding 2012 & 2013, we observe a LR of only 0.0129, implying that excluding these two years may be preferable for the sake of causal inference. Though, as we show below, shortening the sample period has no impact on the qualitative findings and only has a marginal effect on the magnitude of the estimate, which is why we don't consider the relatively high LR to be a concern.

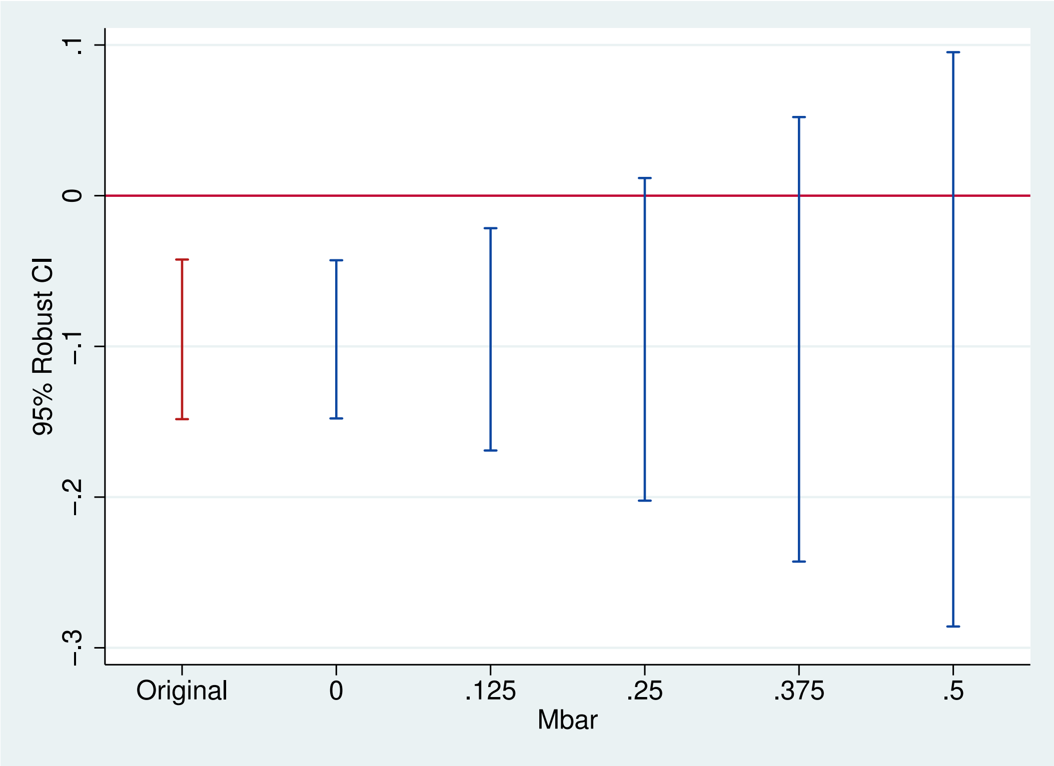


Figure 8: Robust Confidence Intervals for Different Relative Magnitude Restrictions

## Anticipation Effects & Confounding Events - Adjusted Sample Periods

Within this section, we replicate our hedonic analyses by re-estimating Equations 2 & 3. Initially, we embed a third period within the model, to test for anticipation effects. Subsequently, we readjust the sample period to assess the robustness of our conclusions.
Importantly, adjusting - specifically shortening - the sample period serves three practical purposes. First, it aligns with the outcome of the leads- and lags model indicating that shortening the pre-treatment period to 2014 could slightly improve causal inference. Second, it facilitates an examination of potential anticipation effects associated with the relocation, which might interfere with our identification strategy of leveraging the relocation as a natural experiment. Third, it allows us to rule out the possibility that the results are predominantly influenced by confounding events, occurring concurrently within the sample period and having some impact on the local housing market. In this regard, based on thorough qualitative research, we have identified the following potentially confounding urban development and construction projects occurring during our sample period:

I **Pre-Treatment Period:**

- *January 31*, 2014: Rams' Owner Stan Kroenke purchases land in Inglewood, California, and plants the seeds for rumors about a return of the Rams to Los Angeles.
- *March 27*, 2014: Opening of Ballpark Village I; Elements: Cardinals Hall of Fame and Museum, restaurants & bars, rooftop deck, offices.
- *January 5*, 2015: Stan Kroenke announces the plan to construct an 80,000-seat stadium in Inglewood, which fuels speculation about a relocation.

II **Post-Treatment Period**:

- *July 4*, 2018: Re-Opening of the Gateway Arch Museum following a makeover worth $380 million ; Elements: new galleries, walking- and cycling paths, recreational outdoor space.
- *23.11.2018*: Announcement that the BattleHawks (XFL) will play in St. Louis beginning in February, 2020.
- *June 2019*: The St. Louis Blues win the Stanley Cup.
- *September 2019*: Inauguration of the first stage of Union Station's renovated entertainment complex; Elements: ferris wheel, carousel, & mini-golf.
- *December 2019*: Inauguration of the second stage of Union Station's renovated entertainment complex; Elements: aquarium ($45 million) .

**Anticipation Effects I - Announcement of Stadium Construction in 2015**

Against the background of the relocation history outlined in Section 3, a concern might be that anticipatory market reactions could have occurred as early as the beginning of 2015 following the announcement of the stadium construction in Inglewood. To test this, we re-estimate Equation 2, but shorten the pre-treatment period to the announcement on January 5, 2015, thereby incorporating an additional anticipation period within the difference-in-differences constellation, reflecting the last year before the relocation. The coefficient for this period should thus indicate whether there occurred a significant anticipatory market reaction in 2015 relative to the price evolution between the treatment and control area from 2012-2014.

Table 10: Regression Estimates Across Different Error Specifications - Anticipation Effects I

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Inter | 0.0402 | 0.0402 | 0.0402 | 0.0402 | 0.0402 |
| | (0.195) | (0.130) | (0.208) | (0.208) | (0.207) |
| Post | 0.319*** | 0.319*** | 0.319*** | 0.319*** | 0.319*** |
| | (0.022) | (0.021) | (0.032) | (0.033) | (0.032) |
| Impact | 0.132*** | 0.132*** | 0.132* | 0.132 | 0.132* |
| | (0.039) | (0.031) | (0.075) | (0.085) | (0.070) |
| ImpactxInter | 0.0282 | 0.0282 | 0.0282 | 0.0282 | 0.0282 |
| | (0.032) | (0.029) | (0.029) | (0.017) | (0.032) |
| ImpactxPost | -0.0632** | -0.0632*** | -0.0632*** | -0.0632** | -0.0632** |
| | (0.025) | (0.022) | (0.023) | (0.025) | (0.026) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7571 | 0.7571 | 0.7571 | 0.7571 | 0.7571 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

The impact area is defined as a three-mile radius ring around the stadium.

The Inter period includes transactions taking place between January 5, 2015 and the relocation.

Reference are transactions sold before the 05.01.2015.

The full regression results are avilable from the author.

Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10 presents the regression estimates of the base model for the main coefficients of interest. Inter denotes the dummy for the anticipation period. Accordingly, ImpactxInter is the interaction term for properties located in the impact area and sold within the anticipation period. As one can see, in neither column, the difference-in-differences coefficient for this interaction term is significantly different from zero, whereas the coefficient for the post treatment effect remains relatively unaffected. Therefore, the model provides evidence that the announcement of the stadium construction has not provoked anticipatory market reactions in St. Louis' single-family housing market supporting our identification strategy.

**Anticipation Effects II - Announcement of Land Purchase in 2014 & Kink in the Pre-Trends**

Although we postulate that the purchase of land in Inglewood in late January 2014 should not be discernible in terms of an anticipatory market reaction in St. Louis, the parallel trend plot in Figure 1 has shown that there might be a small deviation in pre-trends beginning in 2014. We therefore replicate the approach and re-estimate the model with a widened Inter-period that contains all single-family home transactions occurring between the land purchase on the 31.01.2014, and the filing for relocation on the 04.01.2016.

Table 11: Regression Estimates Across Different Error Specifications - Anticipation Effects II

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Inter2 | -0.0110 | -0.0110 | -0.0110 | -0.0110 | -0.0110 |
| | (0.034) | (0.037) | (0.033) | (0.031) | (0.032) |
| Post | 0.315*** | 0.315*** | 0.315*** | 0.315*** | 0.315*** |
| | (0.022) | (0.021) | (0.032) | (0.032) | (0.031) |
| Impact | 0.0918** | 0.0918** | 0.0918 | 0.0918 | 0.0918 |
| | (0.045) | (0.036) | (0.077) | (0.079) | (0.074) |
| ImpactxInter2 | 0.0730** | 0.0730** | 0.0730* | 0.0730*** | 0.0730* |
| | (0.036) | (0.031) | (0.038) | (0.021) | (0.039) |
| ImpactxPost | -0.0235 | -0.0235 | -0.0235 | -0.0235 | -0.0235 |
| | (0.033) | (0.029) | (0.037) | (0.023) | (0.037) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7571 | 0.7571 | 0.7571 | 0.7571 | 0.7571 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

The impact area is defined as a three-mile radius ring around the stadium.

The Inter2 period includes transactions taking place between January 31, 2014 and the relocation.

Reference are transactions sold before the 31.01.2014.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11 displays the estimation results. The coefficient for ImpactxInter2 is positive and significant across all error specifications, whereas we do not observe a significant coefficient for ImpactxPost anymore, when using 2012 and 2013 as reference years. These results, alongside the previous estimation, therefore suggest that there seems to be some significant change in (log-) average prices between the impact and control area occurring between 2013 and 2014, that is not associated with the treatment in 2016.

Regarding the potential confounding events identified within that time frame, doubts arise as to whether the opening of Ballpark Village I can fully explain the significant findings presented in Table 10. While the adjacent "village" provides consumers with numerous new consumption benefits, it seems questionable whether the intangible benefits associated with the opening of the first phase are as substantial. Likewise, as argued in Section 3, the purchase of land in Inglewood should not have a discernible impact on the market.

Instead, it seems more plausible that the observed price increase reflects the broader economic recovery of the central housing market after the financial crisis of 2008. This may be especially true as downtown areas were hit particularly hard during the crisis, given their concentration of financial establishments. In view of this point, Metzger et al. (2018) affirms that the subprime crisis has largely impacted St. Louis and reports that almost 10% of all owner-occupied homes were foreclosed between 2007 and 2014. Against this background, it may be that the housing market was still somewhat impaired in its functioning during these years.

**Adjusted Sample Period I - Pre-Treatment Period - 2014 & 2015**

Given the prior results, it appears essential to check for the robustness of the main conclusions by shortening the pre-treatment period so that it does not cover the significant price jump anymore.[58] Table 12 contains the estimation results for the main coefficients of the base model when shortening the pre-treatment period to 2014 and 2015. In short, the qualitative conclusions are unaffected by the shortening of the sample period, speaking for the consistency and robustness of the main findings. With 2014 and 2015 as reference years, the model suggests a slightly larger relative price depreciation of 9.23%, which is significant at the highest level across all error specifications.[59]

Table 12: Regression Estimates Across Different Error Specifications - Base Model - 2014-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Impact | 0.168*** | 0.168*** | 0.168** | 0.168** | 0.168** |
| | (0.038) | (0.030) | (0.077) | (0.081) | (0.073) |
| Post | 0.243*** | 0.243*** | 0.243*** | 0.243*** | 0.243*** |
| | (0.018) | (0.016) | (0.025) | (0.031) | (0.027) |
| ImpactxPost | -0.0923*** | -0.0923*** | -0.0923*** | -0.0923*** | -0.0923*** |
| | (0.022) | (0.021) | (0.030) | (0.026) | (0.029) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7593 | 0.7593 | 0.7593 | 0.7593 | 0.7593 |
| Observations | 11048 | 11048 | 11048 | 11048 | 11048 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
The full regression results are available from the author.
The sample period is shortened to 2014-2019.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Adjusted Sample Period II - Pre-Treatment Period 2015**

If we believe that the housing market was still recovering from the subprime crisis in 2014, it could be that the estimates of the base model using 2015 as the sole reference year may better reflect the

[58]While it may be more accurate to shorten the pre-treatment period for the sake of causal inference, there is a trade-off as we lose precision due to smaller sample size.

[59]Similarly, regarding the distance ring models, we do not report any noteworthy differences and still observe significant negative distance-decaying effects expanding up to four miles from the facility. The regression outputs are provided in the Online Appendix.

"pure" market reaction following the relocation of the Rams. In this context, Table 13 presents the estimation results of the base model, when shortening the sample period to 2015 only. As can be seen, the qualitative conclusions are again unaffected by the shortening of the pre-treatment period by one additional year. What is more, we observe almost identical estimates as in the prior case, which also included housing transactions in 2014.[60] Hence, we conclude that the gain from further reducing the pre-treatment period is marginal.

Table 13: Regression Estimates Across Different Error Specifications - Base Model - 2015-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Impact | 0.188*** | 0.188*** | 0.188** | 0.188** | 0.188** |
| | (0.043) | (0.034) | (0.078) | (0.078) | (0.079) |
| Post | 0.179*** | 0.179*** | 0.179*** | 0.179*** | 0.179*** |
| | (0.018) | (0.016) | (0.028) | (0.030) | (0.030) |
| ImpactxPost | -0.0933*** | -0.0933*** | -0.0933** | -0.0933*** | -0.0933** |
| | (0.027) | (0.025) | (0.041) | (0.024) | (0.036) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7522 | 0.7522 | 0.7522 | 0.7522 | 0.7522 |
| Observations | 9730 | 9730 | 9730 | 9730 | 9730 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
The full regression results are available from the author.
The sample period is shortened to 2015-2019.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[60] Regarding the distance ring models, we find that there are once again no visible differences compared to the models based on the full sample period. The regression output is provided in the Online Appendix.

#### Adjusted Sample Period III - Pre & Post-Treatment Period - 2014 - 2018

As listed above, several potentially confounding events occur during the post-treatment period after July 4th, 2018. Consequently, we conduct a final re-estimation of our models, using a minimal sample consisting only of transactions taking place between January 1st, 2014, and July 4th, 2018. The results of the base model are presented in Table 14. Despite the significant sample reduction, the findings remain nearly identical to those of the full sample period.[61]

Table 14: Regression Estimates Across Different Error Specifications - Base Model - 2014-2018

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Impact | 0.192*** | 0.192*** | 0.192* | 0.192* | 0.192** |
| | (0.047) | (0.034) | (0.107) | (0.110) | (0.093) |
| Post | 0.203*** | 0.203*** | 0.203*** | 0.203*** | 0.203*** |
| | (0.017) | (0.016) | (0.023) | (0.029) | (0.025) |
| ImpactxPost | -0.0750*** | -0.0750*** | -0.0750** | -0.0750*** | -0.0750*** |
| | (0.025) | (0.023) | (0.032) | (0.027) | (0.028) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7648 | 0.7648 | 0.7648 | 0.7648 | 0.7648 |
| Observations | 8030 | 8030 | 8030 | 8030 | 8030 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
The full regression results are available from the author.
The sample period is shortened to 01.01.2014 - 04.07.2018.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[61] Similarly, we draw the same qualitative results for the distance ring models. However, the distance-decaying pattern is less discernible. The estimation results are provided in the Online Appendix.

# Appendix B - Additional Robustness Checks - Alternative Model Specifications

## Is the Model Overspecified? - Examining Multicollinearity and Endogeneity

As discussed in Section 4, there is limited theoretical guidance on the appropriate specification of hedonic models, and researchers must navigate a trade-off between including numerous covariates (which can entail multicollinearity) and including fewer covariates (which can result in OVB). Similarly, it must be ensured that there are no endogenous relationships among regressors and the treatment variable that could interfere with the causal inference of the treatment. Therefore, we address these concerns by removing potentially endogenous as well as highly correlated regressors, to test for the consistency of our results.

While we argue that out model is appropriately specified, one potential criticism may be that it includes a large number of covariates, potentially introducing multicollinearity and hampering the interpretation of the coefficients. In fact, Table 15 indicates that the variance inflation factors (VIFs) of several regressors in our base model exceed the typical threshold value of 10. Particularly, the controls for residential proximity to the other two major league stadiums have exorbitantly high VIFs. Furthermore, some neighborhood controls seem to be structurally related, as expected. The Pearson correlation coefficients in Table 16 confirm the assumption of moderate to high linear relationships among these variables. Notably, DistanceEC and DistanceBusch show an almost perfect relationship, which is unsurprising given their proximity, as shown in Figure 3. Nevertheless, it is important to note that the main coefficient of interest, ImpactxPost, has a moderate VIF of only 2.69, and is only highly correlated with the Impact dummy, by construction of the interaction term (Allison (2012)).

Therefore, we contend that the multicollinearity within our model appears to be a relatively minor issue, as it only occurs among some of the independent variables, which does not impair their function as controls. Similarly, despite potentially inflated standard errors, most of the coefficients remain highly significant.[62] Moreover, O'Brien (2007) argues that rules of thumb for VIFs need to be interpreted jointly with other factors that influence the stability of the estimates. Consequently, he posits that large VIFs are not necessarily problematic.
While, in practice, excluding highly correlated variables prevails a common approach to address multicollinearity, O'Brien (2007) cautions that doing so may shift the model and change the underlying theory being tested. Thus, dropping individual regressors should be theoretically motivated. Given the contextual relevance of controlling for the presence of the other two stadiums in downtown, as well as St. Louis' idiosyncratic socio-demographic and urban environment, we assess the specification of our base model as just, despite the structural dependencies among some of the covariates.

Nevertheless, we also follow the common practice of removing highly correlated covariates from our model to demonstrate the consistency of our results. In this vein, Table 17 shows the estimation

[62] From a more technical perspective, it may be remarked that a high VIF does not necessarily coerce a large standard deviation, as the latter is simultaneously determined by the error variance and the total sample variation of a covariate (Wooldridge (2018)).

Table 15: VIFs of the Base and Slim Model

| | (1)<br>Base Model<br>vif | (2)<br>Slim Model<br>vif |
|---|---|---|
| Impact | 9.63 | 8.96 |
| Post | 15.41 | 11.13 |
| ImpactxPost | 2.69 | 2.65 |
| logFloorsize | 4.01 | 4.01 |
| logParcelsize | 1.88 | 1.85 |
| Age | 1.78 | 1.76 |
| Frame | 1.72 | 1.69 |
| Stone | 1.05 | 1.05 |
| Stories | 3.69 | 3.66 |
| Garages | 1.28 | 1.27 |
| Carports | 1.08 | 1.07 |
| Attic | 1.25 | 1.25 |
| PopDensity | 5.16 | 4.04 |
| Crime | 8.43 | |
| Black | 28.75 | |
| Vacancy | 15.30 | |
| Youth | 14.64 | |
| MedianIncome | 12.99 | |
| AccFood | 9.70 | 9.19 |
| Finance | 5.15 | 2.84 |
| Retail | 6.58 | 6.18 |
| DistancePark | 5.14 | 4.96 |
| Local | 7.42 | 5.85 |
| National | 4.90 | 4.70 |
| CertifiedLocal | 9.12 | 5.76 |
| Conservation | 1.96 | 1.94 |
| Preservation | 3.34 | 2.92 |
| Enterprise | 2.70 | |
| Flood100 | 1.13 | 1.11 |
| Flood500 | 1.21 | |
| DistanceBusch | 3347.47 | |
| DistanceEC | 3354.59 | |

Table 16: Selected Correlation Coefficients - Base Model

| | Impact | Post | ImpactxPost | Crime | Black | Vacancy | Youth | MedianIncome | AccFood | DistanceBusch | DistanceEC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Impact | 1.000 | | | | | | | | | | |
| Post | -0.012 | 1.000 | | | | | | | | | |
| ImpactxPost | 0.759 | 0.188 | 1.000 | | | | | | | | |
| Crime | 0.284 | -0.077 | 0.206 | 1.000 | | | | | | | |
| Black | 0.286 | -0.005 | 0.215 | 0.717 | 1.000 | | | | | | |
| Vacancy | 0.216 | -0.043 | 0.134 | 0.802 | 0.810 | 1.000 | | | | | |
| Youth | 0.022 | -0.063 | 0.004 | 0.398 | 0.629 | 0.495 | 1.000 | | | | |
| MedianIncome | -0.029 | 0.269 | 0.043 | -0.637 | -0.556 | -0.631 | -0.446 | 1.000 | | | |
| AccFood | 0.341 | 0.059 | 0.274 | -0.056 | -0.155 | -0.129 | -0.281 | 0.292 | 1.000 | | |
| DistanceBusch | -0.683 | -0.004 | -0.518 | -0.559 | -0.521 | -0.508 | -0.161 | 0.292 | -0.498 | 1.000 | |
| DistanceEC | -0.672 | -0.003 | -0.510 | -0.548 | -0.519 | -0.500 | -0.112 | 0.267 | -0.510 | 0.995 | 1.000 |

results of our base model across three different specifications. Column (1) displays the results of our preferred model specification for ease of comparison. Column (2) depicts the results without the controls for DistanceEC and DistanceBusch, while Column (3) further removes the highly correlated neighborhood controls.[63]

Column (2) reveals that the exclusion of the controls for the other two stadiums has no visible effect on our findings. Likewise, column (3) suggests the same overall conclusions as before, although we obtain a slightly smaller point estimate of 6.03%. Other than that, there are no significant differences relative to our preferred model in column (1). Therefore, we conclude that our preferred specification is adequate, and we emphasize that multicollinearity does not significantly impair the estimation results.

