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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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Abstract

We exploit the relocation of the NFL's Rams franchise as a natural experiment to estimate the effect of proximity on residential property values using hedonic regression models. For a sample of single-family homes transacted within St. Louis between 2012-2019, we find 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 total welfare loss suggest that the intangible benefits emanated by a major league sports franchise may be large enough to justify generous public subsidies for the construction or maintenance of professional sports facilities.

Key words

Hedonic Price Models; Sports Facility; Property Values; Spatial Externalities; NFL; St. Louis

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1 Why Should I Read This Research?

The main contributions of this thesis can be summarized as follows:

I It constitutes the first empirical examination of the impact of the departure of an NFL franchise on residential property values

We explore the relocation of the NFL's Rams franchise in 2016 from St. Louis as a natural experiment to quantify the welfare loss associated with the team's departure. Hitherto, only one paper has analyzed the relocation of two NBA franchises and found significant property value appreciations after the teams left, suggesting that major league sports teams might constitute considerable urban disamenities. However, an NFL franchise might affect the local market differently because the NFL exhibits by far the largest revenue streams of all major leagues, and congestion effects might be considerably lower as an average season consists of only eight home matches, as opposed to over forty games played per NBA, MLB, & NHL home season.

II It provides substantial evidence of large amenity benefits associated with hosting a major league franchise

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 welfare loss amounting up to 520 million $, expressed in 2023 prices. Essentially, this sum is roughly comparable in magnitude to the public funds initially provided for the stadium construction in order to attract the Rams, which was about 550 million $. Therefore, our case study provides evidence that major league sports franchises can produce sufficiently large intangible benefits to justify public subsidization of sports facilities. This may be especially relevant in a context of distressed markets and deserted city cores, where sports teams can take on a central role as catalysts of urban revitalization.

III It accounts for a plethora of property value-shaping urban characteristics typically unaccounted for in the hedonic literature

We control for important urban and geographical characteristics, such as historical designation, zoning, floodplains, and proximity to urban parks, which have been found to have an impact on property prices, respectively. However, only a few related papers in the hedonic literature have accounted for such urban amenities. We exploit a unique geospatial dataset to obtain information on the urban composition of St. Louis, which allows us to minimize the likelihood of omitted-variable bias and address common methodological concerns related to hedonic regression models such as the Age-Period-Cohort Problem.

2 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 a major league host city, which was and still is ubiquitously considered a pivotal status criteria distinguishing top-tier cities. Importantly, aiming to lure in major league franchises, public entities often provided massive public subsidies of several hundred million dollars to largely or even entirely cover the construction costs of a new facility. Stadium proponents typically justify such subsidies arguing that sports facilities generate considerable economic spillover effects within the local economy, for example in terms of income revenue streams and additional 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. Coates (2007)).

Intriguingly, despite 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.[1] 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 might be above all team owners because franchise values have skyrocketed recently.[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 suggests that the direct economic impact of stadiums does not justify public subsidization, it might 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. Typical sports-related benefits include a higher living quality, increased civic pride, or a feeling of social cohesion. If sufficiently large, such amenity benefits might justify generous public subsidies on sports facilities.

Against this background, this thesis explores the intangible 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, Hurt (2021) reports that since the early 1990's, St. Louis polit-

[1] Nowadays, it is not uncommon that the costs for a new major league stadium exceed the billion dollar mark.

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

ical and economic leaders have incrementally embraced a sports-led urban development strategy, whereby sports facilities play a crucial role in promoting entertainment and tourism, and revitalizing the city core's urban landscape as imposing urban landmarks. 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 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 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 welfare loss. To approximate the social costs of 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 Edward Jones Dome, the stadium in which the Rams played from 1995-2015.

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 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 to the market and compare the changes in transaction prices of single-family homes located in vicinity to the stadium to those of properties with similar features located farther away, for the period of 2012-2019. Specifically, we use a difference-in-difference methodology and embed distance rings within hedonic regression models to estimate the relative change in the valuation of residential proximity to the facility.

Ultimately, this thesis contributes to the literature, as it is the first empirical assessment of the effect of the relocation of an NFL franchise on residential property values. To our knowledge, only one paper by Humphreys and Nowak (2017) has hitherto examined the net effect of a team departure on property values in the context of the relocation of two NBA teams. The authors find that property values in Seattle and Charlotte respectively appreciated about 6-7% & 7.5-14% within a one- and

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

[4]C.f. ExploreStLouis.com

two-mile impact area after the relocation, implying that the franchises created disamenities in the local market. In line with their paper, the relocation of the Rams enables us to disentangle the team- from the facility effect, as the Edward Jones Dome was likewise uninterruptedly used as a venue for concerts and conventions throughout the entire sample period.

In this vein, only two other papers have investigated pure team effects prior to this thesis. Firstly, 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%. Secondly, Chikish et al. (2019) study the case of 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 for the non-sports related events they host, or for the surrounding environment of bars and shops for example.

Intriguingly, in contrast to the previous findings, our hedonic model suggests that the Rams' relocation has induced a considerable depreciation in single-family home values of about 7.5% within three-miles from the facility. Additionally, an approximation of the net social costs of the relocation reveals that the welfare loss of the relocation is somewhat comparable in magnitude to the public subsidies provided for the construction of Edward Jones Dome. We contend that the differing findings can be potentially explained by differences in league structures, but might above all be linked to the particular circumstances of the cases under investigation. In this regard, we posit that the purposeful embeddedness of sports facilities into the city core's urban fabric entrenched the bond between sports and St. Louis residents and led to the solidification of substantial amenity benefits. Moreover, St. Louis' distressed economic situation has allowed sports to take a central role in urban revitalization, whereas the previously examined cases of Seattle and Charlotte both exhibited signs of market saturation, which might explain the predominance of congestion effects. Finally, we conclude that public investments in sports teams and sports facilities can be a useful tool in the policymakers toolbox when included in a well-planned sports-led urban development strategy that fits the context and local needs.

This thesis is organized as follows: Section 3 provides a thorough review of the related literature. In Section 4, we introduce our methodology, and in Section 5, we describe the data and variable selection. Section 6 presents the results, and Section 7 concludes and derives policy implications. Finally, we test for the robustness of the results through several robustness checks, which are presented in the Appendix.

3 Literature Review

This section provides a thorough review of the related literature and specifically highlights prior research on externalities generated by the sports industry. For a comprehensive literature review, especially on the direct economic impacts of sports facilities and sports teams, we recommend to read Bradbury et al. (2022) who provide an excellent survey on the subject. If not otherwise stated, their paper constitutes the primary source of reference for the information presented in this section.

Upfront, it is worth noting that the literature has a strong focus on the United States, primarily due to data availability and the structure of the American franchise system. In the US, public subsidies for sports facilities constitute an almost indispensable prerequisite to attract major league sports teams. In contrast, in Europe, teams are usually bound to one specific location, and stadiums are largely privately funded (Gayant (2016)). In this vein, despite the constant expansion of major leagues over time, there still exists an excess demand for major league teams, resulting in intense competition among large municipalities in the US.[5] For cities that are already hosting major league teams, the threat of relocation leverages team's bargaining power and allows to exploit large public subsidies for new or already existing facilities (Humphreys and Zhou (2015)). 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)).

Firstly, there is a vast literature studying the direct economic impacts of sports facilities on the local economy. While typically, ex-ante impact studies conducted by stadium boosters promote stadium constructions stressing large economic spillover effects of stadiums on other related industries, academic ex-post evaluations of stadium constructions reveal quite clearly that stadiums do not yield a significant surplus value. Importantly, the economic impotence of sports has been repeatedly demonstrated in different locations, for different leagues, and at different geographical scale-levels (e.g. see Baade and Dye (1988), Noll and Zimbalist (1997), & Coates (2007) for early surveys on the subject). In short, the overwhelming consensus in the academic literature is that the presence of a major major league sports team seems to neither harm nor benefit the local economy in terms of income, wages, or tax revenue. In this vein, the most common explanation for the null-findings is that sports amenities lead to crowding-out and serve as a substitute rather than a complement to other above all recreational industries.
Simply explained, consumers tend to spend money on spectator sports, that they would have otherwise spent on going to the theater, for example (Coates and Humphreys (2003), Matheson and Baade (2005)).[6] Therefore, while sports subsidies may not improve the allocational efficiency of the market, they do have a significant impact on the distribution of economic activity. Such interventions into the market benefit sports-related industries but can negatively affect non-complementary sectors. For example, Coates and Humphreys (2011) find that hosting an NFL franchise is associ-

[5] Nunn and Rosentraub (1997) note that even within the same metropolitan area, the central city often competes against richer suburbs concerning the concrete site of a new major league stadium.

[6] It is argued that ex-ante impact studies often fail to account for such transfers of economic activity across industries, which is why they typically overestimate the economic surpluses generated by the sports industry.

ated with higher earnings in the sports-related amusement and recreation sector, but this effect is counteracted by decreased earnings and employment in other industries. Additionally, Abbiasov and Sedov (2023) show that NFL and MLB match days lead to increased visits to nearby accommodation, food, and retail businesses.

Against the background of the overwhelmingly insignificant findings concerning the tangible economic benefits generated by sports facilities and teams, a relatively recent strand in the literature has shifted its attention to the question whether sports amenities might produce substantial non-pecuniary, that is intangible benefits, which might again justify public subsidization.
In this regard, 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 their sports-related surrounding environment of shops, bars, and restaurants tailored to enhance the overall fan experience. On top of that, well-designed sports facilities that are neatly blended in the urban fabric, might serve as important urban landmarks and catalysts driving and consolidating urban development, in particular in deserted downtown areas (Chapin (2004), Bachelor (1998)). In this respect, Rosentraub (2006) argues that the null-findings concerning the direct economic impact of sports might be rather negligible if the underlying goal of public investment in sports facilities is the revitalization or fostering of the city core. The author postulates that public investments in the sports sector serve as important signals and increase the general attractiveness of a city, both for residents and investors. Following this logic, subsidies might prevent urban flight and keep both citizens and firms in town, the effect of which would not be easily discernible in macroeconomic data. However, one can more or less rule out the assertion of elevated investments or increased migration to cities hosting major league franchises as both increases should eventually be detectable in the data. For instance, Arif et al. (2022) finds no support for the argument of increased migration flows.

Notwithstanding, Rosentraub's argument that sports increases the attractiveness of a city implicitly alludes to the notion that sports conveys considerable amenity benefits to residents. Among the most highlighted positive externalities generated by sports are an overall higher living quality (e.g. Carlino and Coulson (2004)), increases in social cohesiveness and enhancement of community identity (e.g Johnson et al. (2012)), as well as a feeling of civic pride (e.g. Porsche and Maennig (2008)), especially with regard to sporting success. 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 found to considerably increase traffic congestion (Humphreys and Pyun (2018)), elevate noise levels (Ahlfeldt and Kavetsos (2014)), lead to air pollution (Locke (2019)), accelerate the spread of diseases (Stoecker et al. (2016)), and stimulate criminal activity and police spending (e.g. Kalist and Lee (2016), Pyun et al. (2023)). Eventually, the sign of the total effect reveals which side dominates.
Albeit, in practice, due to the non-pecuniarity of externalities, there exists no direct market metric and the net effect needs to be implicitly derived. Specifically, economic theory proposes two estimation methods to approximate externalities: the contingent valuation method (CVM), also referred to as a *stated-preferences approach*, whereby empiricists rely on surveys to directly ask respondents about their willingness-to-pay (WTP) for keeping a major league franchise in town; and the hedo-

nic regression technique, which this paper employs in the framework of housing prices, and which assumes the existence of an implicit market for individual housing attributes and neighborhood features, enabling to reveal externalities by comparing properties with similar features only differing in terms of exposure to the externality-generating source (Rosen (1974)). The hedonic approach is therefore also known as *revealed preference approach*. Apart from these two methods, empiricists have also approached to explore the net benefits of sports through other lenses such as voting behavior.