Table 17: Regression Estimates - Removing Highly Correlated Covariates

| | (1)<br>Base Model | (2)<br>No Distance Controls | (3)<br>Slim Model |
|---|---|---|---|
| *Target Variables* | | | |
| Impact | 0.145*** | 0.138*** | 0.161*** |
| | (0.036) | (0.035) | (0.036) |
| Post | 0.320*** | 0.323*** | 0.360*** |
| | (0.022) | (0.022) | (0.018) |
| ImpactxPost | -0.0752*** | -0.0752*** | -0.0603*** |
| | (0.021) | (0.021) | (0.021) |
| *Housing Characteristics* | | | |
| logFloorsize | 0.451*** | 0.451*** | 0.451*** |
| | (0.015) | (0.015) | (0.015) |
| logParcelsize | 0.190*** | 0.191*** | 0.188*** |
| | (0.009) | (0.009) | (0.009) |
| Age | -0.00364*** | -0.00364*** | -0.00363*** |
| | (0.000) | (0.000) | (0.000) |
| Frame | -0.115*** | -0.115*** | -0.110*** |
| | (0.008) | (0.008) | (0.008) |
| Stone | 0.105* | 0.106* | 0.115** |
| | (0.055) | (0.055) | (0.054) |
| Stories | 0.248*** | 0.247*** | 0.250*** |
| | (0.010) | (0.010) | (0.010) |

[63] As shown in Table 15, within this reduced "slim" model, no individual coefficient, except for the naturally inflated Post coefficient, exceeds the threshold of 10 anymore.

| | | | |
|---|---|---|---|
| Garages | 0.0886*** | 0.0884*** | 0.0898*** |
| | (0.006) | (0.006) | (0.006) |
| Carports | 0.0170*** | 0.0171*** | 0.0169*** |
| | (0.006) | (0.006) | (0.006) |
| Attic | 0.152*** | 0.152*** | 0.154*** |
| | (0.006) | (0.006) | (0.007) |
| *Demographic Characteristics* | | | |
| PopDensity | -0.00142* | -0.00167** | -0.00309*** |
| | (0.001) | (0.001) | (0.001) |
| Crime | -0.0121*** | -0.0123*** | |
| | (0.004) | (0.004) | |
| Black | -0.353*** | -0.379*** | |
| | (0.082) | (0.077) | |
| Vacancy | -1.133*** | -1.133*** | |
| | (0.249) | (0.249) | |
| Youth | 0.438* | 0.520** | |
| | (0.251) | (0.235) | |
| MedianIncome | 0.00190* | 0.00186* | |
| | (0.001) | (0.001) | |
| *Market Characteristics* | | | |
| AccFood | 0.00759 | 0.00647 | 0.00841* |
| | (0.005) | (0.005) | (0.005) |
| Finance | 0.00583* | 0.00638* | 0.0174*** |
| | (0.003) | (0.003) | (0.003) |
| Retail | -0.0145*** | -0.0138*** | -0.0131*** |
| | (0.004) | (0.004) | (0.003) |
| *Urban Characteristics* | | | |
| DistancePark | -0.200*** | -0.199*** | -0.214*** |
| | (0.015) | (0.015) | (0.015) |
| Local | 0.118*** | 0.119*** | 0.150*** |
| | (0.037) | (0.036) | (0.033) |
| National | 0.0847*** | 0.0856*** | 0.0871*** |
| | (0.016) | (0.016) | (0.016) |

| | | | |
|---|---|---|---|
| CertifiedLocal | 0.248*** | 0.250*** | 0.353*** |
| | (0.034) | (0.033) | (0.026) |
| Conservation | 0.194* | 0.195* | 0.174* |
| | (0.101) | (0.101) | (0.095) |
| Preservation | 0.109*** | 0.109*** | 0.152*** |
| | (0.026) | (0.026) | (0.024) |
| Flood100 | -0.0639** | -0.0614** | -0.0670** |
| | (0.031) | (0.031) | (0.031) |
| DistanceBusch | 0.0104 | | |
| | (0.111) | | |
| DistanceEC | 0.00600 | | |
| | (0.113) | | |
| Constant | 6.387*** | 6.477*** | 6.477*** |
| | (0.173) | (0.160) | (0.149) |
| Census Tract FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7571 | 0.7571 | 0.7524 |
| Observations | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

The Impact area is defined as a three-mile radius ring around the stadium.

Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Furthermore, our supplementary analysis offers evidence that the results are not predominantly influenced by endogeneity within the model. Specifically, we find that whether we include or exclude potentially endogenous socio-demographic regressors, such as the crime covariate, the estimation results remain largely unchanged. We interpret this consistency as bolstering our identification strategy that the relocation serves an exogenous shock unrelated to local changes in neighborhood features.

## Is the Model Underspecified? - Examining Omitted-Variable-Bias

Although we already control for a wide range of covariates, some covariates commonly used in previous hedonic studies were not included in our analysis, either by choice or due to data limitations. In this section, we examine the potential impact of these variables on the estimation results by presenting an intentionally "oversaturated" model.

As mentioned within our concluding discussion, there are two potentially relevant omitted covariates for which information was restricted or unavailable: the proximity of a property to transport infrastructure (such as the nearest bus/train station or the closest highway interchange) and quality of local schools. Both factors have been shown to significantly influence housing values.[64] While the latter omission is presumably less problematic, as the quality of local schools is likely to be mostly captured by our neighborhood controls,[65] the omission of transport amenities needs to be contemplated. Standard urban economic theory suggests a negative correlation between housing values and commuting times, resulting in spatial "peaks" of the house price gradient near transport infrastructure. To the best of our knowledge we are unaware of any major changes in the local transportation infrastructure that may significantly affect our results. However, unfortunately, we are unable to control for the impact of changes in the valuation of proximity to transport infrastructure linked to changes in the consumption of transport infrastructure - such as reduced congestion during games - induced by the departure of the Rams.

In attempting to approximate residential proximity to major transport infrastructure, we additionally include the average commuting time to work as a control variable, retrieved at the zip-code level from the ACS. Similarly, to account for school quality, we add the share of the population with a high-school or academic degree, also available at the zip-code level. Additionally, we test the results by controlling for a set of supplementary local controls commonly used in previous studies, including the average household size, the share of owner-occupied housing, the share of Asian and Hispanic population, the unemployment rate, annual payrolls, various crime measures, and zoning designations.[66] Likewise, we examine the impact of being located within an Empowerment Zone.[67]

Table 18 displays the estimation results of this deliberately oversaturated model. Upon including the supplementary covariates, we draw the same conclusions as before, supporting the robustness of our findings. However, some variables, such as the share of the population holding an academic degree, introduce severe multicollinearity into the model, as expected due to structural dependencies among some independent variables. In this vein, the coefficient for the share of academics is only significant in columns (1) and (2), likely due to collinearity among the neighborhood controls. Additionally, we find that the coefficient for average commuting time is insignificant across all model specifications.[68]

[64] See, for example, Bowes and Ihlanfeldt (2001) for the WTP for proximity to transport amenities, and Black (1999) & Clapp et al. (2008) regarding the WTP concerning education.

[65] Metzger et al. (2018) note that lower educational outcomes in St. Louis' schools are particularly concentrated in low-income neighborhoods.

[66] A summary table for these additional covariates is provided in the Online Appendix.

[67] Empowerment Zones are distressed urban areas providing businesses with federal tax credits.

[68] The "oversaturated" ring models also yield the same results, available upon request.

Table 18: Regression Estimates Across Different Error Specifications - Oversaturated Base Model

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| *Target Variables* | | | | | |
| Impact | 0.1331*** | 0.1331*** | 0.1331 | 0.1331 | 0.1331* |
| | (0.038) | (0.029) | (0.085) | (0.093) | (0.078) |
| Post | 0.2519*** | 0.2519*** | 0.2519** | 0.2519** | 0.2519** |
| | (0.061) | (0.053) | (0.098) | (0.121) | (0.116) |
| ImpactxPost | -0.0717*** | -0.0717*** | -0.0717** | -0.0717** | -0.0717** |
| | (0.022) | (0.020) | (0.031) | (0.028) | (0.032) |
| *Housing Characteristics* | | | | | |
| logFloorsize | 0.4516*** | 0.4516*** | 0.4516*** | 0.4516*** | 0.4516*** |
| | (0.015) | (0.012) | (0.027) | (0.035) | (0.032) |
| logParcelsize | 0.1871*** | 0.1871*** | 0.1871*** | 0.1871*** | 0.1871*** |
| | (0.009) | (0.009) | (0.020) | (0.014) | (0.020) |
| Age | -0.0036*** | -0.0036*** | -0.0036*** | -0.0036*** | -0.0036*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Frame | -0.1107*** | -0.1107*** | -0.1107*** | -0.1107*** | -0.1107*** |
| | (0.008) | (0.008) | (0.014) | (0.013) | (0.013) |
| Stone | 0.1073* | 0.1073* | 0.1073** | 0.1073*** | 0.1073* |
| | (0.055) | (0.057) | (0.052) | (0.035) | (0.057) |
| Stories | 0.2444*** | 0.2444*** | 0.2444*** | 0.2444*** | 0.2444*** |
| | (0.010) | (0.009) | (0.019) | (0.025) | (0.019) |
| Garages | 0.0888*** | 0.0888*** | 0.0888*** | 0.0888*** | 0.0888*** |
| | (0.006) | (0.006) | (0.008) | (0.009) | (0.008) |
| Carports | 0.0173*** | 0.0173*** | 0.0173*** | 0.0173** | 0.0173*** |
| | (0.006) | (0.005) | (0.006) | (0.007) | (0.006) |
| Attic | 0.1512*** | 0.1512*** | 0.1512*** | 0.1512*** | 0.1512*** |
| | (0.006) | (0.007) | (0.009) | (0.008) | (0.010) |
| *Demographic Characteristics* | | | | | |
| PopDensity | -0.0007 | -0.0007 | -0.0007 | -0.0007 | -0.0007 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| PersonCrime | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0004 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) |
| PropertyCrime | -0.0012*** | -0.0012*** | -0.0012 | -0.0012* | -0.0012* |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) |
| Black | -0.3778*** | -0.3778*** | -0.3778** | -0.3778** | -0.3778** |
| | (0.085) | (0.076) | (0.171) | (0.154) | (0.163) |
| Asian | -0.7076** | -0.7076** | -0.7076 | -0.7076 | -0.7076 |
| | (0.322) | (0.294) | (0.668) | (0.563) | (0.557) |
| Hispanic | -1.5223*** | -1.5223*** | -1.5223* | -1.5223** | -1.5223** |
| | (0.452) | (0.382) | (0.854) | (0.709) | (0.641) |
| Vacancy | -0.8617*** | -0.8617*** | -0.8617 | -0.8617* | -0.8617* |
| | (0.259) | (0.208) | (0.552) | (0.477) | (0.433) |
| Youth | 0.3232 | 0.3232 | 0.3232 | 0.3232 | 0.3232 |
| | (0.279) | (0.241) | (0.616) | (0.444) | (0.586) |
| MedianIncome | -0.0015 | -0.0015 | -0.0015 | -0.0015 | -0.0015 |
| | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) |
| Academic | 0.0024** | 0.0024*** | 0.0024 | 0.0024 | 0.0024 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Commutes | -0.0049 | -0.0049 | -0.0049 | -0.0049 | -0.0049 |
| | (0.005) | (0.004) | (0.006) | (0.006) | (0.006) |
| HHsize | -0.0505 | -0.0505 | -0.0505 | -0.0505 | -0.0505 |
| | (0.071) | (0.062) | (0.126) | (0.136) | (0.133) |
| Ownership | 0.0011 | 0.0011 | 0.0011 | 0.0011 | 0.0011 |
| | (0.001) | (0.001) | (0.003) | (0.003) | (0.003) |
| *Market Characteristics* | | | | | |
| Payroll | -0.0000 | -0.0000* | -0.0000 | -0.0000 | -0.0000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Unemployment | -0.0035 | -0.0035 | -0.0035 | -0.0035 | -0.0035 |
| | (0.003) | (0.002) | (0.004) | (0.005) | (0.004) |
| AccFood | 0.0072 | 0.0072 | 0.0072 | 0.0072 | 0.0072 |
| | (0.006) | (0.005) | (0.010) | (0.011) | (0.011) |
| Finance | 0.0129*** | 0.0129*** | 0.0129* | 0.0129* | 0.0129** |
| | (0.004) | (0.004) | (0.006) | (0.006) | (0.005) |
| Retail | -0.0127*** | -0.0127*** | -0.0127** | -0.0127* | -0.0127** |
| | (0.004) | (0.004) | (0.006) | (0.007) | (0.006) |

| | | | | | |
|---|---|---|---|---|---|
| *Urban Characteristics* | | | | | |
| DistancePark | -0.1885*** | -0.1885*** | -0.1885*** | -0.1885*** | -0.1885*** |
| | (0.015) | (0.015) | (0.050) | (0.057) | (0.049) |
| Local | 0.1110*** | 0.1110*** | 0.1110* | 0.1110** | 0.1110** |
| | (0.037) | (0.028) | (0.061) | (0.042) | (0.052) |
| National | 0.0863*** | 0.0863*** | 0.0863 | 0.0863 | 0.0863* |
| | (0.017) | (0.014) | (0.054) | (0.052) | (0.045) |
| CertifiedLocal | 0.2448*** | 0.2448*** | 0.2448*** | 0.2448*** | 0.2448*** |
| | (0.033) | (0.028) | (0.076) | (0.068) | (0.067) |
| Conservation | 0.1975** | 0.1975*** | 0.1975 | 0.1975 | 0.1975 |
| | (0.097) | (0.058) | (0.128) | (0.129) | (0.157) |
| Preservation | 0.1248*** | 0.1248*** | 0.1248** | 0.1248*** | 0.1248*** |
| | (0.027) | (0.022) | (0.055) | (0.037) | (0.045) |
| Enterprise | -0.0053 | -0.0053 | -0.0053 | -0.0053 | -0.0053 |
| | (0.014) | (0.012) | (0.044) | (0.050) | (0.043) |
| Empowerment | 0.0387 | 0.0387 | 0.0387 | 0.0387 | 0.0387 |
| | (0.097) | (0.081) | (0.076) | (0.052) | (0.069) |
| Flood100 | -0.0468 | -0.0468 | -0.0468 | -0.0468 | -0.0468* |
| | (0.031) | (0.031) | (0.043) | (0.038) | (0.028) |
| Flood500 | -0.0030 | -0.0030 | -0.0030 | -0.0030 | -0.0030 |
| | (0.024) | (0.028) | (0.038) | (0.028) | (0.028) |
| DistanceBusch | 0.0663 | 0.0663 | 0.0663 | 0.0663 | 0.0663 |
| | (0.115) | (0.105) | (0.280) | (0.287) | (0.282) |
| DistanceEC | -0.0592 | -0.0592 | -0.0592 | -0.0592 | -0.0592 |
| | (0.118) | (0.107) | (0.293) | (0.297) | (0.302) |
| Constant | 6.8583*** | 6.8583*** | 6.8583*** | 6.8583*** | 6.8583*** |
| | (0.275) | (0.247) | (0.598) | (0.725) | (0.651) |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7581 | 0.7581 | 0.7581 | 0.7581 | 0.7581 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

The impact area is defined as a three-mile radius ring around the stadium.

Standard errors are depicted in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

## Spatial Inequality along Delmar Boulevard: Housing Segregation & Housing Submarkets

Describing housing segregation in St. Louis, the *BBC* has coined the term *"Delmar Divide"*, alluding to the fact that the population living north of Delmar Boulevard is 95% black, while 75% of those living south of the Boulevard are white (Cooperman (2014)), as displayed in Figure 9. This racial segregation is rooted in decades of malfunctioning housing policies and urban development programs that disproportionately benefited more affluent neighborhoods, resulting in other neighborhoods falling behind in terms of economic and social development (Cohen (1990), Judd (1997), Farley (2005)).[69]

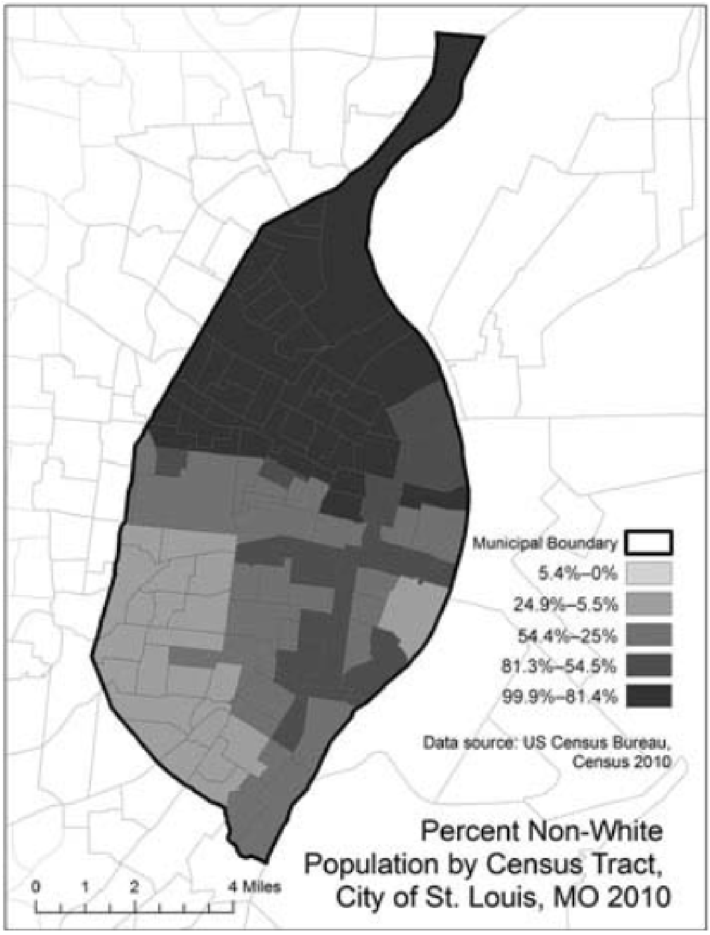



Figure 9: Racial Segregation in St. Louis
Source: Tighe and Ganning (2015), p.658

St. Louis, as depicted by Metzger et al. (2018), exemplifies an extreme case of urban decay, characterized by a 70-year trend of economic and population decline, mirroring the broader trajectory of Rust Belt cities since the latter half of the previous century. In 1950, St. Louis had a population of around 850,000, which has since plummeted by over half to approximately 350,000 in 2000. Suburban areas have seen an influx of affluent, predominantly white families, leaving the central city relatively impoverished and somewhat desolate. This trend of decline and growth is also

[69]While St. Louis is a historically starkly biracial setting (Gordon and Bruch (2020)), since the turn of the millennium, the share of Asians and Latinos has considerably increased in some neighborhoods. Therefore, we also tested for these population groups within our prior robustness check.

evident in residential neighborhoods manifested as spatial inequality, which led Tighe and Ganning (2015) to designate St. Louis as a "divergent city".[70] According to the authors, St. Louis exhibits clear patterns of racial segregation, with the North being predominantly black, characterized by high crime and vacancy rates, while the South is mostly white, featuring vibrant commercial areas and stable real estate markets.

The pronounced demographic divide has potentially profound implications for the housing market. Specifically, housing values in the northern neighborhoods are, on average, considerably lower than in the South. This difference is not solely shaped by market forces but also by patterns of segregation (Gordon and Bruch (2020)). To further understand this dynamic, Hwang (2015) examines the St. Louis Metropolitan Area and identifies four submarkets based on the stratification of housing bundles, following the concept of Goodman and Thibodeau (2003). In the central city, he identifies two polarized submarkets reflecting the aforementioned divide between the North and the South. These findings have implications for hedonic price functions, as they may vary across submarkets (Watkins (2001)).

Against this backdrop, we posit that controlling for annual neighborhood characteristics and local fixed effects, while clustering standard errors on various geographic scales, we can effectively account for and capture the majority of the variation in housing prices associated with demographic developments across neighborhoods. However, given St. Louis's status as an extreme case of spatial inequality, we explore three alternative approaches to address this issue:

a) Following Jud (1980), we replicate our regressions on a *"ghetto"* sample by excluding all transactions occurring in neighborhoods with a Black population exceeding 50%.

b) We add a simple dummy to the model for houses located north of Delmar Boulevard.[71]

c) We include transactions below the threshold value of $30,000 to examine the impact of selectivity bias resulting from our data cleansing process.

For brevity, we only present the regression estimates of the adjusted base models. Albeit, we also tested the three approaches across our ring models and found consistent results, available from the author.

### Approach a) - Ghetto Sample

Table 19 presents the results. While generally consistent with our base model, the point estimate is smaller at 4.71%. Also, clustering the error term renders the coefficients largely insignificant. These findings suggest a stronger market reaction in predominantly black neighborhoods, with the observed effect mitigated by excluding them from the sample.

[70] While racial segregation patterns are evident citywide (as shown in Figure 9), downtown and adjacent neighborhoods exhibit relative diversity. This is good news as it suggests that any price reactions upon relocation are unlikely to be influenced by unobserved spatial clustering concentrated in the impact area.

[71] We consider all properties with a latitude above 38.64351 degrees. This coordinate corresponds to the southernmost intersection of Delmar Boulevard with Vandeventer Avenue.

Table 19: Regression Estimates - Ghetto Sample - Base Model

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Impact | 0.103** | 0.103*** | 0.103 | 0.103 | 0.103 |
| | (0.040) | (0.030) | (0.085) | (0.092) | (0.085) |
| Post | 0.340*** | 0.340*** | 0.340*** | 0.340*** | 0.340*** |
| | (0.023) | (0.021) | (0.038) | (0.039) | (0.033) |
| ImpactxPost | -0.0471** | -0.0471** | -0.0471 | -0.0471* | -0.0471 |
| | (0.023) | (0.022) | (0.029) | (0.025) | (0.034) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7538 | 0.7538 | 0.7538 | 0.7538 | 0.7538 |
| Observations | 11444 | 11444 | 11444 | 11444 | 11444 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
Neighborhoods >50% black residents were excluded.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Approach b) - North-South Divide**

Table 20 depicts the results. Including a dummy for houses located north of Delmar Boulevard does not notably impact the coefficients in terms of direction, significance, or magnitude. As expected, the coefficient of the dummy variable is negative; however, it is insignificant across all specifications. These results do not necessarily invalidate the existence of the Delmar Divide, as we observe the expected sign, and the insignificance is likely due to artificially inflated errors.[72] Thus, we maintain that these findings suggest that our base model adequately addresses price variation attributed to differences in neighborhoods along racial lines.

[72]The VIF for North is quite high at 19.38, and it exhibits moderately high correlations with some neighborhood covariates, particularly with the percentage of the black population ($r = 0.44$).

Table 20: Regression Estimates Allowing for a North-South-Divide - Base Model

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Impact | 0.144*** | 0.144*** | 0.144* | 0.144* | 0.144* |
| | (0.036) | (0.028) | (0.079) | (0.084) | (0.073) |
| Post | 0.320*** | 0.320*** | 0.320*** | 0.320*** | 0.320*** |
| | (0.022) | (0.021) | (0.032) | (0.033) | (0.032) |
| ImpactxPost | -0.0747*** | -0.0747*** | -0.0747*** | -0.0747*** | -0.0747*** |
| | (0.021) | (0.019) | (0.028) | (0.023) | (0.026) |
| North | -0.0385 | -0.0385 | -0.0385 | -0.0385 | -0.0385 |
| | (0.050) | (0.049) | (0.067) | (0.110) | (0.083) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7571 | 0.7571 | 0.7571 | 0.7571 | 0.7571 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
North is a dummy for houses located north of Delmar Boulevard.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Approach c) - Omitting the Lower Price Bound - Selectivity Bias**

As part of our data cleansing process, we originally exclude non-arms length transactions and properties with potentially poor conditions by filtering out transactions priced below $30,000. However, this exclusion may introduce selectivity bias if the population residing in these lower-priced properties exhibits a distinct valuation for proximity to sports amenities.[73] Hence, we re-estimate our models for a sample without lower price bound.[74]

Table 21 presents the results. They indicate that the exclusion of transactions below $30,000 does not significantly bias the findings. However, the difference-in-differences coefficient is slightly larger at 9.26%. This increase in the coefficient could be attributed to larger and positive effects of sports

[73]For instance, it may be that particularly lower-skilled individuals prefer residing close to natural and sports amenities, while higher-skilled individuals may prefer living nearby cultural amenities (C.f. Brueckner et al. (1999)).

[74]Our adjusted sample contains 734 additional sales, of which 92.23% (677) took place north of Delmar Boulevard, as expected.

amenities for houses in the lower tail of the conditional distribution, while the effects diminish and potentially become negative for houses in the upper tail. A similar pattern was observed by Neto and Whetstone (2022) following the announcement of the construction of a new stadium for the Raiders (NFL) in Las Vegas.

Table 21: Regression Estimates Across Different Error Specifications - Base Model - No Price Bound

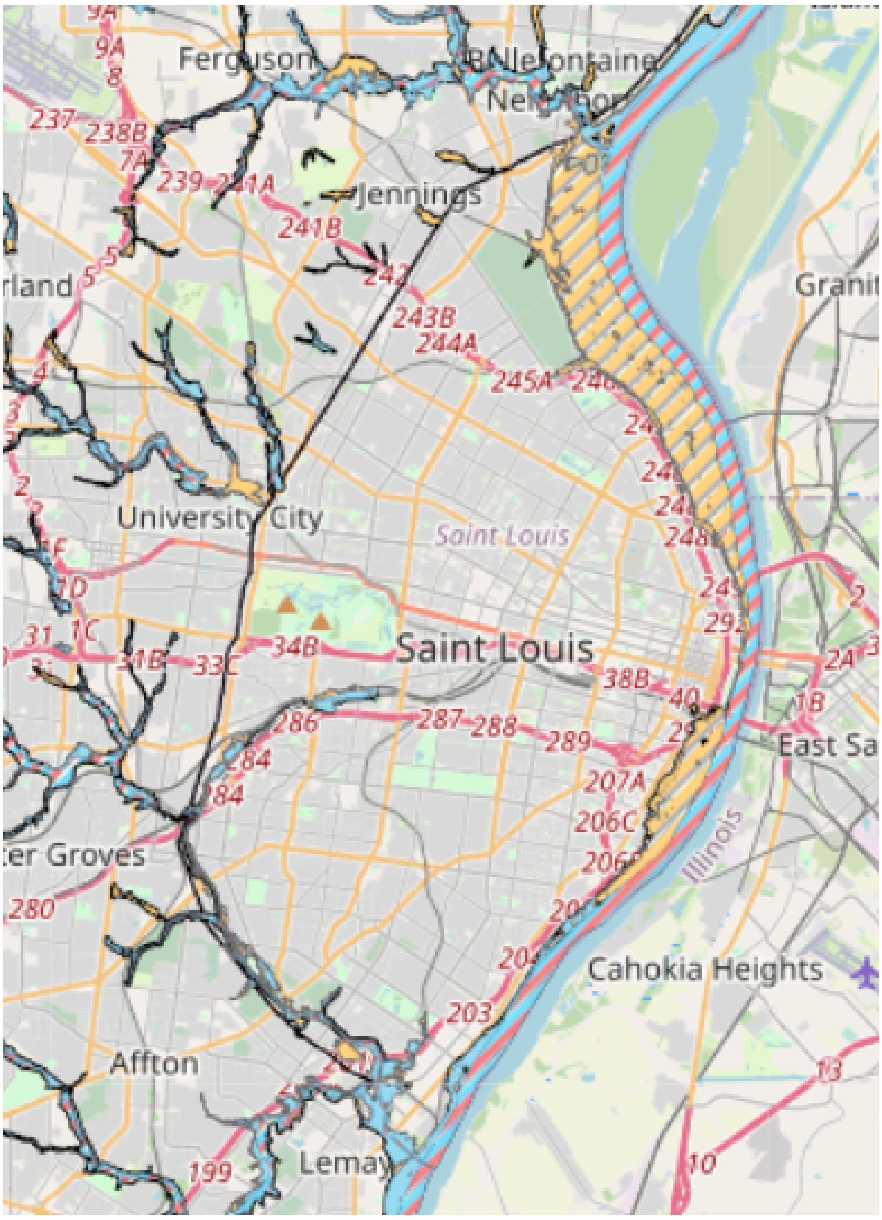
| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Impact | 0.1557*** | 0.1557*** | 0.1557** | 0.1557** | 0.1557** |
| | (0.041) | (0.033) | (0.074) | (0.072) | (0.066) |
| Post | 0.3598*** | 0.3598*** | 0.3598*** | 0.3598*** | 0.3598*** |
| | (0.027) | (0.024) | (0.046) | (0.053) | (0.045) |
| ImpactxPost | -0.0926*** | -0.0926*** | -0.0926*** | -0.0926*** | -0.0926*** |
| | (0.023) | (0.022) | (0.031) | (0.022) | (0.029) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7975 | 0.7975 | 0.7975 | 0.7975 | 0.7975 |
| Observations | 13428 | 13428 | 13428 | 13428 | 13428 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
Sales below a market price of 30,000 Dollars are included in the sample.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In summary, the three additional specifications yield consistent results. Furthermore, the findings hint at a potential difference in the valuation of residential proximity to sports amenities conditional on demographic clusters. St. Louis's idiosyncratic pattern of spatial segregation promises to provide fertile ground for future research to explore this association more deeply. Additionally, owing to low sample size in some northern neighborhoods of the city, we were unable to estimate separate hedonic price functions based on housing submarkets, as suggested by Hwang (2015). This also presents an intriguing puzzle for future research.

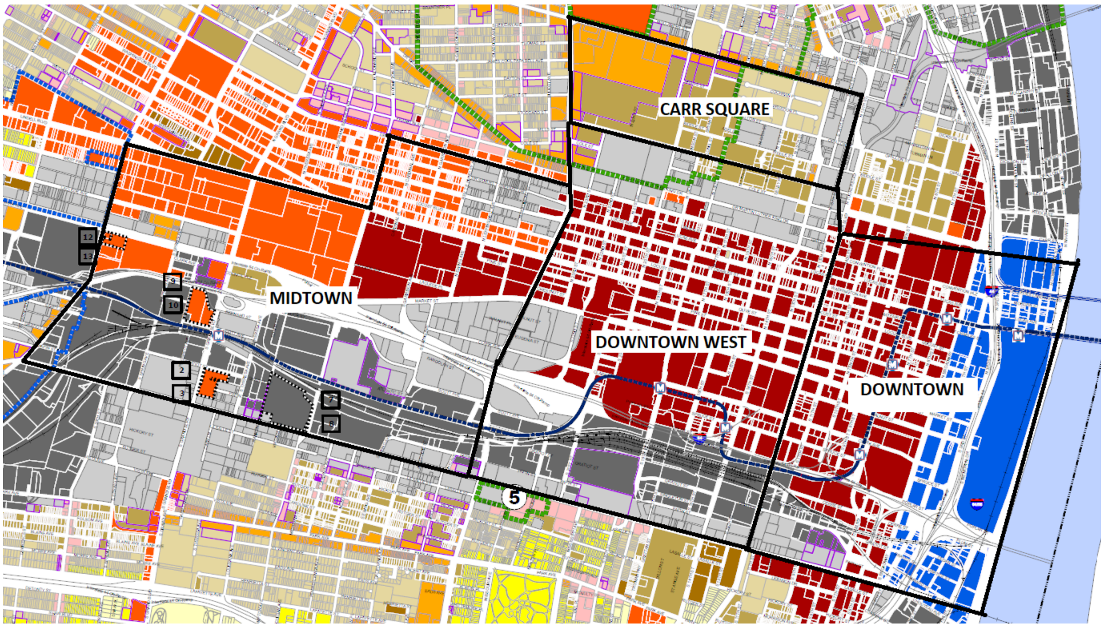
# Supplementary Figures

Figure 10: St. Louis - Floodplains




Source: FEMA Flood Zones Viewer
Color Legend: a) Blue: Flood100 Plain, b) Orange: Flood500 Plain

Figure 11: St. Louis - Zoning Districts - City Center




Source: Own depiction based on the Citywide Zoning District Map
Color Legend: a) Red: Central Business District ; b) Dark Orange: Area Commercial District; c) Light Orange: Local Commercial and Office District ; d) Blue: Jefferson Memorial District ; e) Dark Grey: Unrestricted District , f) Light Grey: Industrial District ; g) Dark Brown: D Multiple-Family Dwelling District ; h) Light Brown: C Multiple-Family Dwelling District.

# Online Appendix

## Supplementary Robustness Checks

### Proximity Model

While we employ distance-rings to investigate the spatial dispersion of the treatment effect, an alternative commonly used approach is to specify a simple proximity model. Thereby, the price of a property is regressed on the property's distance to a facility and non-linearity is often accounted for by additionally including the square of the distance.
Against this backdrop, similar to Kavetsos (2012), we construct a simple proximity model as follows:

$$\begin{aligned}\ln p_{i,t} =& \beta_0 + \delta_1 * \text{Post}_t + \delta_2 * \text{Distance}_i + \delta_3 * \text{Post}_t \times \text{Distance}_i + \\ & \sum_{j=1}^{m} \beta_j x_{j,i,t} + \sum_t \kappa_t y_t + \sum_l \theta_l m_l + \sum_q \psi_q c_q + \epsilon_{i,t}\end{aligned} \tag{6}$$

whereby $\text{Distance}_i$ denotes the distance in miles of property $i$ to the Edward Jones Dome, and $\text{Post}_t \times \text{Distance}_i$ captures the interaction between the post-treatment period dummy and the distance. The remaining model components are defined as before. Table 22 presents the estimation results. Our preferred model specification with robust standard errors is displayed in column (1). Additionally, selected model specifications are presented in columns (2) - (5). In columns (2) and (4), standard errors are clustered on the census tract levels. In columns (3) and (4), the distance controls for the other two stadiums in St. Louis, Busch Stadium and the Enterprise Center, are excluded from the model. This exclusion is due to the proximity of the three stadiums, as shown in Figure 3, which naturally introduces high correlation among the distance variables, leading to multicollinearity. Finally, column (5) presents the regression estimates without any covariates, mainly to demonstrate the inherently high VIFs induced by the interaction terms, as further discussed below.

We observe that the difference-in-differences estimate is highly significant across columns (1) to (4) and exhibits the expected positive sign. Regarding our preferred model, the estimate suggests that, following the relocation of the Rams, each additional mile away from the stadium increases the value of single-family homes by about 1.38% on average, relative to the pre-relocation period. Importantly, these results remain consistent in sign, magnitude, and significance, irrespective of the inclusion of the additional distance controls for the other two stadiums in downtown. Therefore, the observed results align with our main analysis, providing further support to infer that residing closer to the stadium becomes relatively less attractive after the team's departure.
However, although significant in our preferred model, the estimates for the pooled linear distance should be interpreted with caution. One can see that its sign switches when removing the other distance control variables, yet the coefficient remains significant in column (5). These results invite us to test for the presence of multicollinearity.

Table 22: Regression Estimates of the Proximity Model

| | Distance Controls Included | | Distance Controls Excluded | | No Controls |
|---|---|---|---|---|---|
| | (1) Robust | (2) Clustered | (3) Robust | (4) Clustered | (5) Robust |
| Post | 0.2314*** | 0.2314*** | 0.2290*** | 0.2290*** | 0.1375*** |
| | (0.033) | (0.039) | (0.033) | (0.040) | (0.043) |
| Distance | 0.4390** | 0.4390 | -0.0012 | -0.0012 | -0.0720*** |
| | (0.206) | (0.356) | (0.014) | (0.045) | (0.006) |
| PostxDistance | 0.0137*** | 0.0137** | 0.0140*** | 0.0140** | -0.0006 |
| | (0.004) | (0.005) | (0.004) | (0.005) | (0.007) |
| DistanceBusch | -0.1941 | -0.1941 | | | |
| | (0.131) | (0.316) | | | |
| DistanceEC | -0.2458 | -0.2458 | | | |
| | (0.175) | (0.364) | | | |
| Controls | Yes | Yes | Yes | Yes | No |
| Census Tract FE | Yes | Yes | Yes | Yes | No |
| Year FE | Yes | Yes | Yes | Yes | No |
| Month FE | Yes | Yes | Yes | Yes | No |
| Adjusted $R^2$ | 0.7569 | 0.7569 | 0.7568 | 0.7568 | 0.0450 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The full regression results are available from the author.
Standard errors in column (2) and (4) are clustered on the census tract level.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In this vein, Table 23 displays the VIFs for selected coefficients, revealing severe multicollinearity due to a near-perfect linear relationship between *Distance*, *DistanceBusch*, and *DistanceEC*, as shown in Table 24. However, the main coefficient of interest, *PostxDistance*, only shows moderate correlations of around $r = 0.3$ with the distance covariates. Moreover, Table 23 indicates that the coefficient remains unaffected by the multicollinearity induced by the three distance covariates, as its VIF remains relatively constant across the model specifications. In this regard, column (5) suggests that the high VIF naturally arises from the interaction of the variables and is therefore not a cause for concern (C.f. Allison (2012)). Furthermore, given the consistent results for this coefficient, we assert that its estimates are reasonably reliable.