First, concerning prior research relying on the CVM, Bradbury et al. (2022) find that the overall findings of CVM examinations indicate considerable non-use values in terms of quality-of-life and civic pride benefits, yet argue that those values are often small in magnitude relative to facility costs. For example, Johnson et al. (2001) ask Pittsburgh residents about their WTP regarding a new stadium for the Penguins (NHL). The authors report moderate expected aggregated benefits of the new venue ranging between 23,5 - 66 million $. Further, in the context of financing a new stadium to keep the NFL's Jaguars franchise in Jacksonville, Johnson et al. (2007) find that the present value of public goods created by the Jaguars amounts to about 36,5 million $, but that this sum is much lower than the public subsidies provided to attract the franchise in the first place. Within a European context, Heyne et al. (2010) use the CVM method to exploit the 2006 FIFA World Cup in Germany as a natural experiment and compare the WTP of residents for hosting the World Cup final before and after the event. The authors find that the average WTP per respondent has more than doubled from 4.26 to 10.07 €, which they interpret as an indication that sporting events constitute experience goods and that the World Cup has considerably enhanced civic pride and integrated a feel-good factor in German society. Lastly, it is worth noting that the method is not unquestioned and typical criticism relates to downward-biased estimates due to the lack of credibility of the hypothetical relocation scenarios drawn within survey designs. In this regard, closely related to the case of St. Louis, Fenn and Crooker (2009) address this concern and examine the credible relocation threat that the Vikings (NFL) could leave Minnesota if the city cannot provide them with a new stadium. The authors estimate an aggregate 700 million $ welfare value that the Vikings create in Minnesota, which would be sufficiently large to justify the public provision of a new stadium.

Second, voting behavior might be exploited to more accurately assess the expected benefits of new stadiums, as voters face an immediate real outcome. Specifically, referendums usually bring about the advantage of large sample size and allow to discern potential spatial patterns in voting behaviors related to proximity to the stadium. In this view, Fischel (2001) postulates that residents are more likely to vote for or against a public subsidy when they expect an increase or decrease in their property values following the investment, respectively. Insofar, referendums on the provision of funds for stadiums promise to reveal spatial clusters. Dehring et al. (2012) empirically examine Fischel's homevoter hypothesis in the context of a vote on a new stadium for the Cowboys (NFL) in Arlington, Texas, and find that support for the stadium was positively associated with expected increases in property values. Further, Coates and Humphreys (2006) examine two stadium referendums and observe a positive association between proximity to the stadium and the willingness to provide public funds for the renovation of a facility in Green Bay, whereas they do not observe any significant relationship regarding a facility in Houston.
In contrast, Ahlfeldt and Maennig (2012) observe NIMBY (Not In My Backyard) behavior during a

referendum in 2001 on the future site of a professional soccer stadium in Munich, Germany. While residents have generally expressed large support for constructing the stadium within the central city, they have shown stark resentment against proposed stadium sites close to their homes and preferred alternative sites instead. Similarly, Horn et al. (2015) observe NIMBY patterns in Seattle in respect to a referendum on the construction of a new jointly-shared football/soccer stadium in 1997. The authors find that support for the new facility was weakest in the immediate vicinity of the stadium, while the largest support levels were detected in areas within easy access to the facility. Hence, the findings suggest the existence of a *"Goldilocks zone"* situated in commutable distance to a stadium, which is close enough to conveniently experience the amenity benefits, but far enough away to not be exposed to negative congestion externalities. However, Johnson and Hall (2019) cannot affirm this hypothesis and do not discern a significant difference in support for a new NFL stadium in San Diego in 2016, between residents living close to the proposed site and residents living farther away.

Third, this thesis follows the footsteps of a relatively rich and predominantly hedonic literature exploring the effects of sports facilities and teams on surrounding properties from different angles including transaction prices, tax assessment values, monthly rents, value recovery times, as well as mortgage applications. While the majority of papers emphasizes that sports amenities emanate significant positive spatial externalities, which are locally concentrated within a few miles around a facility and typically decrease in a non-linear distance-decaying fashion, a few papers provide evidence that sports can also have a net negative impact, especially in contexts in which the presence of teams substantially amplifies spatial congestion. Overall, while some findings suggest that sports conveys intangible benefits that are sufficiently large to justify public investments in sports facilities, other studies suggest that the aggregate welfare gain does not stand in any relation to the public funds required for hosting a major league franchise.

The first study to explore the benefits of sports facilities on residential properties was conducted by Carlino and Coulson (2004). They examined the impact of the presence of major league teams on monthly rents and wages across several US metropolitan areas from 1993-1999 and found that cities with NFL teams have on average about 8% higher rents in central cities, but the effect does not expand to the broader metropolitan area. Besides, they also observed that wages in those cities are about 2% lower, which they interpret as compensating differentials, meaning that residents are willing to deliberately forgo higher wages in exchange for the quality-of-life benefits generated by a major league sports team. The authors estimate the aggregated annual surplus value to be 186 million $ (in 2023 prices) for an average central city of slightly less than 300.000 households, which they regard as substantial evidence that the quality-of life benefits may justify large subsidies. However, Coates et al. (2006) criticize the results as not being robust against alternative model specifications and data cleansing. Nevertheless, Carlino and Coulson (2006) contradict the criticism and defend their original conclusions. Finally, Kiel et al. (2010) replicate the Carlino and Coulsen model using property values instead of rents and report null-findings regarding the presence of an NFL franchise, which they interpret in the way that the amenity benefits are negated by the increased tax burden levied to pay for the provided public subsidies.

Moreover, Feng and Humphreys (2012) estimate a spatial autoregressive hedonic model on a sample consisting of several US metropolitan areas which host major league teams at some point between 1990-2000 and compare the values of census blocks within a five-mile radius from the stadiums.

The authors estimate that each one-percent increase in distance from a facility leads, on average, to a decline in census block values of about 0.8%. Further, they approximate the median increase of property values within four-mile distance to a respective facility and report substantial differences between cities, ranging from 80 million $ in the smallest case, to a substantial 3.3bn$ in the highest case. Lastly, the authors estimate that the present discounted median value of the additional local property taxes amounts to about 254 million $ which is considerably smaller than the median facility costs of 339 million $.
Furthermore, Huang and Humphreys (2014) also analyze census tract level data and discover that the opening of 56 new facilities between 1995-2008 resulted in significant growth in mortgage applications in close proximity to a stadium. Nonetheless, when controlling for neighborhood features, the estimate renders insignificant and the authors interpret that stadiums were often built in impoverished areas where development would have taken place regardless of the facility, and that the money could have been potentially better spent on alternative projects that were more needed or effective.

Lastly, prior research has likewise studied the impact of minor league sports teams on local housing markets across different cities and observes similar findings to major leagues. Firstly, Agha and Coates (2015) employ a compensating differential approach similar to Carlino and Coulson (2004) and compare rents across 138 metropolitan areas between 1993-2005. The authors find that rents are, on average, 6-8% higher in cities with affiliated minor league teams. Importantly for this thesis, the results suggest that the effect is less pronounced in larger markets, and most dominant in mid-sized cities such as St. Louis. The findings could thus indicate that minor leagues somewhat serve as substitutes for major leagues, which are more likely to be already present in larger cities in which the market is already fairly saturated. Additionally, the authors estimate the average aggregate welfare gain of minor league teams to be roughly around 154 to 465 million $ (in 2023 prices), conditional on population size.
Likewise, Holm (2019) conducts a comparative analysis of the values of census tracts in proximity to a facility to those of census tracts located farther away for a sample of 16 minor league baseball stadiums between 2000 and 2010. The author observes higher values at the end of the decade in census tracts close to the facilities, but notes that these values are not higher than in cities without minor league teams. Consequently, he concludes that minor league stadia can revitalize downtown areas, but they shift economic activity to the center and concentrate growth rather than creating additional growth.

What is more, instead of cross-city comparisons, several studies have focused on the spatial impact of individual stadium projects on local housing markets within the US. For example, the very first paper by Tu (2005) explores the effect of a new NFL stadium in Maryland that was built in 1997. Intriguingly, Tu detects a lower price of single-family homes within a three-mile impact area surrounding the facility. Nevertheless, he employs a difference-in-difference framework to demonstrate that the price discount had already existed before the stadium construction and that the price gap actually closed with the team arrival, indicating a positive internalization of the spatial externalities. Within a similar paper, Feng and Humphreys (2018) examine the opening of two privately financed stadiums (NHL & MLS) in downtown Columbus, and find that for each 10% increase in distance from the facility, single-family property prices decrease, on average, by 1.75%.

Further, with respect to more recent works on the impact of stadiums on property prices, Keeler et al. (2021) provide evidence for the existence of anticipation effects concerning the construction of Staples Center in Los Angleles, which is a multi-venue facility hosting a multitude of sports and entertainment-related events throughout the entire year. The authors find that the announcement increased nearby property prices within up to two miles by about 6-11%, while the inauguration additionally increased prices by 5-6%. The results are insofar insightful as the stadium is used more intensely than other comparable stadiums, which is why congestion effects can be expected to be large. Nonetheless, the findings indicate that the amenity benefits seem to dominate.
Similarly, Neto and Whetstone (2022) also report an appreciation of single-family home values upon announcement of a new stadium in Las Vegas. The authors detect a premium of about 6% within up to five miles around the proposed site, but do not find any significant additional effect of the inauguration of the stadium, arguing that the amenity benefits are already fully absorbed. In addition, a significant contribution of their paper is that they use quantile regressions to reveal that properties in the lower tail of the conditional distribution are associated with value increases, whereas properties in the upper tail of the distribution depreciate in value.
Furthermore, an earlier study by Dehring et al. (2007) has likewise detected anticipation effects associated with a series of public announcement for a new NFL stadium in Dallas-Fort Worth. Contrary to the previously mentioned studies, the authors find that property values declined by about 1.5% in light of the announcements. The depreciation rate is comparable to the anticipated tax burden of the stadium that residents would have to pay off. Thus, they conclude that the amenity effect is not significantly different from zero, and only the negative tax impact drives prices downwards. Similarly, Bradbury (2022) also does not find any significant amenity effect internalized in property assessment values within the context of a new professional baseball stadium in Cobb County, Georgia.
Lastly, Propheter (2021) explores a yet novel angle and examines the recovery time of property tax values after the financial crisis for a sample of three different major league stadiums in Los Angeles. Intriguingly, the author finds that only properties located within three-mile distance to Dodgers Stadium (MLB) experienced accelerated recovery, while there was no significant effect for the other stadiums. The findings are insofar intriguing as Dodgers Stadium is described by the authors as an *"island in a sea of asphalt"*, whereas the other stadiums are more integrated into the urban fabric. This finding stands in contrast to the conventional argument that major league stadiums generate larger spatial externalities when they are better integrated into urban areas (Rosentraub (2009)) and that parking lots prevent the unfolding of amenity benefits (Nelson (2001)). In this regard, Propheter posits that, contrary to common belief, the island-like design might act as a buffer that separates sports-related congestion externalities from residential living quarters.

Previous research on property prices within European contexts has yielded similar results and also provides evidence for the immediate internalization of information into real-estate prices (Fama (1970)). For instance, Kavetsos (2012) examines the impact of the winning bid for the Olympic Games on housing prices in London and discerns a relative price increase in host boroughs of about 3.3%. Besides, a distance ring analysis shows that the impact is fairly far-reaching and expands up to 9 kilometers ($\approx$ 5.6 miles) from the Olympic stadium, which is estimated to create an aggregate increase in the housing stock value of about 1.3bn £.
Further studies in Europe have also found positive amenity effects of sports facilities, yet within a more concentrated impact area. For the Netherlands, Bieze (2021) finds positive distance-decaying

impacts on housing prices within a radius of up to one kilometer from new or renovated stadiums. He ascertains that above all stadiums in urbanized areas emanate larger spatial externalities, relative to those located in more rural areas. For Berlin, Ahlfeldt and Maennig (2009) & Ahlfeldt and Maennig (2010) investigate the impact of two stadiums in a historic neighborhood by studying surrounding land values and find positive effects of 12.19% within up to three kilometers from the facilities, respectively. The authors contend that the direction of the impact largely depends on appropriate location choice and a good urban planning concept that minimizes nuisance from stadiums. Besides, both facilities have considerably increased the location desirability as they were seamlessly integrated into their surrounding neighborhood and allowed to create recreational space.
In a similar vein, Ahlfeldt and Kavetsos (2014) examine the reconstruction of the iconic Wembley Stadium in London and estimate a cumulative relative price increase of 13.5% within a five-mile impact area. Essentially, as the reconstructed facility was built in the exact same location but with a more modern and sophisticated design, the authors attribute the price premium in large parts to "form effects", that is the aesthetic appearance of the stadium as an urban landmark. Besides, another important takeaway from their work is that the authors demonstrate that some highly congested areas experienced relative declines in real-estate values, whereas in total, the amenity benefits dominate.