In conclusion, while the results of the proximity model warrant some caution, they provide additional evidence of the relative price depreciation of residing close to the stadium post-relocation, and therefore support the overall conclusions drawn within this paper.[75]

[75] As a final note, we also tested other model specifications based on prior literature. For instance, we

Table 23: VIFs of the Proximity Model

| | Distance Controls Included | | Distance Controls Excluded | | No Controls |
|---|---|---|---|---|---|
| | (1)<br>Robust<br>vif | (2)<br>Clustered<br>vif | (3)<br>Robust<br>vif | (4)<br>Clustered<br>vif | (5)<br>Robust<br>vif |
| Post | 31.00 | 31.00 | 30.87 | 30.87 | 14.61 |
| Distance | 8098.36 | 8098.36 | 52.25 | 52.25 | 2.54 |
| PostxDistance | 17.15 | 17.15 | 17.13 | 17.13 | 16.13 |
| DistanceBusch | 4336.14 | 4336.14 | | | |
| DistanceEC | 6553.68 | 6553.68 | | | |

Table 24: Correlation Coefficients - Distance Variables

| | Post | PostxDistance | Distance | DistanceEC | DistanceBusch |
|---|---|---|---|---|---|
| Post | 1.000 | | | | |
| PostxDistance | 0.918 | 1.000 | | | |
| Distance | -0.002 | 0.307 | 1.000 | | |
| DistanceEC | -0.003 | 0.305 | 0.996 | 1.000 | |
| DistanceBusch | -0.004 | 0.303 | 0.990 | 0.995 | 1.000 |

restricted the analysis to the impact area and post-relocation period only, aiming to eliminate potential collinearity resulting from the interaction of time and distance, following Ahlfeldt and Maennig (2010). Additionally, we included quadratic distance terms, following Tu (2005). However, we encountered multi-collinearity of similar severity.

### Estimation Results With Neighborhood Fixed Effects

As mentioned earlier, we opt to incorporate census tract fixed effects in our models since the inclusion of neighborhood fixed effects substantially inflates the standard errors of several of the neighborhood covariates, as demonstrated below. However, from a theoretical standpoint, it remains unclear at which scale level the fixed effects should be measured. While census tracts are often appealing as the smallest geographical scale level for which data is available, neighborhood boundaries typically evolve more naturally, making neighborhoods potentially more intuitive geographical clusters. In this context, Table 25 presents the estimation results of the base model using neighborhood fixed effects instead.

Table 25: Regression Estimates Across Different Error Specifications - Base Model - Neighborhood Fixed Effects

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| *Target Variables* | | | | | |
| Impact | 0.0370 | 0.0370 | 0.0370 | 0.0370 | 0.0370 |
| | (0.041) | (0.030) | (0.075) | (0.100) | (0.085) |
| Post | 0.2309*** | 0.2309*** | 0.2309*** | 0.2309*** | 0.2309*** |
| | (0.027) | (0.025) | (0.044) | (0.053) | (0.051) |
| ImpactxPost | -0.0533** | -0.0533*** | -0.0533* | -0.0533* | -0.0533* |
| | (0.022) | (0.020) | (0.028) | (0.026) | (0.031) |
| *Housing Characteristics* | | | | | |
| logFloorsize | 0.4566*** | 0.4566*** | 0.4566*** | 0.4566*** | 0.4566*** |
| | (0.014) | (0.012) | (0.027) | (0.035) | (0.032) |
| logParcelsize | 0.1776*** | 0.1776*** | 0.1776*** | 0.1776*** | 0.1776*** |
| | (0.009) | (0.009) | (0.020) | (0.014) | (0.021) |
| Age | -0.0036*** | -0.0036*** | -0.0036*** | -0.0036*** | -0.0036*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Frame | -0.1260*** | -0.1260*** | -0.1260*** | -0.1260*** | -0.1260*** |
| | (0.008) | (0.007) | (0.014) | (0.013) | (0.012) |
| Stone | 0.1042** | 0.1042* | 0.1042** | 0.1042*** | 0.1042* |
| | (0.053) | (0.057) | (0.051) | (0.035) | (0.058) |
| Stories | 0.2493*** | 0.2493*** | 0.2493*** | 0.2493*** | 0.2493*** |
| | (0.010) | (0.009) | (0.019) | (0.025) | (0.020) |
| Garages | 0.0920*** | 0.0920*** | 0.0920*** | 0.0920*** | 0.0920*** |
| | (0.006) | (0.006) | (0.008) | (0.010) | (0.008) |

| | | | | | |
|---|---|---|---|---|---|
| Carports | 0.0199*** | 0.0199*** | 0.0199*** | 0.0199** | 0.0199*** |
| | (0.006) | (0.005) | (0.007) | (0.008) | (0.006) |
| Attic | 0.1583*** | 0.1583*** | 0.1583*** | 0.1583*** | 0.1583*** |
| | (0.006) | (0.007) | (0.009) | (0.009) | (0.010) |
| *Demographic Characteristics* | | | | | |
| PopDensity | -0.0341*** | -0.0341*** | -0.0341** | -0.0341* | -0.0341* |
| | (0.011) | (0.009) | (0.015) | (0.018) | (0.020) |
| Crime | -0.0075 | -0.0075* | -0.0075 | -0.0075 | -0.0075 |
| | (0.005) | (0.004) | (0.005) | (0.006) | (0.006) |
| Black | 0.8334** | 0.8334** | 0.8334* | 0.8334 | 0.8334 |
| | (0.343) | (0.324) | (0.474) | (0.653) | (0.534) |
| Vacancy | -3.0141*** | -3.0141*** | -3.0141*** | -3.0141* | -3.0141** |
| | (0.784) | (0.657) | (1.061) | (1.718) | (1.287) |
| Youth | -0.9813 | -0.9813 | -0.9813 | -0.9813 | -0.9813 |
| | (1.314) | (1.125) | (1.699) | (2.142) | (1.849) |
| MedianIncome | 0.0070*** | 0.0070*** | 0.0070** | 0.0070* | 0.0070* |
| | (0.001) | (0.001) | (0.003) | (0.003) | (0.004) |
| *Market Characteristics* | | | | | |
| AccFood | 0.0004 | 0.0004 | 0.0004 | 0.0004 | 0.0004 |
| | (0.006) | (0.005) | (0.012) | (0.011) | (0.011) |
| Finance | -0.0102*** | -0.0102** | -0.0102 | -0.0102 | -0.0102 |
| | (0.004) | (0.004) | (0.011) | (0.013) | (0.013) |
| Retail | -0.0082** | -0.0082** | -0.0082 | -0.0082 | -0.0082 |
| | (0.003) | (0.003) | (0.009) | (0.010) | (0.010) |
| *Urban Characteristics* | | | | | |
| DistancePark | -0.1835*** | -0.1835*** | -0.1835*** | -0.1835*** | -0.1835*** |
| | (0.013) | (0.013) | (0.038) | (0.049) | (0.045) |
| Local | 0.1304** | 0.1304** | 0.1304 | 0.1304 | 0.1304 |
| | (0.064) | (0.051) | (0.110) | (0.138) | (0.107) |
| National | 0.0911*** | 0.0911*** | 0.0911** | 0.0911 | 0.0911 |
| | (0.014) | (0.013) | (0.041) | (0.055) | (0.060) |
| CertifiedLocal | 0.1909*** | 0.1909*** | 0.1909** | 0.1909** | 0.1909*** |
| | (0.031) | (0.032) | (0.083) | (0.076) | (0.057) |

| | | | | | |
|---|---|---|---|---|---|
| Conservation | 0.2219** | 0.2219*** | 0.2219 | 0.2219* | 0.2219 |
| | (0.100) | (0.058) | (0.138) | (0.125) | (0.189) |
| Preservation | 0.1276*** | 0.1276*** | 0.1276** | 0.1276*** | 0.1276** |
| | (0.028) | (0.023) | (0.063) | (0.044) | (0.054) |
| Enterprise | -0.0632*** | -0.0632*** | -0.0632* | -0.0632* | -0.0632 |
| | (0.012) | (0.010) | (0.036) | (0.036) | (0.041) |
| Flood100 | -0.1316*** | -0.1316*** | -0.1316*** | -0.1316*** | -0.1316** |
| | (0.029) | (0.031) | (0.049) | (0.035) | (0.050) |
| Flood500 | -0.0339 | -0.0339 | -0.0339 | -0.0339 | -0.0339 |
| | (0.023) | (0.028) | (0.047) | (0.029) | (0.027) |
| DistanceBusch | 0.5953*** | 0.5953*** | 0.5953** | 0.5953** | 0.5953** |
| | (0.105) | (0.098) | (0.257) | (0.238) | (0.288) |
| DistanceEC | -0.5750*** | -0.5750*** | -0.5750** | -0.5750** | -0.5750* |
| | (0.106) | (0.098) | (0.262) | (0.249) | (0.298) |
| Constant | 7.1431*** | 7.1431*** | 7.1431*** | 7.1431*** | 7.1431*** |
| | (0.344) | (0.286) | (0.556) | (0.772) | (0.584) |
| Neighborhood FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7492 | 0.7492 | 0.7492 | 0.7492 | 0.7492 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In short, the overall conclusions remain unchanged. Nevertheless, there are two minor differences to note. Firstly, the use of neighborhood fixed effects yields a smaller point estimate of the treatment effect at 5.33%. Secondly, we observe a decrease in the significance of its coefficient when clustering the standard errors.[76]

Regarding the impact on the covariates, there are no significant differences observed. Nevertheless, it is worth noting the non-significant but negative estimates for Crime and Youth, previously reported as highly significant in Table 5. The non-significance is likely a result of the multicollinearity introduced by the neighborhood fixed effects. In this vein, Table 26 shows the significant increase in the VIFs of the neighborhood coefficients when employing neighborhood fixed effects.

[76]We also re-estimate the distance ring models with neighborhood fixed effects and find consistent results.

Table 26: VIFs of the Base Model - Neighborhood FE

| | vif |
|---|---|
| Impact | 11.03 |
| Post | 22.11 |
| ImpactxPost | 2.89 |
| logFloorsize | 3.91 |
| logParcelsize | 1.76 |
| Age | 1.77 |
| Frame | 1.59 |
| Stone | 1.03 |
| Stories | 3.63 |
| Garages | 1.26 |
| Carports | 1.07 |
| Attic | 1.22 |
| PopDensity | 879.48 |
| Crime | 14.31 |
| Black | 552.91 |
| Vacancy | 160.34 |
| Youth | 376.44 |
| MedianIncome | 12.11 |
| AccFood | 9.49 |
| Finance | 8.75 |
| Retail | 5.64 |
| DistancePark | 3.94 |
| Local | 25.25 |
| National | 3.77 |
| CertifiedLocal | 12.01 |
| Conservation | 1.96 |
| Preservation | 3.60 |
| Enterprise | 1.82 |
| Flood100 | 1.08 |
| Flood500 | 1.17 |
| DistanceBusch | 3052.29 |
| DistanceEC | 2983.49 |

**Does the Model Suffer from Age-Induced Heteroskedasticity? - The Age-Period-Cohort-Problem**

One yet unsolved empirical challenge in the hedonic literature is the so-called *Age-Period-Cohort Problem* (APC), which arises due to the simultaneous inclusion of a building's age, transaction year, and construction year, leading to perfect multicollinearity. In response, most empiricists tend to omit the latter variable. However, Yiu and Cheung (2022) argue that such omission may introduce OVB if consumers value structural or physical building characteristics associated with a certain cohort, leading them to pay a premium for such features. This premium, as Hall (1971) terms it, is known as the *vintage-effect* in durable goods. In this context, Randolph (1988) purports that vintage effects are significant, and that unobserved age-invariant determinants may be correlated with a property's construction year. Similarly, Hall (1971) suggests that cohort effects may also exist for new buildings, if consumers have pure tastes for newer houses.

Although Yiu and Cheung (2022) propose a solution to the APC problem by including external information on the quality and renovation status of a house, such as appraised-improvement values of housing structures, we are unable to replicate their approach due to the lack of reliable information on assessment values of individual properties in our sample. Moreover, as mentioned previously, we incorporate time-invariant structural housing characteristics as covariates within our models, providing a snapshot in time. We argue that this approach is rather unproblematic given our relatively recent sample period, as most structural characteristics typically do not vary over time (e.g., parcel size), and any variations (e.g., in the number of carports) are likely to result in marginal estimation bias. Additionally, all regression coefficients of the housing controls exhibit the expected signs.

Notwithstanding, given that the housing stock in St. Louis is relatively old and encompasses a wide range of building ages, it is possible that our error terms suffer from dwelling age-heteroskedasticity. This is because the likelihood of significant upgrades and renovations, and thus the size of the error term, is likely to increase with dwelling age (Goodman and Thibodeau (1995)).[77]

We adopt two approaches to address the APC problem and the potential non-linearity of age depreciation in our sample. First, we include control dummy variables indicating the listing of a property within the local, local certified, or national historic register. St. Louis exhibits a relatively large share of historic districts, as depicted in Figure 12, owing to its crucial role during the Westward Expansion of the United States in the 19th century.

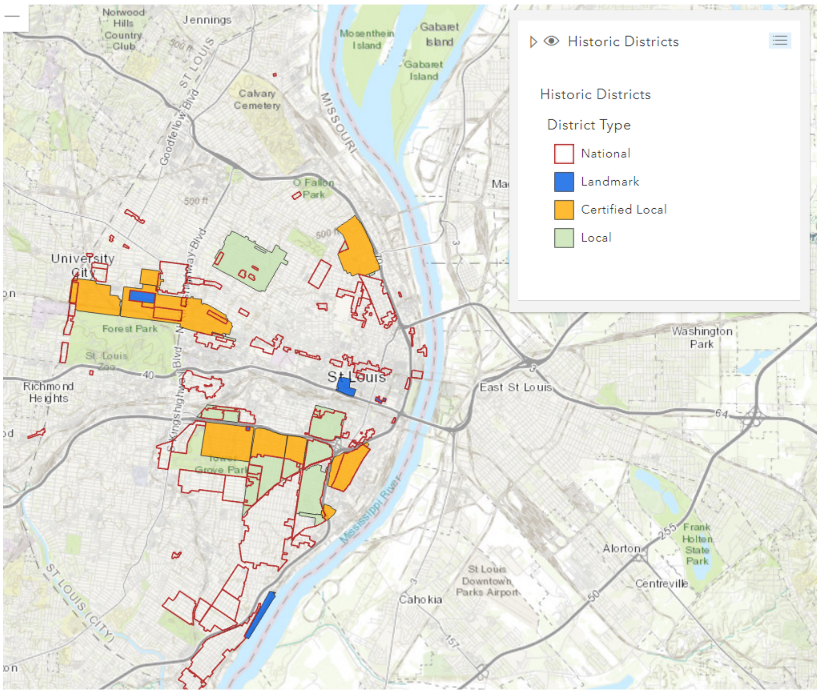
In total, the City of St. Louis designates 18 local historic districts and 10 certified local historic districts.[78] These districts require approval through political ordinance and are subject to strict regulations upon designation. For example, any changes made to the exterior or core structure of properties located in historical districts must be ratified by the Cultural Resources Office.[79]

[77]For a sample of single-family homes in Dallas, the authors show that housing values depreciate non-linearly in age, with a positive age effect observed for houses aged between 20 and 40. Similarly, Cannaday and Sunderman (1986) provide evidence suggesting that the depreciation path of single-family homes may be concave rather than linear.

[78]The latter are eligible for inclusion within the National Register of Historic Places (NRHP).

[79]C.f. Stlouis-mo.gov[1].

Figure 12: Map of the Local and National Historic Districts in St. Louis




Source: www.stlouis-mo.gov

Further, the criteria for eligibility for listing in the NRHP were initially established in the *National Historic Preservation Act of 1966* and synthesized by the City of St. Louis as: *"To qualify, a property must represent an important facet of U.S. history, architecture, archaeology, engineering, or culture; and retain integrity of location, design, setting, materials, workmanship, feeling, and association"*.[80]

In addition to designating historic neighborhoods, the City of St. Louis has made the preservation and conservation of historic buildings and landmarks a central target of its Strategic Land Use Plan.[81] Specifically, St. Louis has established Preservation Review Areas, as depicted in Figure 13, where demolition applications require review due to the significance of these areas on their immediate and surrounding neighborhoods.[82] Additionally, the city has implemented a Housing Conservation Program to ensure that houses meet specific building standards and prevent obsolescence and blight.[83]

[80] C.f. Stlouis-mo.gov[2]. Similarly, local historic designation follows a comparable set of rules and conditions, although the significance yielded by a certain property or group of properties may have predominantly local relevance.

[81] The plan, initially adopted in 2005 and subsequently amended, assigns specific land use designations to each block in the city, guiding residents and investors in maintenance, enhancement, and development efforts.

[82] C.f. Stlouis-mo.gov[3].

[83] C.f. Stlouis-mo.gov[4].

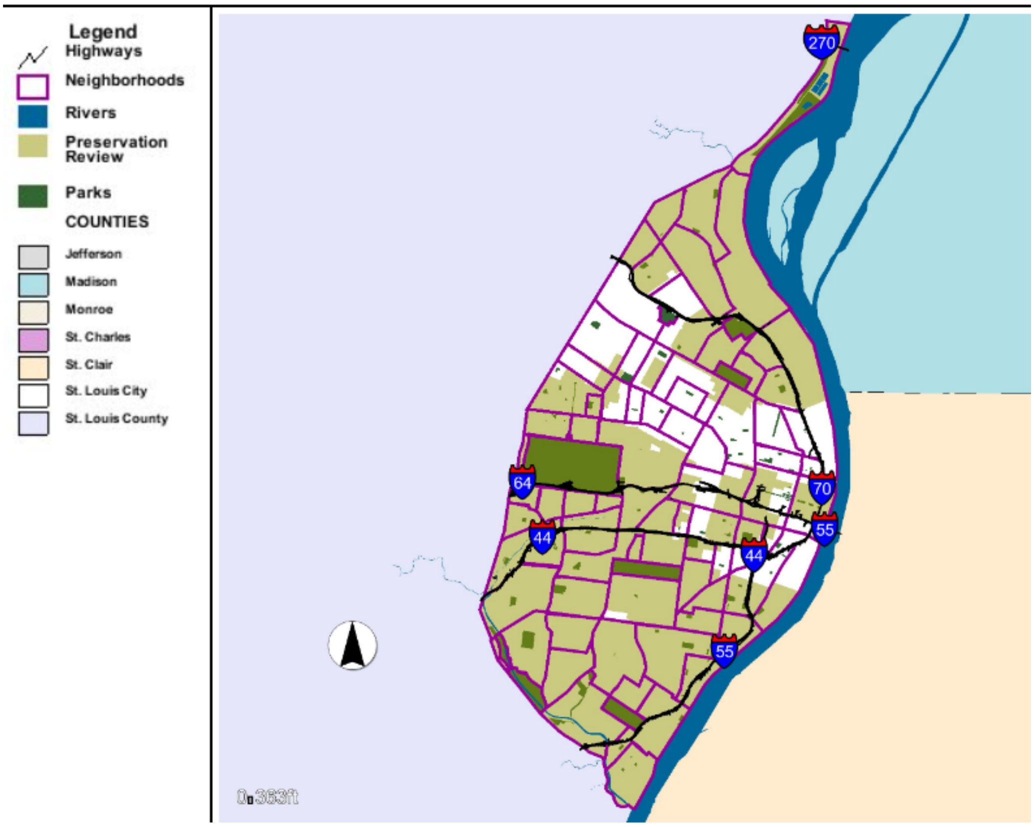



Figure 13: Map of the Preservation Review Areas in St. Louis
Source: Created via Geo St. Louis

Against this backdrop, we postulate that the inclusion of dummy variables representing a property's affiliation with any historic district, a Preservation Review Area, or participation in the Housing Conservation Program can act as a proxy for unobserved building features. These features may include distinctive exterior architectural designs, unique structural elements characteristic of specific building periods, and potential variations in building quality. However, this approach may have limitations in capturing cohort effects associated with more modern building styles.

Our estimations consistently show that the coefficients for the urban control dummies are highly significant across all our models and have the expected signs. Specifically, for our base model presented in Table 4, we estimate that single-family homes located in local, national, or certified local historic districts sell for approximately 12.52%, 8.85%, and 28.15% higher, respectively. Similarly, participation in the Housing Conservation Program corresponds to an average price increase of approximately 21.53%, while homes located in preservation review areas sell for about 11.51% more on average.[84]

To contextualize these findings, we briefly review previous research on historical designation, conservation, and preservation. Mason (2005) provides a comprehensive survey revealing a general consensus about the explicit and tacit benefits of historical designation and preservation, despite some mixed evidence, as noted by Coulson and Leichenko (2001). While onerous rules and regulations may impose negative externalities, the positive externalities associated with historical designation seem to predominate. For instance, Clark and Herrin (1997) show that properties

[84]The percentage effects are calculated as $(\exp(\beta_j) - 1) * 100$ (Halvorsen and Palmquist (1980)).

in Sacramento experienced an average appreciation rate of 17% following historical designation. Similarly, Ford (1989) observes increases in property values in Baltimore upon historical designation, arguing that the listing in a historic register may act as an insurance mechanism, ensuring the preservation of adjacent neighborhoods. An alternative explanation by Gordon and Stowe (2014) suggests that historical designation might alleviate informational asymmetries and even generate spatial spillovers to adjacent neighborhoods.
Further, Leichenko et al. (2001) compare the effects of national and local designation across nine different cities in Texas and observe price increases ranging from 5% to 20% for properties located within historic districts. In line with our findings, the authors detect larger estimates for national historic districts and argue that this premium may be associated with the higher prestige of nationally designated districts, as well as the typically stricter local zoning regulations governing local historic districts. Similarly, Schaeffer and Millerick (1991) arrive at the same qualitative results for a sample of Chicago neighborhoods.
However, the price appreciation within preserved areas may come at the detriment of residents in other parts of the city, particularly when housing preservation artificially restricts housing supply and induces population clustering effects, as in the example of height regulations in New York (Glaeser (2011)). Additionally, Listokin et al. (1998) warn about the potentially adverse effects of historical designation in terms of displacement effects, increased gentrification, and thwarted growth.

In conclusion, while the broader discussion on the potential impacts of historic designation, conservation, or preservation falls beyond the scope of this paper and warrants further investigation, the finding regarding price appreciations for historically preserved properties aligns well with prior literature on historic designation and preservationist policies. While this bolsters the robustness of our findings, it does not definitively rule out the presence of age-related heteroskedasticity in the error term, prompting us to conduct an additional test.

Regarding our second approach, Goodman and Thibodeau (1995) propose addressing age-induced heteroskedasticity by including the square of age into the hedonic price function, thereby allowing for non-linear depreciation effects. In this context, we present the results of our base model including the square of age in Table 27.
As can be seen, the main results of our base model are unaffected when allowing for non-linear age depreciation. The coefficient for age remains highly significant and negative, though, its absolute estimate is slightly larger: $\mid -0.0078 \mid > \mid -0.00364 \mid$. Regarding the coefficient for the square of age, the estimates are highly significant and positive, indicating that the effect of age on price may indeed be best described by a concave relationship. Although the point estimate is relatively low in magnitude, the adjusted model suggests that a 100-year old building sells on average for about 38% less than a new property, which equals a considerable difference in estimates of about 8 percentage points compared to the model omitting the square of age.[85] Notwithstanding, due to the concavity, the difference between the models is rather negligible for buildings at the lower and upper end of the age spectrum.[86]

[85] $\exp(-0.00769 * 100 + 0.0000278 * 100^2) - 1 = -0.3879$ & $\exp(-0.00364 * 100) - 1 = -0.3051$.

[86] For instance, the difference in the estimated depreciation rates of a 150 year old home is only about one percentage point: $\exp(-0.00769 * 150 + 0.0000278 * 150^2) - 1 = -0.4102$ & $\exp(-0.00364 * 150) - 1 = -0.4207$.

In conclusion, while the results suggest that housing depreciation seems to exhibit a concave relationship, allowing for this non-linearity does not have any discernible effect on the sign, significance, and magnitude of any coefficient other than age. Therefore, we contend that our conclusions are robust against age-incuced heteroskedasticity and argue that our model specification including dummies for historical designation is just.

Table 27: Regression Estimates Allowing for Nonlinear Age Depreciation - Base Model

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Impact | 0.142*** | 0.142*** | 0.142* | 0.142* | 0.142** |
| | (0.036) | (0.028) | (0.076) | (0.082) | (0.070) |
| Post | 0.311*** | 0.311*** | 0.311*** | 0.311*** | 0.311*** |
| | (0.022) | (0.021) | (0.032) | (0.032) | (0.032) |
| ImpactxPost | -0.0780*** | -0.0780*** | -0.0780*** | -0.0780*** | -0.0780*** |
| | (0.020) | (0.019) | (0.028) | (0.024) | (0.026) |
| Age | -0.00769*** | -0.00769*** | -0.00769*** | -0.00769*** | -0.00769*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| AgeSquared | 0.0000278*** | 0.0000278*** | 0.0000278*** | 0.0000278*** | 0.0000278*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7581 | 0.7581 | 0.7581 | 0.7581 | 0.7581 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Is Proximity to Parks a Confounding Variable?**

As discussed in Section 4, the inclusion of a covariate capturing the distance to the closest urban park might lead to spurious estimates if the WTP for proximity to urban parks is an endogenous function of the WTP for proximity to sports facilities. Consequently, we re-estimate Equation 4 without this regressor. The results are presented in column (2) of Table 28. Further, in column (4), we test for non-linearity by including a squared coefficient to the model, as prior research provides mixed evidence on how the effects of parks are spatially distributed (More et al. (1988)). Finally, in column (3), we examine the effect of residential proximity to parks using a 600-meter distance control ring.

Table 28: Regression Estimates - Proximity to Urban Parks - Base Model

| | (1) Base Model | (2) No Park | (3) Distance Ring | (4) Quadratic Distance |
|---|---|---|---|---|
| Impact | $0.144^{***}$ | $0.116^{***}$ | $0.162^{***}$ | $0.166^{***}$ |
| | (0.036) | (0.036) | (0.037) | (0.037) |
| Post | $0.320^{***}$ | $0.316^{***}$ | $0.317^{***}$ | $0.322^{***}$ |
| | (0.022) | (0.023) | (0.022) | (0.022) |
| ImpactxPost | $-0.0752^{***}$ | $-0.0727^{***}$ | $-0.0746^{***}$ | $-0.0751^{***}$ |
| | (0.021) | (0.021) | (0.021) | (0.021) |
| DistancePark | $-0.200^{***}$ | | | $-0.479^{***}$ |
| | (0.015) | | | (0.067) |
| ParkRing | | | $0.120^{***}$ | |
| | | | (0.010) | |
| DistancePark2 | | | | $0.163^{***}$ |
| | | | | (0.040) |
| Controls | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7571 | 0.7535 | 0.7561 | 0.7581 |
| Observations | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
The full regression results are avilable from the author.
Robust standard errors are depicted in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Comparing columns (1) and (2) suggests that the inclusion of the covariate for residential proximity to the closest park has only a marginal impact on the magnitude of the point estimate and no effect on its significance. Furthermore, column (3) does not reveal any discernible differences when specifying the covariate for residential proximity to parks as a 600-meter distance ring. Taken together, there does not appear to exist an evident endogenous relationship between the WTP for residing close to the Edward Jones Dome and the WTP for proximity to urban parks or green spaces, interfering with our identification strategy.

Furthermore, compared to the relatively consistent literature on sports amenities, prior evidence of the intangible benefits of natural urban amenities, such as parks and green spaces, is much more ambiguous. While the positive effects of parks on property prices is well-documented, questions remain regarding which types of green spaces matter the most (Panduro and Veie (2013)), which inherent features induce the largest price effects (Morancho (2003)), and how the effects are spatially shaped. Although this paper cannot address all of these questions, the estimates shed some light on the magnitude and spatial distribution of the impact of parks. Specifically, column (1) suggests that each additional mile away from the closest urban park decreases the value of a single-family home by about 18.3% on average.[87] Further, column (4) reveals a positive and significant coefficient for the squared distance, indicating a non-linear effect that decreases in a concave fashion. This implies that the effect is most pronounced in direct proximity to parks and diminishes disproportionately with distance until it completely dissipates at a distance of 2.93 miles.[88] Concerning the distance ring specification in column (3), the point estimate suggests a price premium of approximately 12.75%,[89] for single-family homes located within 600 meters of any of the selected urban parks or green spaces, consistent with prior literature.

Lastly, there are some caveats to report. Firstly, our findings might be affected by selectivity bias as we only include the most important parks based on qualitative criteria. We thereby implicitly assume that only parks of a certain size or reputation have a considerable impact on the housing market. Additionally, another reason for the inability to control for all 108 parks in St. Louis is that we lack substantial information to map the parks within a geographical information system. However, smaller parks, such as playgrounds, may also have a particularly local effect. Secondly, we assume homogeneity in the effect of residential proximity to any of the selected parks, although in reality, considerable differences may exist based on the idiosyncratic features characterizing each park. Unfortunately, we lack sufficient information on such features for more sophisticated analyses. Finally, our findings may exhibit a small measurement error, primarily due to the approach of measuring the distance to the center of each park, as we lack information on concrete entry points to parks.[90]

[87] $(\exp(-0.2) - 1) * 100 = -18.2.$

[88] $\exp(-0.479 * 2.9386 + 0.163 * 2.9386^2) - 1 \approx 0.$

[89] $(\exp(0.12) - 1) * 100 = 12.75.$

[90] For the two largest parks - Forrest Park & Tower Grove Park - we determine eight coordinates reflecting the corners of the rectangular-shaped parks and their respective midpoints.

Table 29: List of the Selected Urban Parks and Green Spaces

| | Name of the Park |
|---|---|
| 1 | Forest Park |
| 2 | Tower Grove Park |
| 3 | Missouri Botanical Garden |
| 4 | Lafayette Park |
| 5 | Citygarden Park |
| 6 | Columbia Bottom Conservatory |
| 7 | Bellefontaine Cemetery |
| 8 | Jefferson Barracks Park |
| 9 | Francis Park |
| 10 | O'Fallon Park |
| 11 | Carondelet Park |
| 12 | Compton Hill Reservoir Park |
| 13 | Fairgrounds Park |
| 14 | Sherman Park |
| 15 | Hyde Park |
| 16 | Rauschenbach Park |
| 17 | St. Louis Place Park |

## Variable Transformations

Figure 14: Log-Transformation of Price

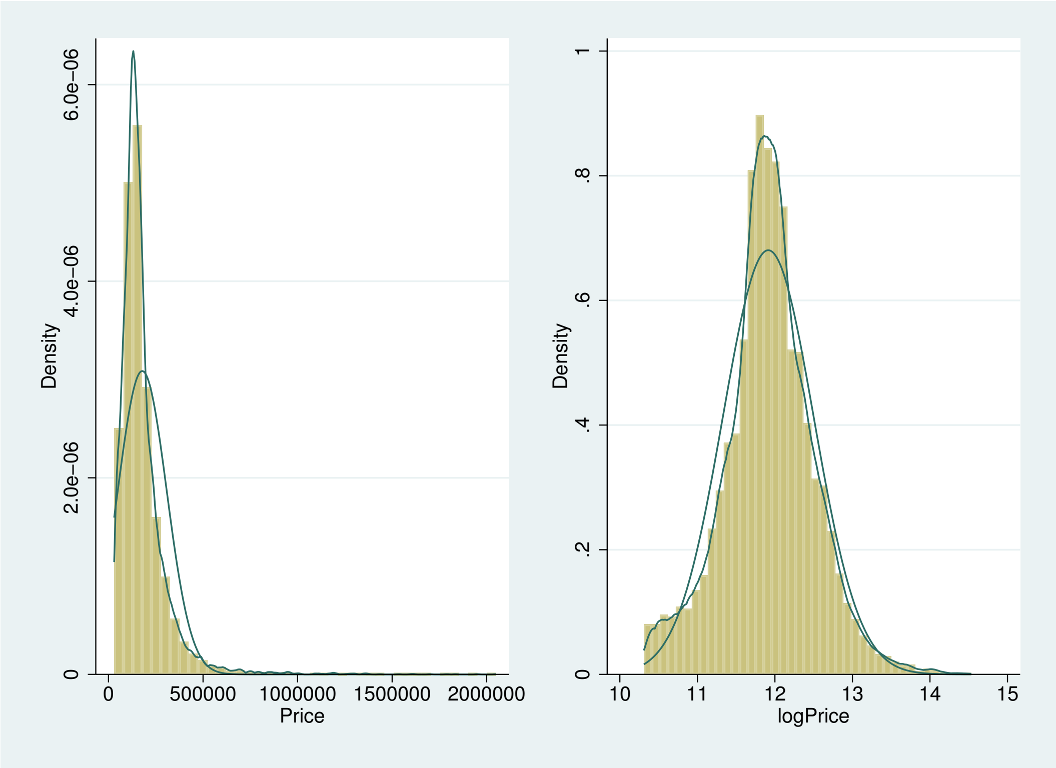



Figure 15: Log-Transformation of Floorsize

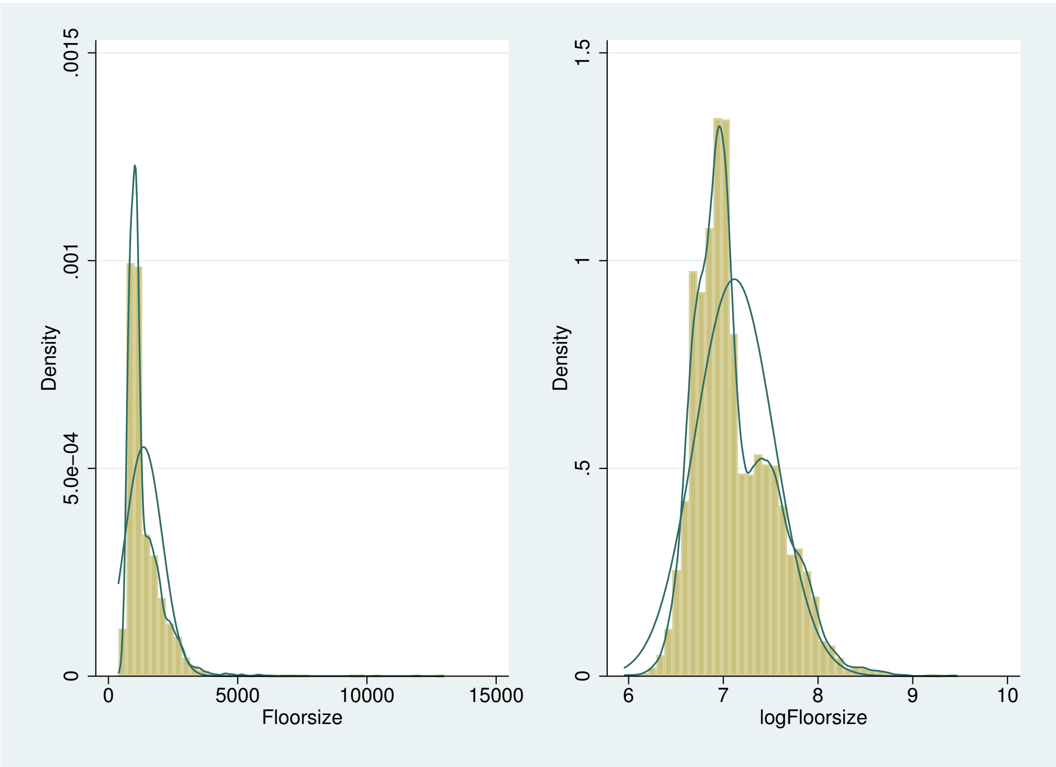
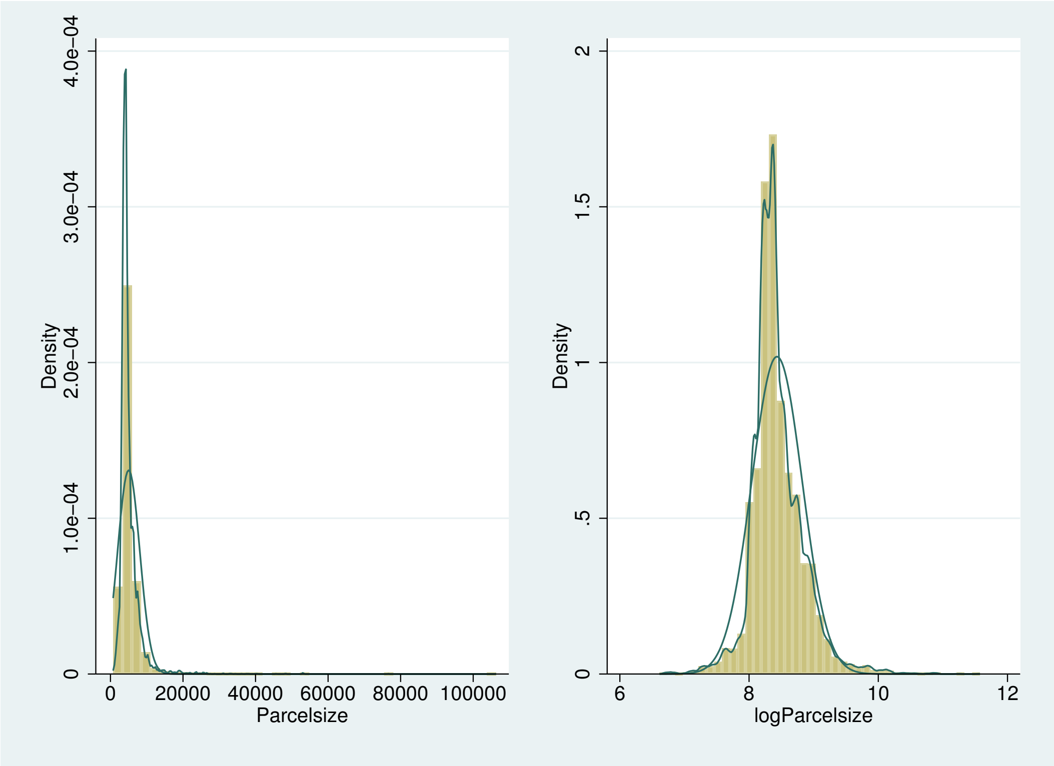


Figure 16: Log-Transformation of Parcelsize



## Supplementary Regression Outputs

### Main Body

Table 30: Regression Estimates Across Different Error Specifications - Base Model