Finally, the sports industry in St. Louis and the impact of the Rams on different facets of the local economy has already been studied by three previous papers. Firstly, Mares and Blackburn (2019) examine the impact of Cardinal games on local crime levels from 1994-2016 and find substantial increases in local crime rates of about 14-16% per game, on average. The impact is highly concentrated within the immediate vicinity of the facility and expands up to 1.5 miles. However, the authors also find signs of displacement effects and observe increases in crime levels in neighborhoods much farther away. The total damages of Cardinal Games are estimated to be around 750.000$ per game, or 1,2 million $ per year. Within their regression specification, the authors also control for the impact of home matches of the Rams and Blues and equally report similar findings for these two franchises. Secondly, Miller (2002) analyzes the construction of Edward Jones Dome in 1995 and discerns that employment rates within the construction sector were neither higher nor lower than usual within the broader metropolitan area, and conclude that the results suggest the existence of substitution effects. Thirdly, Stephenson (2021) studies hotel occupancy rates during Rams and Cardinals match days between 2011-2016. The results are insofar relevant as hotel tax revenue is often brought up as an argument in favor of public subsidies for sports facilities. Concerning the Rams, the authors observe modest increases of 1500 additional rooms rented and 200.000 $ additional revenue created by each home game. Further, Cardinals home matches lead to 2200 additional rooms and 330.000$ in hotel revenue which the authors consider to be large. However, in total the economic surplus value is not large enough to justify public subsidies.
To conclude, to the author's knowledge, no paper has yet examined the impact of sports 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, but negative in the context of crime, the total expected impact of the sports-led urban revitalization strategy on property values remains ambiguous a priori. This thesis aims to close this research gap.

4 Methodology

In light of the scant evidence on mere team effects, this thesis contributes to the literature by examining the novel context of the departure of an NFL franchise and its impact on single-family residential property values. Against the background of the inherent value that sports bears for St. Louis residents, the city's overall distressed economic situation, and the strong dissatisfaction expressed by societal and political actors following the Rams' departure, it is hypothesized that the relocation has induced a relative decline of single-family home values which is most pronounced in the direct vicinity of the stadium and declines with distance to the facility.

From a theoretical point of view, the value of a property can be decomposed and reflects the aggregated value of a property's inherent structural attributes, i.e. the number of bathrooms, as well as its 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 welfare gain or loss associated with sports amenities should be equally capitalized in local property values and reflects consumers aggregated WTP for these amenities (Bradbury (2022)).
Notwithstanding, 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 (Tu (2005)). 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 easily embedded within regression models by regressing the price of a property i on its value-shaping attributes defined above. Thereby, controlling for housing and locational characteristics allows to assign an implicit market price to each singular attribute and enables the empiricist to reveal the externalities generated by hosting a major league team within the local stadium. Simply put, assuming a sufficiently large sample size, comparing properties with similar features that differ in only one or a few distinctive elements allows to eventually lay open the implicit marginal price associated with the distinctive features as the average difference in property prices. By this logic, comparing property values in proximity to the stadium with similar properties 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. Hedonic modeling is therefore also known as a *revealed preference approach*, as it allows to assign an implicit marginal value to non-pecuniary externalities.

Notwithstanding, while the theoretical framework of hedonic regression is clear-struck, 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. Eventually, model specification remains at the researcher's discretion and should be guided by both theoretical and context-specific aspects of the case under investigation. Albeit, in reality, variable selection is also heavily influenced by data availability (Feng and Humphreys (2012)). Generally speaking, 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 (Bayoh et al. (2004)). While the latter causes artificially inflated standard errors which can undermine the precision of the parameter estimates, an OVB implies, as the name suggests, biased point estimates as a result of a structural pattern within the error term that an omitted variable causes. In this light, we check the robustness of our models against both of these concerns and argue that the model is appropriately specified. An in-depth account of these robustness checks is presented in the Appendix.

Furthermore, another common concern that arises with hedonic modeling is that of endogenous variables, which needs to be addressed in further detail. Concretely, in the given case, 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 is 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 (Agha and Coates (2015)). 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.[7] Additionally, it is shown in the Appendix that the inclusion or removal of potentially endogenous independent variables does not alter the results, which is why we argue that endogeneity should be less of a concern.

Further, 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.[8] Consequently, the relocation-induced exogenous variation of housing prices invites to embed the hedonic pricing model within a quasi-experimental difference-in-difference 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 pre-and post-treatment periods and compare the relative price evolution within a treatment area, defined as a three-mile radius ring around the stadium based on previous research, with a control area consist-

[7] 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.

[8] Crucially, a priori, it was also a credible possibility that another franchise could replace the Rams in St. Louis in case of a departure to Los Angeles. With the *Raiders* & *Chargers* on the search for a new destination, the two franchises might have proven instantly apt candidates. 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)).

ing of properties located farther away. A general advantage of the difference-in-difference 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 (Angrist and Pischke (2008)). Typically, the assumption is considered reasonable if the groups follow fairly identical pre-trends. In this respect, we provide a thorough evaluation of the parallel trend assumption in the Appendix illustrating that the pre-trends are approximately similar and statistically insignificant from each other, implying that the parallel trend assumption is fairly justified.[9]

With respect to model specification, hedonic models typically follow one of three functional forms: a) a simple linear model; b) a semi-log equation 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 (Feng and Humphreys (2018)). Hence, we follow the vast majority of the literature and specify a semi-log equation model (Box and Cox (1964)) which has two large advantages. Firstly, the range of housing prices is often very large and possibly heavily influenced by outliers. In this regard, log-transforming the dependent variable allows to dampen the weight of either very low or very high property prices and additionally makes the distribution of prices appear more normal, as is shown in Figure 9 in the Appendix.[10] Secondly, the coefficients of the semi-log model are easily interpretable as semi-elasticities, which is insofar relevant as it allows the implicit marginal prices to vary across different values of the respective covariates, whereas the linear equation model is more strict and forces a constant effect.[11]
Against this backdrop, partly following Kavetsos (2012) & Ahlfeldt and Kavetsos (2014), we first estimate the following difference-in-difference model, which we refer to as our base model:

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

whereby the natural logarithm of the price p of property i sold at time t is regressed on the difference and difference specification and a number of covariates. Concretely, $x_{i,t}$ is a vector including time-invariant structural housing attributes, neighborhood characteristics, market features, as well as urban characteristics associated with property i's location at the point of transaction t. The β_j

[9]It shall be noted that we report only insignificant coefficients within a leads and lags model for the whole sample period from 2012-2019 using 2012 as reference, but find insignificant leads and significant lags when shortening the sample period to 2014-2019. As we demonstrate in the Appendix that the general conclusions are unaffected by the shortening of the sample period, we report the results of our models for the full sample, mainly for econometric reasons of retaining sample size high, allowing to improve precision of the point estimates and to lower multicollinearity concerns (Wooldridge (2018)).

[10]In a similar vein, we also log-transform the parcel size and floor size of a building. Accordingly, their coefficients can be interpreted as elasticities.

[11]The linear model is advantageous in the way that one can directly read the coefficient as a marginal price estimate of an attribute. Nonetheless, the semi-log equation model might still be preferable in the context of housing since, 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 within completely different price categories (Keeler et al. (2021)).

coefficients approximately reflect the percentage effect of a one unit change in x_j $\forall j$.[12] 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, to account for base differences in neighborhood values.[13] Lastly, $\epsilon_{i,t}$ is the error term.

With respect to the difference-in-difference estimates, Post_t is a dummy taking the value one when a property was sold in the post-treatment-, i.e. post-relocation-, period, and 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 δ_3, is the difference-in-difference estimator and 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 heterogenously across space, as suggested by several previous studies. The adjusted ring model looks as follows:

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

The main coefficients of interest are the δ_r's, which are the difference-in-difference estimates for properties located within ring r. The model is estimated twice. $N = a$ corresponds to the specification with one-mile distance rings, while $N = b$ represents the case of half-mile distance rings. In either case, the outermost distance ring constitutes the reference, i.e. control area. In the case of 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 immediate vicinity of the facility, for specification b, we follow Neto and Whetstone (2022) and, at first, only include half-mile distance rings of up to 5 miles, implying that the control area is composed of all houses located farther away. Secondly, based on our findings, we further zoom in and discard all properties

[12] For discrete and continuous coefficients, the precise percentage effect of a Δ-unit change in coefficient β_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)). Essentially, due to the functional form of the exponential function, the estimates for an increase and decrease of the same absolute value might substantially differ. Typically, as the β-coefficients lay right in between those two estimates, they are reported in most cases in which one is one is more interested in the general underlying effect and less in the precise estimate of an increase or decrease (Wooldridge (2018)).

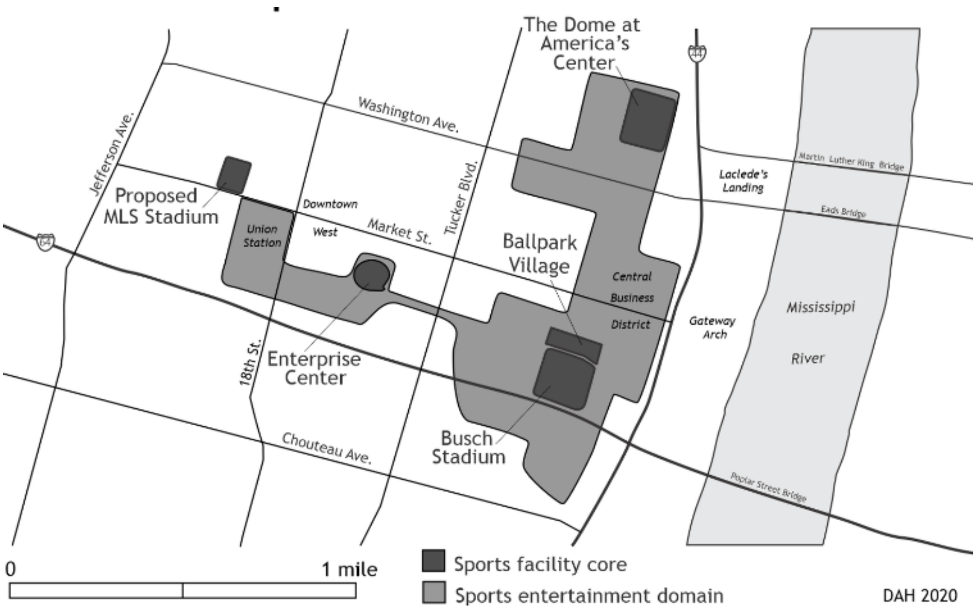
[13] The fixed effects are specified on the census tract level. While they might vastly capture the effect of spatial autocorrelation of housing prices due to shared local public goods, i.e. neighborhood effects (Feng and Humphreys (2018)), a minor limitation of this thesis is that we were not able to control for absolute spatial spillover effects, defined as the impact of adjacent property sales on housing values (Can (1992)). Future research might want to address this issue by including spatial autoregressive lags or errors within the model (Anselin and Bera (1998)).

located farther than five miles away from the stadium and use the 4.5-5 mile ring as the control area.

Regarding the selection of covariates, while the inclusion of housing attributes and neighborhood characteristics within hedonic models is relatively self-evident and needs little methodological explanation, a particular emphasis is laid on the relevance of additionally including controls for local market and urban 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.
Firstly, we include market controls in terms of 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, and hence to the central business district (CBD), as this is where the majority of finance and insurance companies are typically located. Besides, Abbiasov and Sedov (2023) demonstrate that the rate of visits of retail stores and even more so, food and accommodation establishments, situated in the vicinity of the stadium, is positively associated with NFL home game attendance. Hence, controlling for these types of establishments should also capture the effect of potential property value losses induced by a negative demand shock for sports-related industries following the relocation.
Secondly, 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, declines with distance to the CBD where the jobs are located. Further, 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 which downtown areas offer. Thus, as part of our neighborhood characteristics, we control for changes in population density by neighborhood which 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 (Buck et al. (1991)). Potential local changes in within-city-location choice owing to the relocation should therefore also be controlled for.