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| *Target Variables* | | | | | |
| Impact | 0.1444*** | 0.1444*** | 0.1444* | 0.1444* | 0.1444* |
| | (0.036) | (0.028) | (0.080) | (0.084) | (0.073) |
| Post | 0.3205*** | 0.3205*** | 0.3205*** | 0.3205*** | 0.3205*** |
| | (0.022) | (0.021) | (0.032) | (0.033) | (0.032) |
| ImpactxPost | -0.0752*** | -0.0752*** | -0.0752*** | -0.0752*** | -0.0752*** |
| | (0.021) | (0.019) | (0.028) | (0.023) | (0.026) |
| *Housing Characteristics* | | | | | |
| logFloorsize | 0.4508*** | 0.4508*** | 0.4508*** | 0.4508*** | 0.4508*** |
| | (0.015) | (0.012) | (0.027) | (0.035) | (0.032) |
| logParcelsize | 0.1904*** | 0.1904*** | 0.1904*** | 0.1904*** | 0.1904*** |
| | (0.009) | (0.009) | (0.020) | (0.014) | (0.020) |
| Age | -0.0036*** | -0.0036*** | -0.0036*** | -0.0036*** | -0.0036*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Frame | -0.1153*** | -0.1153*** | -0.1153*** | -0.1153*** | -0.1153*** |
| | (0.008) | (0.008) | (0.014) | (0.013) | (0.012) |
| Stone | 0.1055* | 0.1055* | 0.1055** | 0.1055*** | 0.1055* |
| | (0.055) | (0.057) | (0.050) | (0.035) | (0.057) |
| Stories | 0.2476*** | 0.2476*** | 0.2476*** | 0.2476*** | 0.2476*** |
| | (0.010) | (0.009) | (0.019) | (0.025) | (0.019) |
| Garages | 0.0886*** | 0.0886*** | 0.0886*** | 0.0886*** | 0.0886*** |
| | (0.006) | (0.006) | (0.008) | (0.009) | (0.008) |
| Carports | 0.0170*** | 0.0170*** | 0.0170*** | 0.0170** | 0.0170*** |
| | (0.006) | (0.005) | (0.006) | (0.007) | (0.006) |
| Attic | 0.1518*** | 0.1518*** | 0.1518*** | 0.1518*** | 0.1518*** |
| | (0.006) | (0.007) | (0.009) | (0.008) | (0.009) |
| *Demographic Characteristics* | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| PopDensity | -0.0014* | -0.0014** | -0.0014 | -0.0014 | -0.0014 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Crime | -0.0120*** | -0.0120*** | -0.0120** | -0.0120** | -0.0120** |
| | (0.004) | (0.003) | (0.006) | (0.006) | (0.005) |
| Black | -0.3539*** | -0.3539*** | -0.3539** | -0.3539** | -0.3539** |
| | (0.082) | (0.073) | (0.166) | (0.167) | (0.166) |
| Vacancy | -1.1322*** | -1.1322*** | -1.1322** | -1.1322** | -1.1322*** |
| | (0.250) | (0.200) | (0.505) | (0.420) | (0.392) |
| Youth | 0.4385* | 0.4385** | 0.4385 | 0.4385 | 0.4385 |
| | (0.251) | (0.218) | (0.554) | (0.470) | (0.592) |
| MedianIncome | 0.0019* | 0.0019** | 0.0019 | 0.0019 | 0.0019 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| *Market Characteristics* | | | | | |
| AccFood | 0.0076 | 0.0076* | 0.0076 | 0.0076 | 0.0076 |
| | (0.005) | (0.005) | (0.008) | (0.007) | (0.007) |
| Finance | 0.0058* | 0.0058* | 0.0058 | 0.0058 | 0.0058 |
| | (0.004) | (0.003) | (0.006) | (0.006) | (0.006) |
| Retail | -0.0145*** | -0.0145*** | -0.0145** | -0.0145* | -0.0145** |
| | (0.004) | (0.004) | (0.007) | (0.008) | (0.007) |
| *Urban Characteristics* | | | | | |
| DistancePark | -0.2002*** | -0.2002*** | -0.2002*** | -0.2002*** | -0.2002*** |
| | (0.015) | (0.015) | (0.050) | (0.056) | (0.050) |
| Local | 0.1180*** | 0.1180*** | 0.1180* | 0.1180*** | 0.1180** |
| | (0.037) | (0.027) | (0.061) | (0.041) | (0.053) |
| National | 0.0848*** | 0.0848*** | 0.0848 | 0.0848 | 0.0848* |
| | (0.017) | (0.014) | (0.054) | (0.051) | (0.047) |
| CertifiedLocal | 0.2478*** | 0.2478*** | 0.2478*** | 0.2478*** | 0.2478*** |
| | (0.034) | (0.028) | (0.076) | (0.071) | (0.068) |
| Conservation | 0.1945* | 0.1945*** | 0.1945 | 0.1945 | 0.1945 |
| | (0.101) | (0.057) | (0.126) | (0.133) | (0.159) |
| Preservation | 0.1091*** | 0.1091*** | 0.1091** | 0.1091*** | 0.1091** |
| | (0.026) | (0.022) | (0.049) | (0.031) | (0.042) |
| Enterprise | -0.0018 | -0.0018 | -0.0018 | -0.0018 | -0.0018 |
| | (0.014) | (0.012) | (0.044) | (0.051) | (0.043) |

| | | | | | |
|---|---|---|---|---|---|
| Flood100 | -0.0636** | -0.0636** | -0.0636 | -0.0636* | -0.0636** |
| | (0.031) | (0.031) | (0.048) | (0.036) | (0.031) |
| Flood500 | 0.0013 | 0.0013 | 0.0013 | 0.0013 | 0.0013 |
| | (0.024) | (0.028) | (0.041) | (0.026) | (0.028) |
| DistanceBusch | 0.0097 | 0.0097 | 0.0097 | 0.0097 | 0.0097 |
| | (0.111) | (0.101) | (0.281) | (0.303) | (0.301) |
| DistanceEC | 0.0065 | 0.0065 | 0.0065 | 0.0065 | 0.0065 |
| | (0.113) | (0.103) | (0.294) | (0.308) | (0.319) |
| Constant | 6.3883*** | 6.3883*** | 6.3883*** | 6.3883*** | 6.3883*** |
| | (0.174) | (0.147) | (0.344) | (0.377) | (0.367) |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7571 | 0.7571 | 0.7571 | 0.7571 | 0.7571 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The impact area is defined as a three-mile radius ring around the stadium.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 31: Regression Estimates Across Different Error Specifications - One-Mile Distance Rings

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Post | 0.322*** | 0.322*** | 0.322*** | 0.322*** | 0.322*** |
| | (0.027) | (0.026) | (0.043) | (0.043) | (0.041) |
| *Ring Variables* | | | | | |
| Impact1 | 0.870*** | 0.870*** | 0.870*** | 0.870*** | 0.870*** |
| | (0.196) | (0.197) | (0.247) | (0.236) | (0.305) |
| Impact2 | 0.244*** | 0.244*** | 0.244 | 0.244 | 0.244 |
| | (0.080) | (0.072) | (0.191) | (0.162) | (0.165) |
| Impact3 | 0.199*** | 0.199*** | 0.199 | 0.199 | 0.199 |
| | (0.064) | (0.056) | (0.161) | (0.150) | (0.141) |
| Impact4 | 0.097* | 0.097** | 0.097 | 0.097 | 0.097 |
| | (0.053) | (0.048) | (0.128) | (0.124) | (0.113) |

| | | | | | |
|---|---|---|---|---|---|
| Impact5 | -0.064* | -0.064* | -0.064 | -0.064 | -0.064 |
| | (0.039) | (0.037) | (0.101) | (0.102) | (0.098) |
| Impact6 | -0.049* | -0.049* | -0.049 | -0.049 | -0.049 |
| | (0.025) | (0.025) | (0.068) | (0.068) | (0.061) |
| Impact7 | 0.023 | 0.023 | 0.023 | 0.023 | 0.023 |
| | (0.019) | (0.019) | (0.051) | (0.050) | (0.046) |
| Impact1xPost | -0.380*** | -0.380** | -0.380*** | -0.380*** | -0.380*** |
| | (0.109) | (0.166) | (0.094) | (0.093) | (0.126) |
| Impact2xPost | -0.105*** | -0.105*** | -0.105** | -0.105*** | -0.105*** |
| | (0.038) | (0.038) | (0.040) | (0.037) | (0.031) |
| Impact3xPost | -0.069** | -0.069*** | -0.069* | -0.069** | -0.069* |
| | (0.028) | (0.027) | (0.040) | (0.026) | (0.036) |
| Impact4xPost | -0.050* | -0.050** | -0.050 | -0.050 | -0.050 |
| | (0.026) | (0.024) | (0.036) | (0.044) | (0.039) |
| Impact5xPost | -0.005 | -0.005 | -0.005 | -0.005 | -0.005 |
| | (0.025) | (0.024) | (0.035) | (0.030) | (0.030) |
| Impact6xPost | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |
| | (0.019) | (0.020) | (0.024) | (0.026) | (0.021) |
| Impact7xPost | -0.022 | -0.022 | -0.022 | -0.022 | -0.022 |
| | (0.017) | (0.019) | (0.023) | (0.025) | (0.021) |
| *Housing Characteristics* | | | | | |
| logFloorsize | 0.452*** | 0.452*** | 0.452*** | 0.452*** | 0.452*** |
| | (0.015) | (0.012) | (0.028) | (0.036) | (0.032) |
| logParcelsize | 0.195*** | 0.195*** | 0.195*** | 0.195*** | 0.195*** |
| | (0.009) | (0.009) | (0.019) | (0.014) | (0.019) |
| Age | -0.004*** | -0.004*** | -0.004*** | -0.004*** | -0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Frame | -0.116*** | -0.116*** | -0.116*** | -0.116*** | -0.116*** |
| | (0.008) | (0.008) | (0.013) | (0.012) | (0.012) |
| Stone | 0.106* | 0.106* | 0.106** | 0.106** | 0.106* |
| | (0.055) | (0.057) | (0.051) | (0.038) | (0.057) |
| Stories | 0.246*** | 0.246*** | 0.246*** | 0.246*** | 0.246*** |
| | (0.010) | (0.009) | (0.019) | (0.025) | (0.019) |
| Garages | 0.088*** | 0.088*** | 0.088*** | 0.088*** | 0.088*** |
| | (0.006) | (0.006) | (0.008) | (0.009) | (0.008) |

| | | | | | |
|---|---|---|---|---|---|
| Carports | 0.017*** | 0.017*** | 0.017*** | 0.017** | 0.017*** |
| | (0.005) | (0.005) | (0.006) | (0.007) | (0.006) |
| Attic | 0.149*** | 0.149*** | 0.149*** | 0.149*** | 0.149*** |
| | (0.007) | (0.007) | (0.009) | (0.009) | (0.009) |
| *Demographic Characteristics* | | | | | |
| PopDensity | -0.001* | -0.001** | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) |
| Crime | -0.011*** | -0.011*** | -0.011* | -0.011* | -0.011** |
| | (0.004) | (0.003) | (0.006) | (0.006) | (0.005) |
| Black | -0.326*** | -0.326*** | -0.326* | -0.326* | -0.326* |
| | (0.083) | (0.074) | (0.178) | (0.174) | (0.164) |
| Vacancy | -1.149*** | -1.149*** | -1.149** | -1.149*** | -1.149*** |
| | (0.262) | (0.209) | (0.466) | (0.395) | (0.368) |
| Youth | 0.357 | 0.357 | 0.357 | 0.357 | 0.357 |
| | (0.255) | (0.223) | (0.549) | (0.515) | (0.584) |
| MedianIncome | 0.002** | 0.002** | 0.002 | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| *Market Characteristics* | | | | | |
| AccFood | 0.009* | 0.009** | 0.009 | 0.009 | 0.009 |
| | (0.005) | (0.005) | (0.008) | (0.007) | (0.008) |
| Finance | 0.006 | 0.006* | 0.006 | 0.006 | 0.006 |
| | (0.004) | (0.003) | (0.006) | (0.007) | (0.006) |
| Retail | -0.015*** | -0.015*** | -0.015** | -0.015* | -0.015** |
| | (0.004) | (0.004) | (0.007) | (0.008) | (0.007) |
| *Urban Characteristics* | | | | | |
| DistancePark | -0.187*** | -0.187*** | -0.187*** | -0.187*** | -0.187*** |
| | (0.015) | (0.015) | (0.047) | (0.054) | (0.049) |
| Local | 0.131*** | 0.131*** | 0.131** | 0.131*** | 0.131** |
| | (0.038) | (0.028) | (0.059) | (0.041) | (0.052) |
| National | 0.073*** | 0.073*** | 0.073 | 0.073 | 0.073* |
| | (0.017) | (0.014) | (0.044) | (0.043) | (0.040) |
| CertifiedLocal | 0.259*** | 0.259*** | 0.259*** | 0.259*** | 0.259*** |
| | (0.034) | (0.028) | (0.078) | (0.073) | (0.071) |

| | | | | | |
|---|---|---|---|---|---|
| Conservation | 0.179* | 0.179*** | 0.179 | 0.179 | 0.179 |
| | (0.102) | (0.057) | (0.135) | (0.138) | (0.168) |
| Preservation | 0.120*** | 0.120*** | 0.120** | 0.120*** | 0.120*** |
| | (0.026) | (0.022) | (0.049) | (0.031) | (0.043) |
| Enterprise | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| | (0.014) | (0.012) | (0.043) | (0.048) | (0.041) |
| Flood100 | -0.061** | -0.061** | -0.061 | -0.061 | -0.061* |
| | (0.031) | (0.031) | (0.049) | (0.037) | (0.031) |
| Flood500 | 0.005 | 0.005 | 0.005 | 0.005 | 0.005 |
| | (0.024) | (0.028) | (0.037) | (0.025) | (0.025) |
| DistanceBusch | -0.049 | -0.049 | -0.049 | -0.049 | -0.049 |
| | (0.110) | (0.103) | (0.259) | (0.294) | (0.296) |
| DistanceEC | 0.055 | 0.055 | 0.055 | 0.055 | 0.055 |
| | (0.113) | (0.104) | (0.263) | (0.287) | (0.301) |
| Constant | 6.388*** | 6.388*** | 6.388*** | 6.388*** | 6.388*** |
| | (0.192) | (0.166) | (0.392) | (0.407) | (0.387) |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7583 | 0.7583 | 0.7583 | 0.7583 | 0.7583 |
| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

Reference is the outermost distance ring Impact8.

Standard errors are depicted in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 32: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.314*** | 0.314*** | 0.314*** | 0.314*** | 0.314*** |
| | (0.024) | (0.021) | (0.036) | (0.037) | (0.036) |
| *Ring Variables* | | | | | |
| Target2 | 0.415*** | 0.415*** | 0.415** | 0.415*** | 0.415*** |
| | (0.098) | (0.080) | (0.204) | (0.135) | (0.153) |
| Target2_5 | 0.349*** | 0.349*** | 0.349** | 0.349*** | 0.349** |
| | (0.083) | (0.069) | (0.172) | (0.108) | (0.138) |
| Target3 | 0.393*** | 0.393*** | 0.393** | 0.393*** | 0.393*** |
| | (0.072) | (0.060) | (0.170) | (0.125) | (0.131) |
| Target3_5 | 0.286*** | 0.286*** | 0.286** | 0.286*** | 0.286*** |
| | (0.062) | (0.052) | (0.126) | (0.080) | (0.099) |
| Target4 | 0.219*** | 0.219*** | 0.219* | 0.219*** | 0.219** |
| | (0.050) | (0.043) | (0.117) | (0.079) | (0.092) |
| Target4_5 | 0.068* | 0.068** | 0.068 | 0.068 | 0.068 |
| | (0.040) | (0.034) | (0.086) | (0.061) | (0.076) |
| Target5 | -0.027 | -0.027 | -0.027 | -0.027 | -0.027 |
| | (0.030) | (0.026) | (0.080) | (0.085) | (0.085) |
| Target2xPost | -0.111*** | -0.111*** | -0.111*** | -0.111*** | -0.111*** |
| | (0.035) | (0.034) | (0.033) | (0.030) | (0.023) |
| Target2_5xPost | -0.057 | -0.057* | -0.057 | -0.057* | -0.057 |
| | (0.039) | (0.035) | (0.042) | (0.030) | (0.042) |
| Target3xPost | -0.073** | -0.073*** | -0.073* | -0.073* | -0.073* |
| | (0.032) | (0.027) | (0.043) | (0.041) | (0.042) |
| Target3_5xPost | -0.071** | -0.071*** | -0.071** | -0.071 | -0.071* |
| | (0.032) | (0.025) | (0.035) | (0.050) | (0.040) |
| Target4xPost | -0.027 | -0.027 | -0.027 | -0.027 | -0.027 |
| | (0.028) | (0.024) | (0.047) | (0.051) | (0.044) |
| Target4_5xPost | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 |
| | (0.029) | (0.025) | (0.039) | (0.031) | (0.034) |
| Target5xPost | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (0.028) | (0.024) | (0.038) | (0.029) | (0.037) |

| | | | | | |
|---|---|---|---|---|---|
| *Housing Characteristics* | | | | | |
| logFloorsize | 0.451*** | 0.451*** | 0.451*** | 0.451*** | 0.451*** |
| | (0.015) | (0.012) | (0.028) | (0.036) | (0.032) |
| logParcelsize | 0.193*** | 0.193*** | 0.193*** | 0.193*** | 0.193*** |
| | (0.009) | (0.009) | (0.020) | (0.014) | (0.020) |
| Age | -0.004*** | -0.004*** | -0.004*** | -0.004*** | -0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Frame | -0.117*** | -0.117*** | -0.117*** | -0.117*** | -0.117*** |
| | (0.008) | (0.008) | (0.014) | (0.013) | (0.012) |
| Stone | 0.107* | 0.107* | 0.107** | 0.107*** | 0.107** |
| | (0.056) | (0.057) | (0.048) | (0.033) | (0.053) |
| Stories | 0.245*** | 0.245*** | 0.245*** | 0.245*** | 0.245*** |
| | (0.010) | (0.009) | (0.019) | (0.025) | (0.019) |
| Garages | 0.088*** | 0.088*** | 0.088*** | 0.088*** | 0.088*** |
| | (0.006) | (0.006) | (0.008) | (0.009) | (0.008) |
| Carports | 0.017*** | 0.017*** | 0.017*** | 0.017** | 0.017*** |
| | (0.006) | (0.005) | (0.006) | (0.007) | (0.006) |
| Attic | 0.149*** | 0.149*** | 0.149*** | 0.149*** | 0.149*** |
| | (0.006) | (0.007) | (0.010) | (0.009) | (0.010) |
| *Demographic Characteristics* | | | | | |
| PopDensity | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) |
| Crime | -0.012*** | -0.012*** | -0.012** | -0.012** | -0.012** |
| | (0.004) | (0.003) | (0.006) | (0.005) | (0.005) |
| Black | -0.318*** | -0.318*** | -0.318* | -0.318* | -0.318* |
| | (0.088) | (0.075) | (0.175) | (0.171) | (0.176) |
| Vacancy | -1.157*** | -1.157*** | -1.157** | -1.157*** | -1.157*** |
| | (0.264) | (0.211) | (0.461) | (0.398) | (0.375) |
| Youth | 0.348 | 0.348 | 0.348 | 0.348 | 0.348 |
| | (0.260) | (0.225) | (0.546) | (0.496) | (0.610) |
| MedianIncome | 0.003** | 0.003*** | 0.003 | 0.003 | 0.003 |
| | (0.001) | (0.001) | (0.002) | (0.002) | (0.003) |
| *Market Characteristics* | | | | | |

| | | | | | |
|---|---|---|---|---|---|
| AccFood | 0.008 | 0.008* | 0.008 | 0.008 | 0.008 |
| | (0.005) | (0.005) | (0.008) | (0.007) | (0.008) |
| Finance | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| | (0.004) | (0.003) | (0.006) | (0.007) | (0.006) |
| Retail | -0.016*** | -0.016*** | -0.016** | -0.016** | -0.016** |
| | (0.004) | (0.004) | (0.007) | (0.008) | (0.007) |
| *Urban Characteristics* | | | | | |
| DistancePark | -0.196*** | -0.196*** | -0.196*** | -0.196*** | -0.196*** |
| | (0.015) | (0.015) | (0.048) | (0.054) | (0.049) |
| Local | 0.117*** | 0.117*** | 0.117** | 0.117*** | 0.117** |
| | (0.038) | (0.028) | (0.057) | (0.041) | (0.051) |
| National | 0.070*** | 0.070*** | 0.070 | 0.070 | 0.070* |
| | (0.017) | (0.014) | (0.044) | (0.044) | (0.041) |
| CertifiedLocal | 0.242*** | 0.242*** | 0.242*** | 0.242*** | 0.242*** |
| | (0.034) | (0.028) | (0.075) | (0.071) | (0.067) |
| Conservation | 0.192* | 0.192*** | 0.192 | 0.192 | 0.192 |
| | (0.101) | (0.057) | (0.138) | (0.139) | (0.168) |
| Preservation | 0.115*** | 0.115*** | 0.115** | 0.115*** | 0.115*** |
| | (0.026) | (0.022) | (0.049) | (0.031) | (0.042) |
| Enterprise | 0.006 | 0.006 | 0.006 | 0.006 | 0.006 |
| | (0.014) | (0.012) | (0.041) | (0.045) | (0.038) |
| Flood100 | -0.069** | -0.069** | -0.069 | -0.069* | -0.069** |
| | (0.031) | (0.031) | (0.047) | (0.034) | (0.030) |
| Flood500 | -0.003 | -0.003 | -0.003 | -0.003 | -0.003 |
| | (0.024) | (0.028) | (0.040) | (0.026) | (0.028) |
| DistanceBusch | -0.007 | -0.007 | -0.007 | -0.007 | -0.007 |
| | (0.110) | (0.104) | (0.256) | (0.291) | (0.299) |
| DistanceEC | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 |
| | (0.113) | (0.105) | (0.267) | (0.288) | (0.311) |
| Constant | 6.227*** | 6.227*** | 6.227*** | 6.227*** | 6.227*** |
| | (0.177) | (0.150) | (0.354) | (0.370) | (0.354) |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7580 | 0.7580 | 0.7580 | 0.7580 | 0.7580 |

| Observations | 12695 | 12695 | 12695 | 12695 | 12695 |
|---|---|---|---|---|---|

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

Reference are properties located outside of a 5 mile radius ring around the stadium.

Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 33: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 5 Mile Radius

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.331*** | 0.331*** | 0.331*** | 0.331*** | 0.331*** |
| | (0.050) | (0.048) | (0.053) | (0.046) | (0.053) |
| *Ring Variables* | | | | | |
| Target0_5 | 0.169 | 0.169 | 0.169 | 0.169 | 0.169 |
| | (0.167) | (0.432) | (0.175) | (0.125) | (0.178) |
| Target1 | 0.752*** | 0.752** | 0.752*** | 0.752*** | 0.752* |
| | (0.212) | (0.297) | (0.198) | (0.213) | (0.381) |
| Target1_5 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 |
| | (0.134) | (0.141) | (0.180) | (0.105) | (0.181) |
| Target2_0 | 0.110 | 0.110 | 0.110 | 0.110 | 0.110 |
| | (0.116) | (0.111) | (0.159) | (0.083) | (0.151) |
| Target2_5 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 |
| | (0.094) | (0.090) | (0.125) | (0.077) | (0.122) |
| Target3 | 0.219*** | 0.219*** | 0.219* | 0.219* | 0.219** |
| | (0.075) | (0.072) | (0.124) | (0.106) | (0.094) |
| Target3_5 | 0.166*** | 0.166*** | 0.166** | 0.166* | 0.166** |
| | (0.061) | (0.058) | (0.079) | (0.082) | (0.068) |
| Target4 | 0.074* | 0.074* | 0.074 | 0.074 | 0.074 |
| | (0.041) | (0.040) | (0.055) | (0.047) | (0.053) |
| Target0_5xPost | -0.343*** | -0.343 | -0.343*** | -0.343*** | -0.343*** |
| | (0.119) | (0.247) | (0.059) | (0.059) | (0.050) |
| Target1xPost | -0.190 | -0.190 | -0.190** | -0.190* | -0.190* |
| | (0.130) | (0.338) | (0.078) | (0.106) | (0.095) |
| Target1_5xPost | -0.112 | -0.112 | -0.112** | -0.112* | -0.112** |

| | | | | | |
|---|---|---|---|---|---|
| | (0.092) | (0.111) | (0.046) | (0.056) | (0.053) |
| Target2_0xPost | -0.075* | -0.075 | -0.075 | -0.075** | -0.075* |
| | (0.044) | (0.049) | (0.052) | (0.032) | (0.038) |
| Target2_5xPost | -0.041 | -0.041 | -0.041 | -0.041 | -0.041 |
| | (0.042) | (0.045) | (0.046) | (0.041) | (0.044) |
| Target3xPost | -0.065* | -0.065* | -0.065 | -0.065 | -0.065 |
| | (0.037) | (0.037) | (0.055) | (0.055) | (0.049) |
| Target3_5xPost | -0.069* | -0.069* | -0.069 | -0.069 | -0.069 |
| | (0.039) | (0.035) | (0.050) | (0.061) | (0.050) |
| Target4xPost | -0.025 | -0.025 | -0.025 | -0.025 | -0.025 |
| | (0.035) | (0.034) | (0.053) | (0.044) | (0.043) |
| *Housing Characteristics* | | | | | |
| logFloorsize | 0.541*** | 0.541*** | 0.541*** | 0.541*** | 0.541*** |
| | (0.028) | (0.024) | (0.041) | (0.066) | (0.040) |
| logParcelsize | 0.193*** | 0.193*** | 0.193*** | 0.193*** | 0.193*** |
| | (0.016) | (0.017) | (0.024) | (0.023) | (0.023) |
| Age | -0.003*** | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| Frame | -0.103*** | -0.103*** | -0.103*** | -0.103*** | -0.103*** |
| | (0.030) | (0.025) | (0.031) | (0.019) | (0.025) |
| Stone | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 |
| | (0.127) | (0.111) | (0.089) | (0.079) | (0.136) |
| Stories | 0.139*** | 0.139*** | 0.139*** | 0.139*** | 0.139*** |
| | (0.022) | (0.019) | (0.033) | (0.046) | (0.030) |
| Garages | 0.102*** | 0.102*** | 0.102*** | 0.102*** | 0.102*** |
| | (0.012) | (0.012) | (0.018) | (0.014) | (0.015) |
| Carports | 0.032*** | 0.032*** | 0.032** | 0.032*** | 0.032*** |
| | (0.011) | (0.010) | (0.012) | (0.011) | (0.011) |
| Attic | 0.153*** | 0.153*** | 0.153*** | 0.153*** | 0.153*** |
| | (0.014) | (0.015) | (0.022) | (0.024) | (0.021) |
| *Demographic Characteristics* | | | | | |
| PopDensity | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) |
| Crime | -0.010* | -0.010** | -0.010 | -0.010 | -0.010 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.006) | (0.005) | (0.006) | (0.007) | (0.006) |
| Black | 0.044 | 0.044 | 0.044 | 0.044 | 0.044 |
| | (0.175) | (0.148) | (0.270) | (0.218) | (0.220) |
| Vacancy | -1.923*** | -1.923*** | -1.923*** | -1.923** | -1.923*** |
| | (0.385) | (0.344) | (0.661) | (0.826) | (0.637) |
| Youth | -0.829 | -0.829* | -0.829 | -0.829 | -0.829 |
| | (0.529) | (0.450) | (0.821) | (0.572) | (0.677) |
| MedianIncome | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 |
| | (0.003) | (0.002) | (0.004) | (0.004) | (0.004) |
| *Market Characteristics* | | | | | |
| AccFood | 0.009 | 0.009 | 0.009 | 0.009 | 0.009 |
| | (0.012) | (0.010) | (0.022) | (0.019) | (0.021) |
| Finance | -0.023 | -0.023 | -0.023 | -0.023 | -0.023 |
| | (0.034) | (0.029) | (0.039) | (0.049) | (0.050) |
| Retail | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 |
| | (0.015) | (0.013) | (0.025) | (0.025) | (0.026) |
| *Urban Characteristics* | | | | | |
| DistancePark | -0.354*** | -0.354*** | -0.354*** | -0.354*** | -0.354*** |
| | (0.053) | (0.051) | (0.091) | (0.077) | (0.095) |
| Local | 0.102** | 0.102*** | 0.102 | 0.102** | 0.102 |
| | (0.045) | (0.036) | (0.073) | (0.048) | (0.077) |
| National | 0.109*** | 0.109*** | 0.109** | 0.109** | 0.109** |
| | (0.024) | (0.024) | (0.049) | (0.046) | (0.041) |
| CertifiedLocal | 0.285*** | 0.285*** | 0.285** | 0.285*** | 0.285** |
| | (0.049) | (0.042) | (0.110) | (0.085) | (0.111) |
| Conservation | 0.197* | 0.197*** | 0.197 | 0.197 | 0.197 |
| | (0.103) | (0.068) | (0.121) | (0.141) | (0.164) |
| Preservation | 0.065** | 0.065** | 0.065 | 0.065* | 0.065 |
| | (0.029) | (0.028) | (0.049) | (0.034) | (0.043) |
| Enterprise | -0.050** | -0.050** | -0.050 | -0.050 | -0.050 |
| | (0.023) | (0.023) | (0.045) | (0.044) | (0.045) |
| Flood100 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) |
| Flood500 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

| | (.) | (.) | (.) | (.) | (.) |
|---|---|---|---|---|---|
| DistanceBusch | -0.218 | -0.218 | -0.218 | -0.218 | -0.218 |
| | (0.176) | (0.188) | (0.256) | (0.282) | (0.273) |
| DistanceEC | 0.117 | 0.117 | 0.117 | 0.117 | 0.117 |
| | (0.187) | (0.195) | (0.275) | (0.314) | (0.309) |
| Constant | 7.231*** | 7.231*** | 7.231*** | 7.231*** | 7.231*** |
| | (0.349) | (0.333) | (0.527) | (0.541) | (0.492) |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7857 | 0.7857 | 0.7857 | 0.7857 | 0.7857 |
| Observations | 3768 | 3768 | 3768 | 3768 | 3768 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

Reference are properties located 4-5 miles from the stadium.

Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**Appendix A**

Table 34: Regression Estimates Across Different Error Specifications - One-Mile Distance Rings - 2014-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Post | 0.272*** | 0.272*** | 0.272*** | 0.272*** | 0.272*** |
| | (0.024) | (0.024) | (0.033) | (0.041) | (0.037) |
| Impact1 | 0.942*** | 0.942*** | 0.942*** | 0.942** | 0.942*** |
| | (0.305) | (0.286) | (0.353) | (0.363) | (0.342) |
| Impact2 | 0.336*** | 0.336*** | 0.336* | 0.336* | 0.336* |
| | (0.088) | (0.079) | (0.191) | (0.168) | (0.172) |
| Impact3 | 0.324*** | 0.324*** | 0.324** | 0.324* | 0.324** |
| | (0.068) | (0.060) | (0.161) | (0.159) | (0.149) |
| Impact4 | 0.215*** | 0.215*** | 0.215* | 0.215 | 0.215* |
| | (0.058) | (0.052) | (0.128) | (0.139) | (0.125) |
| Impact5 | -0.005 | -0.005 | -0.005 | -0.005 | -0.005 |
| | (0.042) | (0.040) | (0.106) | (0.110) | (0.102) |
| Impact6 | -0.014 | -0.014 | -0.014 | -0.014 | -0.014 |
| | (0.028) | (0.028) | (0.070) | (0.074) | (0.065) |
| Impact7 | 0.054*** | 0.054** | 0.054 | 0.054 | 0.054 |
| | (0.021) | (0.022) | (0.052) | (0.051) | (0.047) |
| Impact1xPost | -0.393*** | -0.393* | -0.393*** | -0.393*** | -0.393*** |
| | (0.113) | (0.210) | (0.041) | (0.040) | (0.040) |
| Impact2xPost | -0.132*** | -0.132*** | -0.132*** | -0.132*** | -0.132*** |
| | (0.043) | (0.042) | (0.049) | (0.033) | (0.050) |
| Impact3xPost | -0.128*** | -0.128*** | -0.128*** | -0.128*** | -0.128*** |
| | (0.031) | (0.030) | (0.039) | (0.029) | (0.037) |
| Impact4xPost | -0.113*** | -0.113*** | -0.113*** | -0.113** | -0.113*** |
| | (0.029) | (0.027) | (0.034) | (0.046) | (0.039) |
| Impact5xPost | -0.041 | -0.041 | -0.041 | -0.041 | -0.041 |
| | (0.028) | (0.027) | (0.033) | (0.033) | (0.030) |
| Impact6xPost | -0.007 | -0.007 | -0.007 | -0.007 | -0.007 |
| | (0.021) | (0.022) | (0.024) | (0.028) | (0.025) |
| Impact7xPost | -0.051*** | -0.051** | -0.051** | -0.051** | -0.051** |

| | (0.019) | (0.021) | (0.022) | (0.024) | (0.021) |
|---|---|---|---|---|---|
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7608 | 0.7608 | 0.7608 | 0.7608 | 0.7608 |
| Observations | 11048 | 11048 | 11048 | 11048 | 11048 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The sample period is shortened to 2014-2019.
Reference is the outermost distance ring Impact8.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 35: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 2014-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.241*** | 0.241*** | 0.241*** | 0.241*** | 0.241*** |
| | (0.019) | (0.016) | (0.029) | (0.035) | (0.030) |
| Target2 | 0.496*** | 0.496*** | 0.496** | 0.496*** | 0.496*** |
| | (0.106) | (0.087) | (0.206) | (0.137) | (0.166) |
| Target2_5 | 0.494*** | 0.494*** | 0.494*** | 0.494*** | 0.494*** |
| | (0.088) | (0.074) | (0.172) | (0.109) | (0.145) |
| Target3 | 0.481*** | 0.481*** | 0.481*** | 0.481*** | 0.481*** |
| | (0.076) | (0.064) | (0.171) | (0.127) | (0.145) |
| Target3_5 | 0.381*** | 0.381*** | 0.381*** | 0.381*** | 0.381*** |
| | (0.067) | (0.057) | (0.128) | (0.096) | (0.116) |
| Target4 | 0.315*** | 0.315*** | 0.315*** | 0.315*** | 0.315*** |
| | (0.056) | (0.048) | (0.115) | (0.092) | (0.107) |
| Target4_5 | 0.098** | 0.098** | 0.098 | 0.098 | 0.098 |
| | (0.043) | (0.038) | (0.088) | (0.064) | (0.082) |
| Target5 | 0.007 | 0.007 | 0.007 | 0.007 | 0.007 |
| | (0.035) | (0.029) | (0.088) | (0.092) | (0.094) |
| Target2xPost | -0.108*** | -0.108*** | -0.108** | -0.108*** | -0.108** |
| | (0.040) | (0.038) | (0.046) | (0.026) | (0.044) |

| | | | | | |
|---|---|---|---|---|---|
| Target2_5xPost | -0.127*** | -0.127*** | -0.127*** | -0.127*** | -0.127*** |
| | (0.042) | (0.039) | (0.041) | (0.027) | (0.034) |
| Target3xPost | -0.085** | -0.085*** | -0.085* | -0.085* | -0.085* |
| | (0.035) | (0.030) | (0.044) | (0.047) | (0.050) |
| Target3_5xPost | -0.102*** | -0.102*** | -0.102*** | -0.102* | -0.102** |
| | (0.034) | (0.028) | (0.033) | (0.051) | (0.042) |
| Target4xPost | -0.069** | -0.069** | -0.069 | -0.069 | -0.069 |
| | (0.032) | (0.027) | (0.048) | (0.057) | (0.045) |
| Target4_5xPost | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | (0.031) | (0.028) | (0.037) | (0.036) | (0.037) |
| Target5xPost | -0.023 | -0.023 | -0.023 | -0.023 | -0.023 |
| | (0.032) | (0.028) | (0.039) | (0.029) | (0.032) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7607 | 0.7607 | 0.7607 | 0.7607 | 0.7607 |
| Observations | 11048 | 11048 | 11048 | 11048 | 11048 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The sample period is shortened to 2014-2019.
Reference are properties located outside of a 5 mile radius ring around the stadium.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 36: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 5 Mile Radius & 2014-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Post | 0.214*** | 0.214*** | 0.214*** | 0.214*** | 0.214*** |
| | (0.038) | (0.037) | (0.049) | (0.055) | (0.046) |
| Target0_5 | 0.198 | 0.198 | 0.198 | 0.198 | 0.198 |
| | (0.174) | (0.429) | (0.171) | (0.128) | (0.179) |
| Target1 | 0.620** | 0.620** | 0.620*** | 0.620*** | 0.620* |
| | (0.254) | (0.309) | (0.206) | (0.209) | (0.339) |
| Target1_5 | 0.121 | 0.121 | 0.121 | 0.121 | 0.121 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.144) | (0.153) | (0.190) | (0.120) | (0.178) |
| Target2_0 | 0.118 | 0.118 | 0.118 | 0.118 | 0.118 |
| | (0.127) | (0.120) | (0.168) | (0.095) | (0.154) |
| Target2_5 | 0.160 | 0.160* | 0.160 | 0.160* | 0.160 |
| | (0.099) | (0.097) | (0.130) | (0.085) | (0.126) |
| Target3 | 0.244*** | 0.244*** | 0.244* | 0.244** | 0.244** |
| | (0.080) | (0.077) | (0.124) | (0.111) | (0.105) |
| Target3_5 | 0.204*** | 0.204*** | 0.204** | 0.204** | 0.204*** |
| | (0.066) | (0.063) | (0.081) | (0.094) | (0.072) |
| Target4 | 0.116** | 0.116** | 0.116** | 0.116** | 0.116* |
| | (0.047) | (0.046) | (0.055) | (0.052) | (0.060) |
| Target0_5xPost | -0.359*** | -0.359 | -0.359*** | -0.359*** | -0.359*** |
| | (0.121) | (0.245) | (0.056) | (0.061) | (0.050) |
| Target1xPost | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) |
| Target1_5xPost | -0.125 | -0.125 | -0.125* | -0.125** | -0.125* |
| | (0.090) | (0.119) | (0.070) | (0.054) | (0.068) |
| Target2_0xPost | -0.071 | -0.071 | -0.071 | -0.071* | -0.071 |
| | (0.050) | (0.055) | (0.062) | (0.035) | (0.061) |
| Target2_5xPost | -0.102** | -0.102** | -0.102* | -0.102** | -0.102** |
| | (0.046) | (0.051) | (0.051) | (0.040) | (0.044) |
| Target3xPost | -0.074* | -0.074* | -0.074 | -0.074 | -0.074 |
| | (0.040) | (0.040) | (0.055) | (0.062) | (0.056) |
| Target3_5xPost | -0.097** | -0.097** | -0.097* | -0.097 | -0.097** |
| | (0.042) | (0.040) | (0.050) | (0.066) | (0.048) |
| Target4xPost | -0.057 | -0.057 | -0.057 | -0.057 | -0.057 |
| | (0.040) | (0.039) | (0.056) | (0.049) | (0.046) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7821 | 0.7821 | 0.7821 | 0.7821 | 0.7821 |
| Observations | 3309 | 3309 | 3309 | 3309 | 3309 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
Reference are properties located 4-5 miles from the stadium.
The sample period is shortened to 2014-2019.