However, the integration of Edward Jones Dome into a designated sports-and entertainment district consisting likewise of *Enterprise Center*, a multipurpose-arena which is home of the St. Louis Blues (NHL), and *Busch Stadium*, an open-air baseball stadium hosting the St. Louis Cardinals (MLB), poses insofar an additional empirical challenge for the isolation of the proximity effect since the three major league stadia only lay a few hundred meters away from each other, as Figure 1 displays. To ensure unbiasedness of the difference-in-difference estimate, it is hence indispensable to equally control for proximity to the other two stadia. Likewise, it might be that the relocation of the Rams has also elicited a decrease in WTP for proximity to the other two stadia as a result of potentially foregone spatial synergies leveraged by the presence of three, instead of two major league teams. Furthermore, considerable changes in the spatial externalities generated by the other two teams and equally taking place over the course of the sample period would interfere with our identification strategy and lead to spurious regression estimates. Fortunately, the Blues and the Cardinals have both played uninterruptedly within their stadiums throughout the time frame under investigation.

Figure 1: St. Louis - Sports Entertainment District



Source: Hurt (2021)

Nevertheless, in 2017, the Blues launched a privately financed three-year renovation plan for Enterprise Center worth about 150 million $, and consisting of incremental infrastructural upgrades in terms of 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 certainly enhanced the consumption experience, it seems plausible to doubt whether the aforementioned renovation works have generated additional spatial externalities comparable in magnitude to the effect of the construction of a completely new stadium, or the arrival or departure of a team. Further, 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 because these upgrades occurred gradually. Thus, we posit that the renovation of Enterprise Center should not interfere with our identification strategy.[14]

Nonetheless, 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 winner at the end of the 2018/2019 season. Although in January 2019, the Blues had the worst record of any NHL team at the time, the franchise eventually barely reached the playoffs and totally unexpectedly won the league following a series of consecutive tight matches (Augustyn (2023)). If the Blues' unanticipated success story has evoked significant spatial externalities, for example in terms of increased civic pride or social cohesion among supporters,[15] or in the negative sense, increased congestion, for example as a result of fan gatherings, those externalities should be

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

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

capitalized into residential property values and would bias the results if 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 partial public subsidies for the construction of the stadium in 2006. The project is split into three phases, of which the first phase, *Ballpark Village I*, opened in March 2014, and consisted of the construction of a 120.000 square feet structural complex offering plenty of 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 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, underlining the popularity of Ballpark village and its substitutional effect on the local economy (Hurt (2021)).
To test for the robustness of our findings in the light of the potentially confounding events, we respectively run our models over a shortened pre-and post-treatment period allowing to exclude potentially spurious transactions from the sample. For the sake of brevity, we only present 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.[16] In short, the findings are in line 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 last methodological remark, Breusch-Pagan tests (Breusch and Pagan (1980)) indicate that the error terms within our models are heteroskedastic. Generally, the issue of serial correlation of the error term is well-documented for micro-level data exhibiting group structures and might lead to spurious regressions (Moulton (1986), Moulton (1990), & Bertrand et al. (2004)). Econometric theory proposes two remedies to deal with heteroskedasticity, namely to either report robust standard errors (Huber (1967), & White (1980)), or to cluster standard errors on the scale-level on which the in-group error correlation is assumed. To date, there exists no clear-struck case for the superiority of either method and previous studies using hedonic methods to examine the impact of sports facilities have equally relied on either approach. In respect to St. Louis, both methods appear theoretically justified and pertinent in their respective way.
On the one hand, robust standard errors might be insofar preferable as they address the more general case of heteroskedasticity of unknown source and are equivalent to homoskedastic errors. Besides, as we are only examining one city context, geographical clusters, i.e. census tracts, are exposed to the same urban laws and economic policies, which is why one might argue that due to lack of substantial heterogeneity, clustering might not be theoretically supported (Tita et al. (2006)).
Notwithstanding, on the other hand, it also seems reasonable to assume that the covariance-variance matrix is block-diagonal, implying that there is serial correlation within but not among geographical clusters (Wooldridge (2018)). While local fixed effects are likely to capture most of the variance in local prices associated with spatial autocorrelation, clustered standard errors might account for

[16] At the same time, the shortening of the pre-and post sample period equally enables us to exclude that the findings are driven by potentially confounding construction projects, taking place over the sample period within the impact area, such as the renovation of Union Station in 2014, or the makeover of the iconic Gateway Arch Museum re-inaugurated in July, 2018.

the remaining random group effects in the error term in case of heterogeneous treatment effects (Abadie et al. (2017)). Plus, it might even be advisable to cluster standard errors for experimental design reasons, as the assignment mechanism for the treatment is naturally spatially clustered around the stadium (Mckenzie (2017)). Though, clustering remains somewhat of an empirical puzzle in econometrics (Abadie et al. (2023)) and there is no straightforward theoretical answer on which geographical scale-level the error terms would need to be clustered.[17] Eventually, it seems plausible to construct a respective argument for the use of clustered standard errors on either the census tract, neighborhood, or ward level.
Against this backdrop, we report robust standard errors within our preferred model specification primarily due to their "flexibility" advantage, but likewise follow Mares and Blackburn (2019) and examine the differences between different error constellations by running our models with robust, "normal" OLS, as well as clustered standard errors. In the latter case we cluster on the three above mentioned scales. Similarly, we find that the differences in significance levels are relatively trivial suggesting that the model is justly fitted (King and Roberts (2015)).

Finally, to assay the robustness of our results, we are testing the findings across several alternative model specifications and further examine and discuss common econometric and methodological issues arising with hedonic modeling in the Appendix. In brief, the additional checks provide supplementary evidence of the consistency and robustness of the general findings.

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

5 Data

This section outlines the composition of our sample and discusses the selection of control variables. We thereby proceed in a consecutive manner and group the covariates, as suggested by Equation 1.

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 parcel 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 01.01.2012 and 31.12.2019 ($n = 43.818$). We then merged this information with data on a parcels location and, when available, information on building attributes. The sample period is purposely selected such that we respectively observe a balanced pre- and post-treatment phase of about four years surrounding the relocation in January 2016. This period is long enough to adequately discern capitalization effects, relocation-induced population dynamics and changes in neighborhood features at both large and minor scales. However, the sample period is also short enough to moderate potential bias from nearby urban development projects (Keeler et al. (2021)).[18]

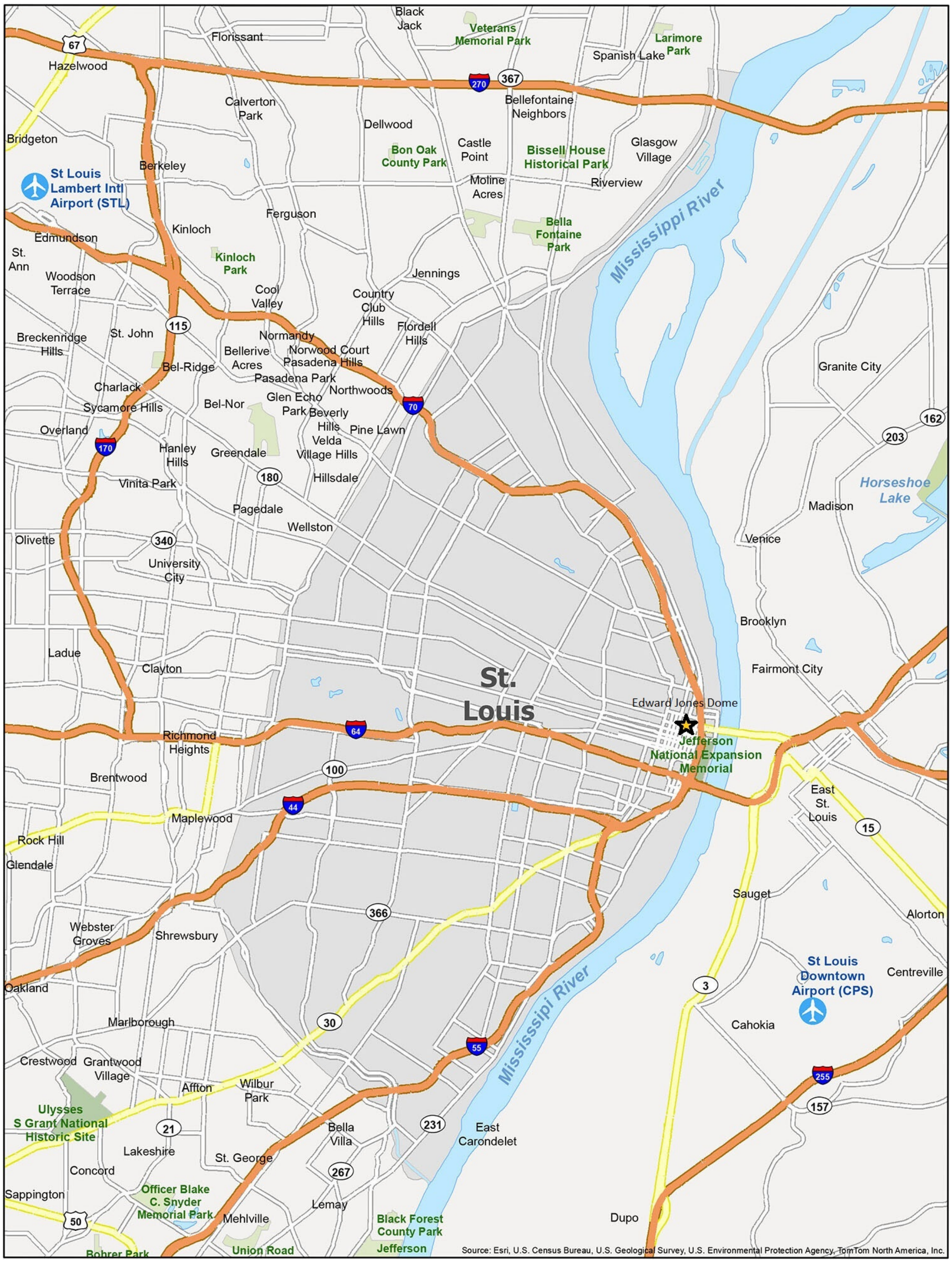
Furthermore, as the parcel data is restricted to the City of St. Louis, the sample area is conceptually predetermined by the city fringe, which was established in 1876 and has remained unchanged ever since (Metzger et al. (2018)). This is advantageous, as it allows for comparison of the treatment effect across properties situated within a fairly homogeneous context of long-term economic and urban policies. However, as shown in Figure 2, 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 boarder and overlaps into East St. Louis, as shown in Figure 3, whereas we are only able to analyze properties which were transacted within St. Louis.[19]
In this context, we rely on address information from the parcel records to calculate each property's coordinates via Google's geocoding API.[20] Next, we computed the geodesic distance of each property

[18] Apart from the fact that parcel sale data was only available up and including 2019, the end date is contextually pertinent because since February 2020, St. Louis hosts the BattleHawks (XFL), a minor-league football team, in Edward Jones Dome.

[19] Generally, this limitation is not per se troublesome, because East St. Louis is imposed to different state and city laws. Above all, the residents of East St. Louis free-ride on the presence of major league sports in St. Louis, as the accumulated tax burden of public subsidies for the sports industry is borne solely by taxpayers residing in St. Louis, St. Louis County, and Missouri. Additionally, the width of the river may serve as a natural barrier to prevent negative congestion spillovers, while the general amenity benefits, i.e. increased quality of life, are likely to remain unchanged. Though, it might be questioned whether positive externalities in terms of increased civic pride and social cohesion would be equally pronounced in East St. Louis.

[20] At first, addresses were geocoded via *Nominatim*, which is a free geographical information service (GIS) running on *Open Street Maps*. Upon initial use of Nominatim, we observed that the output was somewhat unreliable. Specifically, several hundred addresses could not be found, while for others, Nominatim had

Figure 2: St. Louis - City Map



Source: gisgeography.com

from 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 sale, 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% ($n = 40842$) of the data, followed by commercial, industrial, or miscellaneous parcels totaling about 6,2 % ($n = 2697$), and lastly mixed-residential parcel sales only accounting for 0.71% ($n = 313$) of the data. Ultimately, we only kept residential parcel sales.

The retrieved building information reflect a snapshot in time of primarily time-invariant structural housing attributes, namely, the parcel size, floor size, exterior facade, i.e. brick, stone, or frame wall, number of stories, number of carports, number of garages, building year, and information on whether a house has an attic. Unfortunately, information on whether a building has a central air condition or heating system, 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 categorically incomplete. Moreover, it must be unfortunately remarked that a substantial number of building records exhibits zero- or missing values across the selected structural housing attributes. Facing the trade-off of either reducing the number of independent variables to increase the sample size and include as many observations as possible, or to discard observations with missing or zero values and to control for as many housing attributes as possible to increase the precision of the estimates and to prevent OVB (Agha and Coates (2015)), we opted for the latter as it is widely reported that structural housing attributes alone account for the vast majority of variation in housing prices and as our final sample size, as shown below, prevails adequately high.[21]

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. It was difficult to distinguish the specific value of each individual property in these cases, 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 hedonic studies, we restrict our analysis to single-family residential homes only. This enables us to contextualize our results and to elaborate on potential differences

interpolated coordinates for addresses for which it only recognized the street name, leading to duplicates. To improve accuracy, we subsequently switched to Google which is widely considered to be the most precise GIS on the market. Fortunately, having geocoded addresses twice enabled us to compare small deviations in outputs and to verify the precision of our final coordinates.