The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 37: Regression Estimates Across Different Error Specifications - One-Mile Distance Rings - 2015-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.202*** | 0.202*** | 0.202*** | 0.202*** | 0.202*** |
| | (0.026) | (0.026) | (0.030) | (0.031) | (0.026) |
| Impact1 | 0.842*** | 0.842*** | 0.842*** | 0.842** | 0.842*** |
| | (0.298) | (0.314) | (0.318) | (0.354) | (0.314) |
| Impact2 | 0.376*** | 0.376*** | 0.376** | 0.376** | 0.376** |
| | (0.098) | (0.087) | (0.189) | (0.167) | (0.164) |
| Impact3 | 0.355*** | 0.355*** | 0.355** | 0.355** | 0.355** |
| | (0.076) | (0.067) | (0.164) | (0.159) | (0.152) |
| Impact4 | 0.238*** | 0.238*** | 0.238* | 0.238* | 0.238* |
| | (0.066) | (0.058) | (0.134) | (0.139) | (0.125) |
| Impact5 | -0.030 | -0.030 | -0.030 | -0.030 | -0.030 |
| | (0.049) | (0.046) | (0.103) | (0.108) | (0.099) |
| Impact6 | -0.042 | -0.042 | -0.042 | -0.042 | -0.042 |
| | (0.033) | (0.033) | (0.068) | (0.069) | (0.059) |
| Impact7 | 0.048* | 0.048* | 0.048 | 0.048 | 0.048 |
| | (0.026) | (0.027) | (0.047) | (0.043) | (0.037) |
| Impact1xPost | -0.322*** | -0.322 | -0.322*** | -0.322*** | -0.322*** |
| | (0.100) | (0.241) | (0.042) | (0.036) | (0.039) |
| Impact2xPost | -0.127** | -0.127** | -0.127** | -0.127*** | -0.127** |
| | (0.052) | (0.051) | (0.057) | (0.028) | (0.053) |
| Impact3xPost | -0.117*** | -0.117*** | -0.117** | -0.117*** | -0.117** |
| | (0.037) | (0.036) | (0.053) | (0.026) | (0.044) |
| Impact4xPost | -0.106*** | -0.106*** | -0.106*** | -0.106** | -0.106*** |
| | (0.035) | (0.033) | (0.034) | (0.040) | (0.039) |
| Impact5xPost | -0.024 | -0.024 | -0.024 | -0.024 | -0.024 |
| | (0.035) | (0.032) | (0.033) | (0.031) | (0.028) |
| Impact6xPost | 0.012 | 0.012 | 0.012 | 0.012 | 0.012 |
| | (0.026) | (0.027) | (0.023) | (0.027) | (0.025) |

| | | | | | |
|---|---|---|---|---|---|
| Impact7xPost | -0.048** | -0.048* | -0.048*** | -0.048** | -0.048*** |
| | (0.024) | (0.026) | (0.017) | (0.017) | (0.014) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7540 | 0.7540 | 0.7540 | 0.7540 | 0.7540 |
| Observations | 9730 | 9730 | 9730 | 9730 | 9730 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The sample period is shortened to 2015-2019.
Reference is the outermost distance ring Impact8.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 38: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 2015-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.176*** | 0.176*** | 0.176*** | 0.176*** | 0.176*** |
| | (0.019) | (0.016) | (0.032) | (0.034) | (0.034) |
| Target2 | 0.548*** | 0.548*** | 0.548** | 0.548*** | 0.548*** |
| | (0.118) | (0.095) | (0.213) | (0.143) | (0.166) |
| Target2_5 | 0.522*** | 0.522*** | 0.522*** | 0.522*** | 0.522*** |
| | (0.100) | (0.084) | (0.181) | (0.110) | (0.152) |
| Target3 | 0.544*** | 0.544*** | 0.544*** | 0.544*** | 0.544*** |
| | (0.085) | (0.070) | (0.183) | (0.130) | (0.153) |
| Target3_5 | 0.429*** | 0.429*** | 0.429*** | 0.429*** | 0.429*** |
| | (0.075) | (0.063) | (0.141) | (0.094) | (0.123) |
| Target4 | 0.364*** | 0.364*** | 0.364*** | 0.364*** | 0.364*** |
| | (0.067) | (0.055) | (0.128) | (0.105) | (0.119) |
| Target4_5 | 0.080 | 0.080* | 0.080 | 0.080 | 0.080 |
| | (0.050) | (0.044) | (0.086) | (0.064) | (0.083) |
| Target5 | 0.021 | 0.021 | 0.021 | 0.021 | 0.021 |
| | (0.045) | (0.036) | (0.091) | (0.098) | (0.096) |
| Target2xPost | -0.115** | -0.115** | -0.115** | -0.115*** | -0.115** |

| | | | | | |
|---|---|---|---|---|---|
| | (0.047) | (0.046) | (0.054) | (0.026) | (0.047) |
| Target2_5xPost | -0.109** | -0.109** | -0.109* | -0.109* | -0.109** |
| | (0.051) | (0.049) | (0.058) | (0.062) | (0.042) |
| Target3xPost | -0.092** | -0.092*** | -0.092 | -0.092* | -0.092 |
| | (0.041) | (0.035) | (0.058) | (0.048) | (0.060) |
| Target3_5xPost | -0.104*** | -0.104*** | -0.104*** | -0.104** | -0.104*** |
| | (0.040) | (0.034) | (0.035) | (0.044) | (0.037) |
| Target4xPost | -0.071* | -0.071** | -0.071 | -0.071 | -0.071 |
| | (0.042) | (0.035) | (0.057) | (0.066) | (0.058) |
| Target4_5xPost | 0.029 | 0.029 | 0.029 | 0.029 | 0.029 |
| | (0.038) | (0.033) | (0.033) | (0.043) | (0.046) |
| Target5xPost | -0.037 | -0.037 | -0.037 | -0.037 | -0.037 |
| | (0.041) | (0.034) | (0.046) | (0.031) | (0.032) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7539 | 0.7539 | 0.7539 | 0.7539 | 0.7539 |
| Observations | 9730 | 9730 | 9730 | 9730 | 9730 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The sample period is shortened to 2015-2019.
Reference are properties located outside of a 5 mile radius ring around the stadium.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 39: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 5 Mile Radius & 2015-2019

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Post | 0.168*** | 0.168*** | 0.168*** | 0.168*** | 0.168*** |
| | (0.039) | (0.038) | (0.052) | (0.057) | (0.056) |
| Target0_5 | 0.135 | 0.135 | 0.135 | 0.135 | 0.135 |
| | (0.175) | (0.457) | (0.164) | (0.123) | (0.169) |
| Target1 | 0.516 | 0.516 | 0.516** | 0.516* | 0.516 |
| | (0.336) | (0.336) | (0.198) | (0.282) | (0.401) |

| | | | | | |
|---|---|---|---|---|---|
| Target1_5 | 0.112 | 0.112 | 0.112 | 0.112 | 0.112 |
| | (0.153) | (0.181) | (0.187) | (0.133) | (0.193) |
| Target2_0 | 0.154 | 0.154 | 0.154 | 0.154 | 0.154 |
| | (0.144) | (0.134) | (0.173) | (0.116) | (0.168) |
| Target2_5 | 0.169 | 0.169 | 0.169 | 0.169 | 0.169 |
| | (0.114) | (0.111) | (0.135) | (0.099) | (0.138) |
| Target3 | 0.286*** | 0.286*** | 0.286** | 0.286** | 0.286** |
| | (0.092) | (0.087) | (0.137) | (0.132) | (0.118) |
| Target3_5 | 0.244*** | 0.244*** | 0.244** | 0.244** | 0.244*** |
| | (0.078) | (0.073) | (0.102) | (0.104) | (0.083) |
| Target4 | 0.154** | 0.154*** | 0.154** | 0.154** | 0.154** |
| | (0.060) | (0.057) | (0.069) | (0.067) | (0.074) |
| Target0_5xPost | -0.292*** | -0.292 | -0.292*** | -0.292*** | -0.292*** |
| | (0.111) | (0.282) | (0.055) | (0.050) | (0.047) |
| Target1xPost | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) |
| Target1_5xPost | -0.143 | -0.143 | -0.143*** | -0.143*** | -0.143*** |
| | (0.090) | (0.149) | (0.040) | (0.042) | (0.046) |
| Target2_0xPost | -0.087 | -0.087 | -0.087 | -0.087* | -0.087 |
| | (0.064) | (0.065) | (0.069) | (0.041) | (0.068) |
| Target2_5xPost | -0.097* | -0.097 | -0.097 | -0.097 | -0.097* |
| | (0.057) | (0.063) | (0.067) | (0.075) | (0.051) |
| Target3xPost | -0.090* | -0.090* | -0.090 | -0.090 | -0.090 |
| | (0.048) | (0.048) | (0.070) | (0.061) | (0.069) |
| Target3_5xPost | -0.118** | -0.118** | -0.118** | -0.118* | -0.118** |
| | (0.050) | (0.048) | (0.057) | (0.067) | (0.046) |
| Target4xPost | -0.069 | -0.069 | -0.069 | -0.069 | -0.069 |
| | (0.050) | (0.048) | (0.058) | (0.053) | (0.056) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7751 | 0.7751 | 0.7751 | 0.7751 | 0.7751 |
| Observations | 2901 | 2901 | 2901 | 2901 | 2901 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

Reference are properties located 4-5 miles from the stadium.

The sample period is shortened to 2015-2019.
Target1xPost, Flood1, & Flood2 were omitted due to collinearity.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 40: Regression Estimates Across Different Error Specifications - One-Mile Distance Rings - 2014-2018

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.231*** | 0.231*** | 0.231*** | 0.231*** | 0.231*** |
| | (0.024) | (0.025) | (0.031) | (0.035) | (0.033) |
| Impact1 | 1.118*** | 1.118*** | 1.118** | 1.118** | 1.118** |
| | (0.415) | (0.328) | (0.476) | (0.459) | (0.442) |
| Impact2 | 0.346*** | 0.346*** | 0.346 | 0.346* | 0.346* |
| | (0.104) | (0.090) | (0.225) | (0.180) | (0.198) |
| Impact3 | 0.340*** | 0.340*** | 0.340* | 0.340* | 0.340** |
| | (0.080) | (0.070) | (0.186) | (0.179) | (0.170) |
| Impact4 | 0.197*** | 0.197*** | 0.197 | 0.197 | 0.197 |
| | (0.066) | (0.059) | (0.136) | (0.143) | (0.136) |
| Impact5 | -0.007 | -0.007 | -0.007 | -0.007 | -0.007 |
| | (0.048) | (0.045) | (0.117) | (0.118) | (0.116) |
| Impact6 | -0.016 | -0.016 | -0.016 | -0.016 | -0.016 |
| | (0.030) | (0.031) | (0.076) | (0.077) | (0.071) |
| Impact7 | 0.050** | 0.050** | 0.050 | 0.050 | 0.050 |
| | (0.022) | (0.023) | (0.055) | (0.055) | (0.052) |
| Impact1xPost | -0.528*** | -0.528** | -0.528*** | -0.528*** | -0.528*** |
| | (0.109) | (0.234) | (0.066) | (0.062) | (0.060) |
| Impact2xPost | -0.099** | -0.099** | -0.099** | -0.099*** | -0.099* |
| | (0.045) | (0.046) | (0.044) | (0.034) | (0.050) |
| Impact3xPost | -0.109*** | -0.109*** | -0.109** | -0.109*** | -0.109*** |
| | (0.034) | (0.032) | (0.042) | (0.030) | (0.036) |
| Impact4xPost | -0.109*** | -0.109*** | -0.109*** | -0.109** | -0.109*** |
| | (0.031) | (0.029) | (0.034) | (0.043) | (0.039) |
| Impact5xPost | -0.033 | -0.033 | -0.033 | -0.033 | -0.033 |
| | (0.030) | (0.029) | (0.029) | (0.026) | (0.023) |

| | | | | | |
|---|---|---|---|---|---|
| Impact6xPost | -0.004 | -0.004 | -0.004 | -0.004 | -0.004 |
| | (0.023) | (0.024) | (0.025) | (0.025) | (0.023) |
| Impact7xPost | -0.046** | -0.046** | -0.046** | -0.046* | -0.046** |
| | (0.021) | (0.023) | (0.021) | (0.024) | (0.020) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7662 | 0.7662 | 0.7662 | 0.7662 | 0.7662 |
| Observations | 8030 | 8030 | 8030 | 8030 | 8030 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

The sample period is shortened to 01.01.2014 - 04.07.2018.

Reference is the outermost distance ring Impact8.

The full regression results are available from the author.

Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 41: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 2014-2018

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) Robust | (2) OLS | (3) Census Tract | (4) Ward | (5) Neighborhood |
| Post | 0.206*** | 0.206*** | 0.206*** | 0.206*** | 0.206*** |
| | (0.018) | (0.017) | (0.026) | (0.033) | (0.028) |
| Target2 | 0.564*** | 0.564*** | 0.564** | 0.564*** | 0.564*** |
| | (0.119) | (0.100) | (0.240) | (0.138) | (0.188) |
| Target2_5 | 0.541*** | 0.541*** | 0.541*** | 0.541*** | 0.541*** |
| | (0.099) | (0.085) | (0.199) | (0.124) | (0.166) |
| Target3 | 0.507*** | 0.507*** | 0.507** | 0.507*** | 0.507*** |
| | (0.089) | (0.074) | (0.196) | (0.152) | (0.167) |
| Target3_5 | 0.358*** | 0.358*** | 0.358** | 0.358*** | 0.358*** |
| | (0.076) | (0.065) | (0.136) | (0.104) | (0.127) |
| Target4 | 0.308*** | 0.308*** | 0.308** | 0.308*** | 0.308*** |
| | (0.063) | (0.054) | (0.121) | (0.100) | (0.114) |
| Target4_5 | 0.105** | 0.105** | 0.105 | 0.105 | 0.105 |
| | (0.048) | (0.042) | (0.100) | (0.080) | (0.095) |
| Target5 | 0.012 | 0.012 | 0.012 | 0.012 | 0.012 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.039) | (0.031) | (0.096) | (0.104) | (0.105) |
| Target2xPost | -0.079* | -0.079* | -0.079* | -0.079*** | -0.079* |
| | (0.042) | (0.042) | (0.040) | (0.028) | (0.042) |
| Target2_5xPost | -0.075* | -0.075* | -0.075* | -0.075*** | -0.075** |
| | (0.042) | (0.042) | (0.043) | (0.013) | (0.031) |
| Target3xPost | -0.091** | -0.091*** | -0.091 | -0.091** | -0.091* |
| | (0.039) | (0.033) | (0.055) | (0.044) | (0.050) |
| Target3_5xPost | -0.111*** | -0.111*** | -0.111*** | -0.111** | -0.111** |
| | (0.038) | (0.031) | (0.037) | (0.049) | (0.055) |
| Target4xPost | -0.058* | -0.058* | -0.058 | -0.058 | -0.058 |
| | (0.033) | (0.030) | (0.046) | (0.047) | (0.039) |
| Target4_5xPost | 0.017 | 0.017 | 0.017 | 0.017 | 0.017 |
| | (0.034) | (0.030) | (0.029) | (0.032) | (0.031) |
| Target5xPost | -0.028 | -0.028 | -0.028 | -0.028 | -0.028 |
| | (0.035) | (0.030) | (0.038) | (0.025) | (0.030) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7662 | 0.7662 | 0.7662 | 0.7662 | 0.7662 |
| Observations | 8030 | 8030 | 8030 | 8030 | 8030 |

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
The sample period is shortened to 01.01.2014 - 04.07.2018.
Reference are properties located outside of a 5 mile radius ring around the stadium.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 42: Regression Estimates Across Different Error Specifications - Half-Mile Distance Rings - 5 Mile Radius & 2014-2018

| | Robust Se | Normal Se | Clustered Se | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Robust | OLS | Census Tract | Ward | Neighborhood |
| Post | 0.208*** | 0.208*** | 0.208*** | 0.208*** | 0.208*** |
| | (0.041) | (0.040) | (0.045) | (0.049) | (0.036) |
| Target0_5 | 0.472** | 0.472 | 0.472** | 0.472*** | 0.472** |
| | (0.193) | (0.441) | (0.231) | (0.151) | (0.216) |

| | | | | | |
|---|---|---|---|---|---|
| Target1 | 0.987*** | 0.987** | 0.987*** | 0.987*** | 0.987*** |
| | (0.279) | (0.402) | (0.299) | (0.126) | (0.321) |
| Target1_5 | 0.156 | 0.156 | 0.156 | 0.156 | 0.156 |
| | (0.162) | (0.169) | (0.245) | (0.121) | (0.215) |
| Target2_0 | 0.144 | 0.144 | 0.144 | 0.144* | 0.144 |
| | (0.145) | (0.134) | (0.225) | (0.079) | (0.197) |
| Target2_5 | 0.204* | 0.204* | 0.204 | 0.204*** | 0.204 |
| | (0.113) | (0.109) | (0.177) | (0.068) | (0.161) |
| Target3 | 0.264*** | 0.264*** | 0.264 | 0.264** | 0.264* |
| | (0.093) | (0.087) | (0.159) | (0.111) | (0.136) |
| Target3_5 | 0.177** | 0.177** | 0.177** | 0.177** | 0.177** |
| | (0.071) | (0.070) | (0.084) | (0.072) | (0.084) |
| Target4 | 0.093* | 0.093* | 0.093* | 0.093* | 0.093* |
| | (0.049) | (0.049) | (0.053) | (0.045) | (0.055) |
| Target0_5xPost | -0.507*** | -0.507* | -0.507*** | -0.507*** | -0.507*** |
| | (0.127) | (0.268) | (0.072) | (0.068) | (0.057) |
| Target1xPost | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (.) | (.) | (.) | (.) | (.) |
| Target1_5xPost | -0.146 | -0.146 | -0.146* | -0.146** | -0.146 |
| | (0.118) | (0.156) | (0.074) | (0.062) | (0.104) |
| Target2_0xPost | -0.043 | -0.043 | -0.043 | -0.043 | -0.043 |
| | (0.053) | (0.058) | (0.054) | (0.031) | (0.056) |
| Target2_5xPost | -0.056 | -0.056 | -0.056 | -0.056** | -0.056* |
| | (0.048) | (0.053) | (0.048) | (0.022) | (0.033) |
| Target3xPost | -0.091** | -0.091** | -0.091 | -0.091 | -0.091* |
| | (0.045) | (0.044) | (0.063) | (0.055) | (0.054) |
| Target3_5xPost | -0.108** | -0.108** | -0.108** | -0.108* | -0.108* |
| | (0.045) | (0.042) | (0.047) | (0.061) | (0.059) |
| Target4xPost | -0.036 | -0.036 | -0.036 | -0.036 | -0.036 |
| | (0.041) | (0.041) | (0.052) | (0.040) | (0.043) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Census Tract FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.7972 | 0.7972 | 0.7972 | 0.7972 | 0.7972 |
| Observations | 2379 | 2379 | 2379 | 2379 | 2379 |

The coefficients are estimated as ordinary least squares.

The dependent variable is the natural logarithm of the recorded transaction price.

Reference are properties located 4-5 miles from the stadium.

The sample period is shortened to 01.01.2014 - 04.07.2018.

The full regression results are available from the author.

Standard errors are depicted in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

## Supplementary Tables

Table 43: Supplementary Variable Definitions

| Variable | Description |
|---|---|
| *Target Variables* | |
| Distance | Distance in miles to the Edward Jones Dome |
| PostxDistance | Interaction term of Post and Distance |
| *Demographic Characteristics* | |
| Asian | Share of the Asian population, neighborhood level |
| Hispanic | Share of the Hispanic population, neighborhood level |
| Academic | Share of the population holding an academic degree, zip-code level |
| Commutes | Average time to work, zip-code level |
| HHsize | Average household size, zip-code level |
| Ownership | Share of owner-occupied housing, zip-code level |
| PersonCrime | Crimes against the person per 1000 people$/10$, neighborhood level |
| PropertyCrime | Property crimes per 1000 people$/10$, neighborhood level |
| *Market Characteristics* | |
| Unemployment | Unemployment rate of the population 16 years or older, zip-code level |
| Payroll | Annual payroll in $, zip-code level |
| *Urban Characteristics* | |
| Empowerment | Dummy for houses within an Empowerment Zone, (1 = Yes) |
| ParkRing | Dummy for houses located within 600 feet distance to a park (1 = Yes) |
| DistancePark2 | Squared Distance to the closest urban park in miles |
| North | Dummy for houses located north of Delmar Boulevard (1 = Yes) |

Table 44: Supplementary Summary Statistics

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| *Target Variables* | | | | |
| Distance | 5.44 | 1.47 | 0.31 | 7.81 |
| PostxDistance | 3.36 | 2.88 | 0.00 | 7.81 |
| *Demographic Characteristics* | | | | |
| Asian | 0.04 | 0.03 | 0.00 | 0.17 |
| Hispanic | 0.05 | 0.03 | 0.00 | 0.13 |
| Academic | 46.66 | 21.21 | 5.70 | 98.10 |
| Commutes | 23.46 | 2.40 | 15.80 | 31.80 |
| HHsize | 2.13 | 0.19 | 1.52 | 2.79 |
| Ownership | 51.88 | 10.00 | 8.70 | 74.30 |
| PersonCrime | 7.81 | 7.34 | 0.00 | 152.77 |
| PropertyCrime | 43.36 | 19.33 | 18.57 | 305.54 |
| *Market Characteristics* | | | | |
| Payroll | 409,226.50 | 386,047.27 | 36,765.00 | 3,005,552.00 |
| Unemployment | 28.61 | 5.63 | 15.30 | 52.10 |
| *Urban Characteristics* | | | | |
| ParkRing | 0.16 | 0.36 | 0.00 | 1.00 |
| North | 0.06 | 0.23 | 0.00 | 1.00 |
| Empowerment | 0.04 | 0.19 | 0.00 | 1.00 |
| Observations | 12695 | | | |

Additional explanatory variables used in the Appendix.