[21] Yet, it needs to be noted that this choice is deliberately at the expense of potential selectivity bias in the data, since Coates et al. (2006) argue that missing or zero values might not occur randomly but above all in lower-priced properties. Though, in light of 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 in case of the exclusion of several structural housing attributes.

from previously examined settings. Moreover, since 78,35% ($n = 31.972$) of all residential sales within the sample period were single-family homes, the selection provides ample sample size to conduct hedonic price regressions and examine potential heterogeneous treatment effects across space by dividing the sample area into consecutive distance rings. Table 1 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.[22] To enhance and ensure comparability, we group the first four half-mile rings together in our second estimation of Equation 3 ($N = b$), following Neto and Whetstone (2022). We designate this joint two-mile ring *Target2*.[23]

Table 1: 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

In this context, it is also noteworthy that data limitations leave few alternatives to the selection of

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

[23] To limit the sample area to an eight-mile radius disk, we removed one individual outlier located in the far North of St. Louis more than nine miles away from Edward Jones Dome.

single-family homes. Instead of single-family homes, some hedonic papers opt to analyze apartment buildings or condominiums. In general, there is again no clear theoretical guideline dictating the superiority of either choice over the other. Rather, the selection of housing types to be analyzed is at the researchers' discretion and should be evaluated based on the unique characteristics of the case under study. 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 above all zoning ordinances, might lead to detect different effects in magnitude conditional on building types. In this respect, due to the integration of Edward Jones Dome into the CBD, 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 inversely with distance to the city core. Unfortunately, the retrieved data only contains information on transactions of entire parcels, meaning that we are lacking 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 are also lacking substantial information on building characteristics of multiple-family residential buildings and hence would not be able to include them within our hedonic regression models.

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 ($n = 13872$; 43,39%) and promise to be the least biased and most "pure" market transactions. Other sales type, 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 property and inclusion of these observations would considerably bias the estimated vector of marginal prices of housing characteristics. Besides, we shortly comment on the exclusion of foreclosures and investor sales from the sample as they make up a considerable total share of 19.66% of all single-family home transacted over the sample period. Both, foreclosures ($n = 3290$) and investor sales ($n = 2995$), are typically characterized by rapid closure as the sellers are often in a financially distressed situation and coerced to sell, while the buyers often strategically target the purchase of undervalued properties in the need of light renovations, with the aim to maintain and refurbish the property and to ultimately sell it at a favorable time for a considerable premium.[24] Hence, we discard these two sale types, since the recorded transaction price is likely to not only reflect the aggregated market value of the individual housing attributes but also the underlying circumstances surrounding the transaction.

Further, consistent with prior literature, we limit our analysis to transactions over 30.000$. This cutoff value is conservative and well-below half the median value of valid single-family home transaction in the sample, which is 145.000$. Lower-priced properties were excluded as they are more likely to have unobserved qualitative deficiencies or significant mortgage debt, which could lead to biased estimates. However, as St. Louis housing market is deeply segregated and some areas experience

[24] C.f. Investopedia, & Zillow.

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 introduce 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 replicated our models using a sample without a lower price bound and find that the results were unaffected.[25] This robustness check is presented in the Appendix.

Eventually, the final sample comprises a total of $n = 12695$ observations. Table 2 provides a comprehensive summary of the data. According to the sample, the average single-family home sells for a price of 178.497$ and has a floor size of 1360 square feet and a parcel size of 5028 square feet. The home is approximately 86 years old at the time of the sale, has one and a half stories, features brick walls, has one garage but no carport, and lacks an attic.

Table 2: 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
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

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

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

Finally, Table 3 provides an overview and brief definition of all the variables used in the regression models. In the following subsections, we further outline the data source, contextual and theoretical motivation, and practical limitations of the remaining independent variables contained within the vector of covariates. We first discuss the selected socio-demographic characteristics reflecting neighborhood features, continue with market characteristics, and eventually elaborate on the chosen urban controls.

Neighborhood and Market Characteristics

With respect to our neighborhood controls, we retrieve data from two primary sources. First, socio-demographic information were retrieved from the 2010 and 2020 US Census and available on the neighborhood level.[26] Aiming to better depict variation in local neighborhood characteristics, we construct annual weighted averages, assuming a fairly linear trend of the evolution of socio-demographic compositions of neighborhoods. As St. Louis' housing market is starkly segregated along racial lines, as further elaborated on in the Appendix, we control for the share of the Black population, as well as for the share of vacant housing per neighborhood. Additionally, to account for spatial differences in age structure per neighborhood, for example associated with the presence of many families locating in proximity to schools, young adults locating in affordable quarters providing plenty consumption opportunities, or inversely, elderly people who might prefer to live in calmer neighborhoods, we also control for the share of youth per neighborhood. Further, as mentioned earlier, it is crucial to consider population density as a factor. However, since this information is not directly reported, we had to construct the statistic ourselves. To accomplish this, we matched the annual population numbers per neighborhood from the Census Data with information on the size of each neighborhood retrieved from Wikipedia. The scale has been adjusted such that a one-unit increase represents the percentage effect of a 100-person population increase, enhacing readability of the coefficient.[27]

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

[27] As described in greater detail in the Appendix and summarized in table 44, we have also tested the robustness of the findings against the inclusion of a set of supplementary socio-demographic variables, including the proportion of population with a high-school or academic degree, the proportion of Asians and Latinos, or the average household size. While the general findings remain the same, the inclusion

Table 3: 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 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 Busch Stadium (MLB)
DistanceEC	Distance in miles to Enterprise Center (NHL)

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 to account for income-related price differences.

Unfortunately, while the ACS and US Census also report precise information of socio-demographic variables on smaller geographic areas, i.e the census tract level, we were not able to use them for our analysis, due to small deviations in the reported census tracts depicted on the transaction records, preventing us from neatly merging the data. Generally, it might have been preferable to control the local characteristics on the census tract level, as it constitutes the smallest urban scale-level on which data is typically available and by construction, census tracts are designed in a way to represent populations with similar characteristics within areas that are fairly alike in population size and area (Holm (2019)). Although this may be beneficial for the sake of comparability, it simultaneously presents a point of weakness, as it can be questioned whether census tracts appropriately incorporate neighborhood dynamics and proportions (Clapp and Wang (2006)). In this logic, controlling on the neighborhood scale might account for more natural geographical clustering, as many of todays' neighborhood boundaries are the manifested result of incremental population dynamics and urban policies taking place over the long run. Besides, several neighborhoods in St. Louis look back at a long and rich history of significant community-shaping events, fostering the community spirit of the respective neighborhood and sustaining its unique character.

In a similar vein, one might also discuss the use of neighborhood fixed effects instead of census tract fixed effects. There are three remarks to make. First, economists hold discordant views on whether local fixed effects should be measured on the same scale level as the covariates and there might be pertinent arguments supporting either side. Second, as explained in the previous section, the primal function of local fixed effects is to account for base differences and to cater for spatial autocorrelation, i.e. neighborhood effects, in local property prices, which is why it is in our given case preferable to measure fixed effects on the smallest available urban scale-level. Third, a more banal reason for the selection of census tract fixed effects is that the inclusion of neighborhood fixed effects raises the concern of multicollinearity within the model. Against this backdrop, we rely on census tract fixed effects within our preferred model specification, but equally present the overall consistent findings using neighborhood fixed effects instead in the Appendix.

As a final measure of neighborhood characteristics, we also incorporate the total crime rate per 1000 residents by neighborhood and year, using crime statistics from the St. Louis Metropolitan Police Department. Crime is an essential control variable, as previous studies have shown a negative association between (single-family-) property values and crime rates (C.f. Buck et al. (1991), Lynch and Rasmussen (2001), & Tita et al. (2006)). Additionally, crime rates have been found to increase urban flight (Cullen and Levitt (1999)) and affect housing transactions and vacancy rates (Boggess et al. (2013)). Further, St. Louis exhibits one of the worst crime statistics of large cities in the US, consistently ranking first or second in terms of violent and property crimes, according to Wikipedia. Finally, crime is a well-documented negative externality associated with sporting events, and the

of additional covariates raised concerns of multicollinearity within the model. This suggests that these variables are highly correlated, and that the selected controls are sufficient in capturing the joint variation in housing prices.

Rams' relocation may have led to changes in spatial crime patterns that need to be accounted for. In this vein, the study by Mares and Blackburn (2019) is of particular importance to the given context. The authors examine St. Louis crime levels from 1994-2016 and reveal a substantial increase of about 14-16% during home games of the St. Louis Cardinals, with the most pronounced effects in the immediate vicinity of the stadium. Furthermore, they also ascertain displacement effects in neighborhoods located relatively far away from the stadium. The estimated annual damages amount to up to 1.2 million \$. Importantly, the authors include home games of the Rams and Blues as control variables within their analysis for which they report similar findings.
Notwithstanding, in a framework similar to this thesis, Pyun and Hall (2019) exploit the relocation of the NFL franchise *Lions* from Pontiac to Detroit as a natural experiment but do not observe significant changes in local crime rates in Pontiac after the relocation. However, it needs to be taken into account that crime plays a much larger role for the City of St. Louis and the context is therefore incomparable. In any case, it seems indispensable to account for general but also potential relocation-induced changes in local crime patterns. As a final note, we apply a scale transformation to enhance the readability of the point estimate and the crime-coefficient therefore represents the approximate percentage effect of an increase in ten total crimes per 1000 residents.

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 have rescaled the numbers such that the corresponding β_j coefficient respectively indicates the approximate percentage effect of ten additional establishments.

Urban Characteristics

Finally, our vector of covariates likewise covers a range of mainly dummy variables indicating information on the urban setting of a transacted single-family home. The parcel records obtained from Geo St. Louis contain valuable geographical information on historical designation, housing preservation and conservation, enterprise zones, and floodplains. Each of the aforementioned factors has been found to have a significant impact on property values. In this light, St. Louis' distinctive geographical location and historical significance still reflected within architectural styles, exterior building walls, and monuments, serve as the motivation for selecting them as control variables.

Considering St. Louis' distinctive geography, which is located at the confluence of the two largest rivers in the US, the Mississippi and the Missouri, and lacks surrounding mountains for shielding, the city is exposed to severe weather conditions including heavy flooding.[28] Several papers have shown that the risk of flooding and associated reparation costs are absorbed in residential housing prices and visible in the form of a general price discount of up to 7,5 % in the US (Daniel et al. (2009)). In turn, residing close to a river might also provide recreational amenity benefits which would be visible in form of a price appreciation of properties located along the waterfront (Eves (2002)). As shown in Figure 12 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

[28] C.f. Newamerica.com

a one percent chance of being equaled or exceeded each year, whereas the 500-year floodplain is statistically flooded once in 500 years.

Further, regarding the remaining urban control variables listed above, an extensive account of the policy framework and empirical evidence for each variable is provided in the Appendix. In this section, for the sake of conciseness, we provide a brief summary of the main reasons for their selection, specifically in the context of their impact on property values.
This being mentioned, St. Louis looks back at a rich and eventful history in which it has played a pivotal role for the westward expansion of the United States. Its iconic gateway arch, a 192-meter tall steel structure situated at the eastern edge of Downtown at the river bank of the Mississippi, commemorates the city's significant past as a designated *gateway to the west* during the 19th century. In a similar fashion, St. Louis' housing stock is relatively old and plenty of properties and urban monuments bear witness of the city's glorious past. Accordingly, as Figure 6 in the Appendix portrays, a significant portion of the city has been historically designated as either local, certified local, or national historic districts, whereby the latter two districts are not only designated by the City for their historical relevance, but are also listed within the National Register of Historic Places (NRHP). Historically designated neighborhoods characterize that they are stringently regulated and each alteration of a building's exterior or structural features necessitates a special permit.

Against this background, Mason (2005) surveys that there exists a general consensus in the empirical literature that historical designation significantly appreciates property values. Several explanations have been put forward for this associated price premium. For example, Ford (1989) argues that historical listing serves as an insurance mechanism guaranteeing residents continuity of neighborhood facets, Gordon and Stowe (2014) underline that historical designation eradicates informational asymmetry and generates spatial spillovers on adjacent neighborhoods, while Rypkema (2002) highlights the inherent value that designated properties incorporate for which they were registered in the first place. Hence, dummies for the three historic districts are included to account for this potential price premium. Additionally, they serve an important function as proxies for unobserved external building features characteristic of a certain building period. Thus, their inclusion can be regarded as an approximate remedy to the common Age-Period-Cohort Problem (APC) arising in hedonic modeling, that is the dilemma that the simultaneous inclusion of a building's age, construction year, and building year, would introduce perfect multicollinearity within the model. Therefore, it is required to omit one variable, in our case the building year, which might however 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)), implying that housing values depreciate in a non-linear fashion in age (Cannaday and Sunderman (1986)). The dummies for historical designated properties might cater for both concerns.

Furthermore, we also include dummies for single-family homes laying in a Preservation Review Area, and for properties being under the Housing Conservation Program. Preservationist and conservationist efforts constitute central targets within the city's Strategic Land Use Plan. Firstly, properties situated in a Preservation Review Area require city approval before any proposed demolition can proceed. The city thereby aims to stabilize neighborhoods and to reduce the impact of abandoned

housing and vacant land on adjacent property values (Griswold and Norris (2007), Han (2014)). Secondly, houses taking part in the Housing Conservation Program have to abide by specific qualitative building standards. Hence, such properties might be on average in a better condition and the housing conservation dummy should elicit potentially associated differences in single-family home values.
Lastly, a dummy is constructed for single-family homes located within an Enterprise Zone, which is an urban area designed to attract new investment and businesses to settle, offering favorable conditions, such as tax abatement. If commercial or industrial land use evokes substantial negative externality flows to nearby residential properties, we might expect to see a price reduction in single-family homes located within an Enterprise Zone.

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.[29] 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 posit that citizens might be willing to pay a premium for residing close to parks. Although there is a general consensus in the literature that parks provide considerable amenity benefits which are capitalized in nearby land and property values, the evidence on which types of green space generate substantial consumption amenities (Panduro and Veie (2013)), and which facets - such as size, views, or internal features - are most important (Morancho (2003)) is less clear. Typically though, More et al. (1988) review that several paper provide evidence for distance-decaying effects, similar to what is posited regarding sports amenities. Controlling for proximity to urban parks is essential not only because of its impact on property prices, but also because the valuation of proximity to sports facilities and urban spaces might manifest a complementary or substitutional relationship. In this regard, one might suspect that a control variable for proximity to parks might lead to spurious estimates if the WTP for residing nearby urban parks is an endogenous function of the WTP for proximity to sports facilities. Hence, we conduct an additional robustness check, presented in the Appendix, and demonstrate that the findings are robust against the inclusion or exclusion of the regressor for the distance to parks and likewise ascertain the same conclusions when using a 600 meter distance control ring for parks instead.

[29] The City of St. Louis reports that there are 108 parks within the city boundaries. Based on qualitative criteria, above all in terms of size, location, and popularity, we have identified the 17 most relevant urban parks in St. Louis, listed in Table 23. Thereby, we make two somewhat strong assumptions: first, that only parks exceeding a certain size generate substantial and discernible amenity benefits; and second, that the impact of parks is approximately homogeneous, meaning that it is consistent irrespective of differences in attributes.

6 Empirical Results

6.1 Results of the Base Model

This section presents the results of our ordinary least squares estimations of Equations 2 & 3. By construction, the interpretation of the marginal effect of any coefficient presupposes that all other independent variables are held constant and evaluated at their mean. For the sake of scarcity, we do not make this explicit each time but would like to mention upfront that this section constitutes ceteris paribus interpretations.

Table 4: Regression Estimates of the Base Model

	(1) Model 1	(2) Model 2	(3) Model 3	(4) 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

Against this backdrop, Table 4 presents the estimation results of Equation 2. The columns represent four different specifications of the base model, in which we gradually add control variables to examine their impact on the results. In this regard, column (1) shows the results when only controlling for structural housing attributes and proximity to the other two stadiums. The adjusted R^2 has a value of 0.5524, indicating that Model 1 can already explain more than half of the price variation in the sample data. Adding fixed effects to the model, considerably increases the adjusted R^2 to 0.7401, as shown in column (2). Columns (3) and (4) add neighborhood and market characteristics, as well as urban controls, respectively. The additional inclusion slightly increases the goodness of fit and we observe the largest adjusted R^2 value of 0.7571 in Model 4, which we consider our preferred model specification. This value is similar to those reported in previous hedonic studies and is decently large. Our analysis shows that the qualitative findings across the four specifications of the base model are identical, and there are no major differences in terms of direction, magnitude, and statistical significance among the independent variables. Hence, the results suggest that the inclusion of additional covariates improves the precision of the estimates and helps isolate the treatment effect (Wooldridge (2018)). In the following, we briefly outline the findings for the covariates, before eventually elaborating on the estimates of our target variables.

In general, most of the covariates are highly significant and almost all exhibit the expected sign. With respect to the estimates for housing attributes, the data suggests that larger parcels and buildings unsurprisingly sell for a higher price, but that housing values depreciate in age. Further, we discern that garages, carports, and attics, elevate the value of single-family homes in the sample. Lastly, relative to houses exhibiting a brick wall, stone houses sell for a premium, whereas houses with a frame wall sell for 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 also suggests that higher crime and vacancy rates are associated with lower transaction values. On the other hand, 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, which are both only significant at the ten percent level. Concerning the rate of youth per neighborhood, 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 that exhibit family-friendly characteristics, for example in terms of school quality, safety, and noise.
The sign of the coefficient for population density is negative, which is rather unexpected, in view of the theoretical prediction of the Monocentric-City Model. Yet, it should be noted that the null of non-significance is only rejected at the ten percent level and the point estimate relatively low in magnitude. In this regard, the estimate might be indicative of the vast diversity of neighborhoods in St. Louis in terms of size and population. In particular, it seems plausible that the time frame under investigation is too short and the sample size insufficiently small to detect considerable impacts of inner-city population dynamics. Moreover, while the negative sign somewhat contradicts urban economic theory,[30] the findings do not appear entirely implausible. For instance, the subject of our analysis are single-family homes, and it might be that property owners prefer to live in areas that are less crowded and less congested and therefore 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. Besides, we find that the

[30]Nonetheless, it should be noted that the overall findings very much align with urban economic theory in general, and the Monocentric-City Model in particular. Precisely, 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 very likely that density patterns do not perfectly align with proximity to the city core.

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, and a larger number of finance and insurance establishments suggests 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 on the zip-code level might not adequately capture local trends in establishment numbers.[31]

As for the urban controls, one can see that 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 from the closest urban park or green space lowers the value of a single-family home by about 18.14%,[32] 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%,[33] which is 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 does not pose a large issue, as we show in the Appendix that the insignificance very likely results from an almost perfect correlation of the coefficients given the stadiums adjacency. 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 in the Appendix. In short, all coefficients are significant and positive, as expected. Furthermore, the magnitude of the point estimates accords with those of previous findings.

Finally, in respect to our target variables, the analysis reveals that all three difference-in-difference coefficients are statistically significant at the highest level and have the expected sign. Firstly, 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. Secondly, the post-relocation dummy is also positive and it might reflect a general long-term recovery of St. Louis' housing market following the economic crisis that started in 2008.

Eventually, the difference-in-difference estimate reflecting the treatment effect of the Rams' depar-

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

[32] $(\exp(-0.2002 * 1) - 1) * 100 = -18,1433.$

[33] $(\exp(-0.0636) - 1) * 100 = -6.16197.$

ture 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, a single family home located within three-miles to Edward Jones Dome sold for a substantial discount of 7.52% relative to properties with similar characteristics transacted within the control area. Those 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 exploited the relocation as a natural experiment allowing 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, we discussed in Section 4, that there are theoretical arguments both for and against the use of robust standard errors instead of clustering the error terms. To ensure that our findings are not affected by the choice of error specification, we estimate our preferred base model across different error specifications, whereby we additionally cluster the error term at three different scale-levels: census tract, ward, and neighborhood. For the sake of comparability, we also report the results of the base model with standard OLS errors. Table 5 summarizes the regression output for the main variables of interest, while the full regression output is provided in Table 30 in the Appendix. Column (1) presents the results of our preferred model with robust standard errors, column (2) depicts the estimates using OLS errors, while columns (3) - (5) show the estimation results for the clustered standard errors at different levels.

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

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) 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, the main coefficient of interest, ImpactxPost, is significant at the highest level. This supports the overall consistency and robustness of the 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 the different error specifications result in minor changes in the significance of some individual covariates, these changes are negligible and the overall significance of the covariates appears reasonable.

6.2 Results of the Distance Ring Models

One-Mile Distance Rings

Further delving into the exploration of the foregone amenity benefits associated with the relocation, we would like to know 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, to check for the consistency of the findings, we also report regression estimates for the different error specifications and the full regression output is provided in Table 31 in the Appendix.

Table 6: 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)
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, our preferred model specification with robust standard errors, depicted in column (1), indicates that the values of single-family homes tend to be higher the closer a property is located to the stadium and thus to the downtown area. Importantly, the sample suggests that the price gradient of single-family homes decreases concavely in distance, implying a distance decaying pattern. Simply put, the estimated relative price differences among adjacent distance rings is considerably large for the first distance rings, but becomes less pronounced for rings located farther away. Besides, while we find significant coefficients for distances up to seven miles, it is worth noting that we observe a significant switch in sign at the five-mile mark. This might be interpreted in the way that the aggregated positive spillovers generated by the city's core seem to expand 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 considerably large 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. Those results also consolidate our selection of a three-mile treatment area, which was originally specified in an ad-hoc manner, based on prior findings raging from highly localized effects only extending about one kilometer from the stadium (Bieze (2021)) to spillover effects observed as far as nine kilometers ($\approx$ 5.59 miles) away from the facility (Kavetsos (2012)).

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 restrict the potential target area to a five-mile radius ring around the stadium, implying that the control group consists of all property transactions taking place outside this area. We also do so as amenity benefits are typically found to be highly localized and the eight mile ring might not constitute an ideal control area. Besides, as 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, because it reduces sample size per ring which might be at the expense of statistical precision. In effect, as Table 1 shows, in particular the first four rings around the stadium are scarcely populated as a result of zoning ordinances and commercial and industrial land use within the broader downtown area. To circumvent this issue, we therefore at first group them together following 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)	(2)	(3)	(4)	(5)
	Robust	OLS	Census Tract	Ward	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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Column (1) refers to our preferred model specification with robust standard errors. Briefly looking at the pooled target area dummies, we observe positive and significant estimates for all rings up to a distance of four and a half miles. Again, we observe a distance decaying pattern that is however less clear pronounced. In general, we discern similar significance levels across the alternative error specifications.

Regarding the interaction terms, we find significant effects up to three and a half miles. We still observe a distance-decaying structure of the treatment effect, but notice that the relative differences are much smaller in magnitude and the range goes 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 dampened and absorbed by grouping the first two miles together. Overall, the individual significance levels of the diff-in-diff estimates vary slightly more across the different specifications, however, it is not surprising due to the aforementioned limitation in sample size per ring.

Finally, we further zoom in and also estimate the model with half-mile rings for the first two miles. Besides, the sample is limited to a five-mile ring around the facility and the reference area consists of the five-mile ring, which was insignificant 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.

Nevertheless, negative and significant treatment effects can still be observed up to three and a half miles from Edward Jones Dome. However, the significance levels of individual distance rings differ 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 ring 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 previous results.

Lastly, a significant advantage of the estimated model is that it specifically illustrates the concavity of the treatment effect across space. In terms of magnitude, the relocation-induced price discount is estimated to be between 34.3% and 6.5%, conditional on 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 major league sports franchises can yield considerable positive externalities capitalized into higher property values of about 7.5% within a three-mile radius from the stadium. However, this finding alone is somewhat difficult to grasp for researchers and policymakers alike. The question regarding the justification of generous public subsidies for sports facilities, requires to contextualize the findings. In this spirit, we approximate the social welfare loss induced by the relocation and compare it to the total public spending on the stadium. It is demonstrated 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. However, due to limitation 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 aggregated social 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. Firstly, the number of total housing units per neighborhood in 2015 is proxied as the average of the 2010 and 2020 Census data. Secondly, 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. Based on our sample, we obtain a median transaction price of 229.500$. Though, this value is naturally elevated as a result of the sample selection and data cleansing, which is why we consider it as an upper price bound. For our lower price bound, we use the median sales price of all residential buildings transacted in 2015 within the impact area (166625$), whereby we include valid sales, but also foreclosures, investor sales, and unverified valid sales, which, as argued before, typically sell at a discount relative to valid sales.

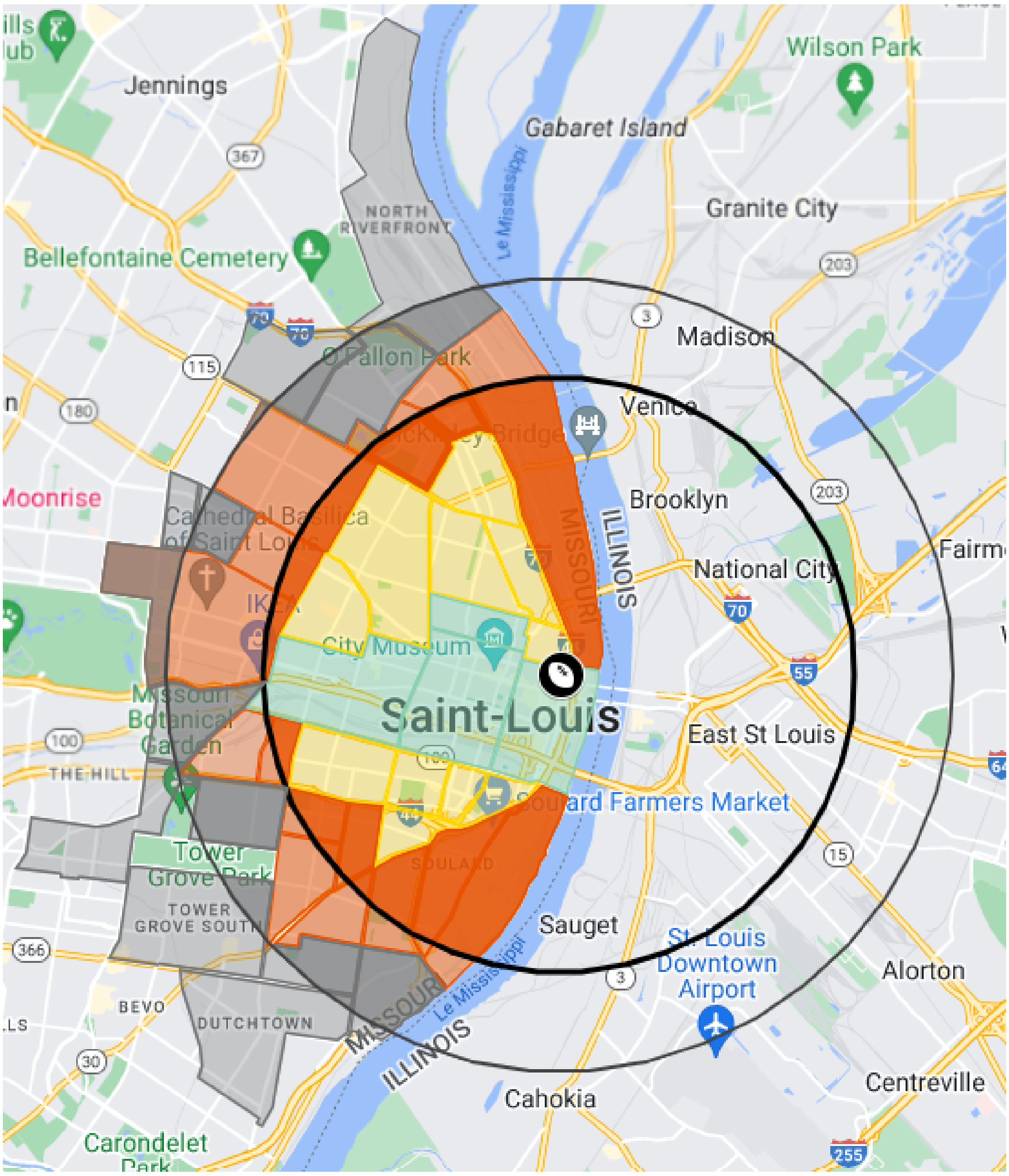
Our hedonic price regressions reveal significant property price discounts expanding about three to four miles from the stadium. However, neighborhood boundaries are shaped in somewhat arbitrary patterns across space. In this respect, Figure 3 shows that while some neighborhoods (in yellow) are fully enclosed, others (in red) intersect the three-mile impact area, displayed by the inner thick ring. As for those intersecting areas, it is assumed that the housing units are approximately equally dispersed across space. In this vein, with the help of Google My Maps, we were able to compute the share of each neighborhood falling into the impact area. This allowed us to approximate the total number of housing units ($n_3 = 35551$) laying within three-mile distance to Edward Jones Dome. Lastly, the estimated social costs based on the three-mile area can be considered as a rather conservative estimate. The one-mile ring model suggested that the impact of the relocation might as well be observed in properties located up to four miles away from the stadium. To also provide an extended estimate, we therefore likewise estimate the total welfare loss based on a four-mile impact area ($n_4 = 52856$), for which we undergo the same steps as for the three-mile area.[34]

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, simply because some dwellings are shared by several units. Similarly, the median price per housing unit is typically not the same as the median price per dwelling. As we only have information on the number of housing units, but price information on sales of entire dwellings, we had to approximate the per unit price of properties by building type. Concretely, 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. Further, we approximate the share of each residential building type within the impact area based on their share of transaction over the entire sample period. Thereby, it is implicitly assumed that the observed shares of transaction per building type fairly correspond to their share in the 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. Against this background, we are able to approximate the number of buildings per building type located within the impact area.

Unfortunately, we were not able to follow this approach for six neighborhoods within the three-mile impact areas, as they did not exhibit any or only a few residential housing transactions over the sample period. Specifically, this means that we lack sufficient information to make assumptions on the composition of the building stock within those neighborhoods. Two of these neighborhoods - Kosciusko and Botanical Heights - were simply excluded from the analysis, since Kosciusko is a mere industrial neighborhood exhibiting only 5 housing units in 2020, according to the Census data, and as for Botanical Heights, only 1.4% of the neighborhood falls into the three-mile area. Nevertheless, the remaining four neighborhoods - Downtown, Downtown West, Midtown, and Carr Square - account for a considerable share of about one third ($n = 10535$) 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 implies, as elaborated earlier, that we do not observe sales of individual apartments and condominiums, but only sales of

[34] The upper price bound of the four-mile impact area in 2015 was identical to the three-mile value of 229500$, but the lower bound of 145.000$ is smaller, as was expected in view of the expanded area.

Figure 3: 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.

whole apartment complexes. Figure 3 shows that the concerned neighborhoods, distinguished in green, belong to large degrees to St. Louis' CBD and entertainment district, which is why it seems plausible to assume that the predominant building type should be above all apartment buildings. Moreover, the city's core is primarily characterized by commercial and industrial land use, as Figure 13 displays and as previously reported within works of Hurt (2021) & Mares and Blackburn (2019). Although the number of parcel sales is low, our data tells a similar story and out of 128 recorded parcel sales, 90,63% constituted commercial or industrial sales, whereas we only observe five transactions of multiple-family residential buildings across the four concerned neighborhoods.

In this context, it appears almost certain 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 cities downtown areas are roughly comparable in size and composition. According to a report by Dickson (2020), there were 9511 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. We must therefore 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 might however be 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 $b_{j,i}$ is 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 of the multiple-family buildings sold over the sample period. Lastly, δ_i stands for 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$, and an upper estimate of 350.837.879$.[35] Regarding the four-mile specification, the inflation adjusted price range is estimated to be 329.012.021$ - 520.746.612$. The results clearly emphasize

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

that the departure of the Rams has caused a substantial value reduction of the local housing stock. Conversely, the findings underline that the welfare gains generated by an NFL franchise can be sufficiently large to justify public subsidies for stadium projects. However, 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$, expressed in 2023 prices. Additionally, it needs to be considered that the total public expenses for the stadium were substantially larger as the bond dept and maintenance costs were paid off over a 30-year time span in 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 peace of the financing history of the stadium is equally 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)). In respect to this sum, the lawsuit implicitly revealed 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 contract.[36]

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 Edward Jones Dome was built in 1995 and is outdated by today's standards (Humphreys (2019)). Nowadays, many new stadiums constitute 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 did cost more than 4bn$ in total, although it must be said that the facility was entirely privately financed. In respect to the case of St. Louis, in late December 2015, the city board unveiled last minute plans for a new stadium in the hope to prevent the Rams' relocation to Los Angeles or to lure in another franchise to St. Louis. The total costs of the stadium were projected to amount up to 985 million $, whereby the plans foresaw 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. Yet, a public commitment to cover the entire construction costs, as was the case for Edward Jones Dome, would have very likely not resulted in net positive benefits.

[36] The contract originally constituted a thirty-year lease agreement from 1995-2025. A clause foresaw that the Rams had the right to abstain from the contract at the end of each ten-year interval, should the stadium not be ranked among the top 25% stadiums in the NFL. Due to quick technological advancements, Edward Jones Dome was already "outdated" in 2005, but the Rams did not make use of their right, such that the contract prolonged until 2015. In 2015, the Rams also decided to stay in St. Louis, but the lease would only prolong on an annual-basis from that point on. Eventually, in 2016, the clause enabled the Rams to relocate penalty-free.

Finally, in light of constantly augmenting 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 rather small relative to the additional costs of such features, public contributions for stadium projects should not be determined in terms of a fixed percentage share of the total costs, as it can be historically observed (Bradbury (2022)), but rather assessed in respect to 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 regarding future public-private stadium projects (Hanau (2016)).

7 Concluding Discussion

This thesis exploited 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 immediate vicinity of the stadium and decreases in a non-linear distance decaying pattern. Further, we estimate the cumulative social costs to lay 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, and demonstrate that the results are robust against alternative model specifications and data cleansing, and rule out that potential anticipation effects, confounding events, or endogenous regressors do significantly bias the estimates.
Taken together, the findings suggest that a major league team can create substantially large positive externalities which may justify public subsidies for sports facilities. It appears plausible that the findings are somewhat generalizable and indicative above all for other mid-sized cities, where sports plays an integral role for urban revitalization. Nevertheless, such as for every case study, the results are dependent on a set 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 to contextualize and better grasp the observed findings. Above all, they may explain why our thesis reveals positive team effects, whereas prior research has found that major league teams have emanated net negative externalities.

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 prior hedonic studies, the estimated price discount of 7.5% is fairly moderate and reflects an approximate average of prior findings. Similarly, our estimated 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),[37] 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. However, the impact of the relocation is unsurprisingly smaller than the estimated 1.3 billion pound 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 social welfare loss in St. Louis is considerably larger than this number, emphasizing the importance of the Rams for the city.

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

[37] Unfortunately, we were not able to certainly determine to which year the price estimate relates and therefore 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 have above all studied the impact associated with NBA teams, this thesis has analyzed the team effects associated with an NFL franchise. It is worth noting that there are considerable differences between the leagues, particularly in respect to the number of games. While a typical NFL season only consists of about eight home matches, the average NBA home season exhibits more than 40 matches. In this respect, NBA games are primarily attended by local residents arriving shortly before the match begins, whereas football matches attract many fans living farther away who often stay for the weekend, implying that game-related traffic is more distributed over several days (Abbiasov and Sedov (2023)). Hence, it may be argued that congestion should be a larger issue surrounding NBA matches, which could somewhat 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, it appears plausible that the hosting of an NFL franchise conveys additional status value to a city.

Secondly, it might be that the facility-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. Similar to this logic, Nelson (2001) argues that stadiums should not be surrounded by large parking lots as they would prevent the unfolding of positive spillovers. Counterintuitively, we contend that the integration of Edward Jones Dome into the CBD might have helped to prevent the spread of congestion externalities on residential living quarters. Similar to the reasoning of Propheter (2021), who postulates that a large parking lot around Dodgers Stadium potentially acts as a buffer to prevent nuisance, such as noise and congestion, we argue that the primarily commercial and industrial land use around Edward Jones Dome, as shown in Figure 13, might fulfill a similar function. As shown in Table 1, our sample only consists of 13 transactions taking place within a one-mile radius from the stadium. Therefore, it might be that 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. Thereupon, Hurt (2021) describes that the Dome is part of a large convention center which makes it somewhat physically isolated. Further, the author judges that the immediate surrounding is rather unexciting and "dead". In this vein, 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 might be at the benefit of local residents, as it is likely to minimize match-related nuisance. This reasoning aligns with Ahlfeldt and Maennig (2009) & Ahlfeldt and Maennig (2010), who reason that the emanation of positive externalities from a facility largely depends on the policymakers ability to limit congestion effects as much as possible, especially by selecting an adequate location and by neatly integrating the facility into its surrounding neighborhood. As a last note, the question to which degree different facility-designs and location choices influence the impact of sports facilities on the real-estate market promises to be an interesting puzzle for future research.

Thirdly, the relatively large welfare loss induced by the relocation is likely to stand in a direct relation to St. Louis' distressed economic and demographic situation and the fact that sports plays an essential role as a driver of urban revitalization of the city core. Over the last century, St. Louis has lost much of its old glamour and the sports industry might act as a beacon of hope which makes residents somewhat forget about the problems of the city. Besides, it is rather unusual for a city of the size of St. Louis to have three major league teams. Insofar, it might be that feelings of community identity and civic pride are particularly vigorous in St. Louis. The Rams' departure elicited a highly emotional response from fans and public official alike, bearing witness of the deep-seated societal and political significance of the team in the city. As previously mentioned, Wagoner (2019) speaks of a "philanthropic void left behind by the Rams" and additionally emphasizes that more recently, the departure has eventually 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 have been playing their home games in the old stadium of the Rams and constantly exhibit one of the highest attendance ratings across the league (Barrabi (2020)), further highlighting the special bond between football in particular, and sports in general, and the St. Louis community.

Fourthly, closely related to the previous point, the Rams have highlighted within their relocation application that St. Louis does not provide 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 usual for empirical works, we need to report a few caveats of this thesis. For instance, regarding the model specification, we were unfortunately not able to obtain information on the proximity of single-family homes to transports industries 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 unfortunately not able to find a decent proxy for proximity to transport infrastructures. Nevertheless, we believe that any resulting omitted variable bias should be relatively minor, as we do not anticipate significant changes in St. Louis' transportation infrastructure following the Rams' departure.
Furthermore, another data-related limitation is that we were only able to acquire information on parcel sales and hence laid a focus 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 check the robustness of the results for alternative residential building types. In this regard, 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, since those building types are typically more prevalent in downtown areas than single-family homes, as already elaborated

earlier. Consequently, it might have been that we would have observed a different sign for these building types, and that the overall results 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 somehow correlated with the treatment. In this vein, it would have been desirable to additionally run repeated sales regressions, either for the whole sample, i.e. Chikish et al. (2019), or embedded within the model using a repeated-sales sample, i.e. Humphreys and Nowak (2017), to exclude 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 presented in this thesis suggest that sports facilities and sports teams can generate substantial quality-of-life benefits, enhance social cohesion, and stimulate civic pride. Taken together, these intangible benefits may be large enough to justify generous public subsidies from an economic perspective. Secondly, in particular in non-saturated and distressed markets, a well-planned sports-led urban development strategy may serve as an essential anchor for downtown revitalization. This is especially because a major league sports team's presence can enhance the perceived attractiveness and credibility of a city, sending a positive signal to businesses and residents.

While this thesis suggests that sports subsidies can constitute a useful tool in the policymaker's toolbox, it should be noted that this study cannot determine whether public funds might be better invested in other sectors that generate 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, Alexander and Kern (2004) argue that above all franchise owners have benefited from publicly provided stadiums in the past, as team values typically skyrocket when teams move to a new stadium. As mentioned before, franchise owners hold considerable bargaining power over their host city, as the franchise system enables teams to leverage their position by threatening for relocation. Additionally, there exists a general excess demand for sports teams resulting in a competition between municipalities which is carried out on the question which city makes larger concessions in terms of public funding. If the main profiteers of this goading process are especially the franchise owners and less the residents, it seems desirable to increase corporate accountability, and to simultaneously toughen relocation regulations. Future public-private stadium projects may find promising opportunities in exploring new blended-financing mechanisms, which offer increased involvement from franchises, thereby increasing their "skin in the game".

The *sports communities model* is a specific example of such a mechanism, which was for instance utilized for the construction of Busch stadium in the early 2000's. It has the potential to increase corporate accountability and to raise taxes in a more targeted and equitable manner. Under this approach, a city provides public subsidies for a new stadium that are equivalent in value to the expected tax revenue increases of an adjacent neighborhood that the franchise is responsible for developing and managing. Both the city and the franchise benefit, as the adjacent neighborhood creates additional income streams from offices, retail, and residential uses for the franchise, while the city's public subsidies are directly offset, and residents are not directly charged with the tax burden (Hanau (2016)).

With respect to more stringent regulation policies, public officials within current host cities are advised to unite their efforts and to hold the NFL more accountable for any relocation-related damages. Potentially, the recent lawsuits settled in favor of the City of St. Louis, resulting in damage payments in height of 820 million $ from the Rams and NFL, may discourage future relocations. However, it is worth noting that the Rams also had to pay a heavy 600 million $ relocation fee, which was apparently insufficient to disincentivize the Rams from moving to Los Angeles. For the Rams, the relocation turned out to be a financial and sporting success, as the franchise instantly doubled in value and also won the Super Bowl in 2022.

Finally, the case of St. Louis is also a lesson in terms of public-private contracts. A clause in the original 30-year lease agreement allowed the Rams to break the contract without having to pay a penalty, should Edward Jones Dome not be ranked in the top quarter of all NFL stadiums. Eventually, this clause turned out detrimental, as the Rams parted and the City of St. Louis, St. Louis County, and the state of Missouri were left behind with substantial debt payments of 144 million $.

To conclude, sports subsidies have the potential to generate significant intangible benefits for residents and serve as a catalyst for urban revitalization, making them an appealing policy tool for policymakers. However, the appropriateness of investments in the sports sector should be carefully assessed in light of local needs and contextual idiosyncrasies. Additionally, cities are encouraged to explore new blended-financing mechanisms that increase teams' financial responsibility and reduce their vulnerability to relocation threats.

References

Abadie, Alberto et al. *When Should You Adjust Standard Errors for Clustering?* Working Paper 24003. Cambridge, Massachusetts: National Bureau of Economic Research, 2017.

— "When Should You Adjust Standard Errors for Clustering?" In: *The Quarterly Journal of Economics* 138.1 (2023), pp. 1–35.

Abbiasov, Timur and Dmitry Sedov. "Do Local Businesses Benefit from Sports Facilities? The Case of Major League Sports Stadiums and Arenas". In: *Regional Science and Urban Economics* 98 (2023), p. 103853.

Agha, Nola and Dennis Coates. "A Compensating Differential Approach to Valuing the Social Benefit of Minor League Baseball". In: *Contemporary Economic Policy* 33.2 (2015), pp. 285–299.

Ahlfeldt, Gabriel M. and Georgios Kavetsos. "Outlook, Progress and Challenges of Stadium Evaluation". In: *International Handbook on the Economics of Mega Sporting Events*. Edward Elgar Publishing, 2012.

— "Form or Function?: The Effect of New Sports Stadia on Property Prices in London". In: *Journal of the Royal Statistical Society* 177.1 (2014), pp. 169–190.

Ahlfeldt, Gabriel M. and Wolfgang Maennig. "Arenas, Arena Architecture and the Impact on Location Desirability: The Case of 'Olympic Arenas' in Prenzlauer Berg, Berlin". In: *Urban Studies* 46.7 (2009), pp. 1343–1362.

— *The Impact of Sports Arenas on Land Values: Evidence from Berlin*. Working Paper. University of Hamburg, 2010.

— "Voting on a NIMBY Facility: Proximity Cost of an "Iconic" Stadium". In: *Urban Affairs Review* 48.2 (2012), pp. 205–237.

Alexander, Donald L. and William Kern. "The Economic Determinants of Professional Sports Franchise Values". In: *Journal of Sports Economics* 5.1 (2004), pp. 51–66.

Allison, Paul. *When Can You Safely Ignore Multicollinearity?* 2012. URL: https://statisticalhorizons.com/multicollinearity/ (visited on 02/22/2023).

Alonso, William. *Location and Land Use: Toward a General Theory of Land Rent*. London: Havard University Press: Oxford University Press, 1964.

Angrist, Joshua D. and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. 1st ed. Princeton University Press, 2008.

Anselin, Luc and Anil K. Bera. "Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics". In: *Handbook of Applied Economic Statistics*. New York: CRC Press, 1998, pp. 237–289.

Arif, Imran et al. "New Sports Facilities Do Not Drive Migration Between Us Cities". In: *Economics of Governance* 23.3/4 (2022), pp. 195–217.

Augustyn, Adam. *St. Louis Blues*. 2023. URL: https://www.britannica.com/biography/Jacques-Plante (visited on 03/20/2023).

Baade, Robert A. and Richard F. Dye. "An Analysis of the Economic Rationale for Public Subsidization of Sports Stadiums". In: *The Annals of Regional Science* 22.2 (1988), pp. 37–47.

Bachelor, Lynn W. "Stadiums as Solution Sets: Baseball, Football and the Revival of Downtown Detroit". In: *Review of Policy Research* 15.1 (1998), pp. 89–102.

Barrabi, Thomas. *XFL Attendance on the Rise Through 3 Weeks*. 2020. URL: https://www.foxbusiness.com/sports/xfl-attendance-week-3-ratings (visited on 01/31/0203).

Bayoh, Isaac, Elena Irwin, and Brian Roe. "The Value of Clean Dairy Air: Accounting for Endogeneity and Spatially Correlated Errors in a Hedonic Analyses of the Impact of Animal Operations on Local Property Values". In: *American Agricultural Economics Association Annual Meeting*. Denver, 2004.

Bertrand, Marianne, Esther Duflo, and Sendil Mullainathan. "How Much Should We Trust Differences-in-Difference Estimates?" In: *Quarterly Journal of Economics* 119 (2004), pp. 249–275.

Bieze, Gijs. "Stadium Development in the Netherlands: The Effect on Surrounding House Prices". MA thesis. University of Groningen, 2021.

Black, Sandra E. "Do Better Schools Matter? Parental Valuation of Elementary Education". In: *The Quarterly Journal of Economics* 114.2 (1999), pp. 577–599.

Boggess, Lyndsay N., Robert T. Greenbaum, and George E. Tita. "Does Crime Drive Housing Sales? Evidence from Los Angeles". In: *Journal of Crime and Justice* 36.3 (2013), pp. 299–318.

Bowes, David R. and Keith R. Ihlanfeldt. "Identifying the Impacts of Rail Transit Stations on Residential Property Values". In: *Journal of Urban Economics* 50.1 (2001), pp. 1–25.

Box, George and David Cox. "An Analysis of Transformations". In: *Journal of the Royal Statistical Society. Series B (Methodological)* 26.2 (1964), pp. 211–252.

Bradbury, John Charles. "Does Hosting a Professional Sports Team Benefit the Local Community? Evidence from Property Assessments". In: *Economics of Governance* 23.3 (2022), pp. 219–252.

Bradbury, John Charles, Dennis Coates, and Brad R. Humphreys. "The Impact of Professional Sports Franchises and Venues on Local Economies: A Comprehensive Survey". In: *Journal of Economic Surveys* (2022).

Breusch, Trevor and Adrian Pagan. "The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics". In: *The Review of Economic Studies* 47.1 (1980), pp. 239–253.

Brueckner, Jan K., Jacques-François Thisse, and Yves Zenou. "Why Is Central Paris Rich and Downtown Detroit Poor?" In: *European Economic Review* 43.1 (1999), pp. 91–107.

Buck, Andrew J. et al. "A Von Thünen Model of Crime, Casinos and Property Values in New Jersey". In: *Urban Studies* 28.5 (1991), pp. 673–686.

Can, Ayse. "Specification and Estimation of Hedonic Housing Price Models". In: *Regional Science and Urban Economics* 22.3 (1992), pp. 453–474.

Cannaday, Roger E. and Mark A. Sunderman. "Estimation of Depreciation for Single-Family Appraisals". In: *AREUEA Journal: Journal of the American Real Estate & Urban Economics Association* 14.2 (1986), pp. 255–273.

Carlino, Gerald and N Edward Coulson. "Compensating Differential and the Social Benefit of the NFL: Reply". In: *Journal of Urban Economics* 60 (2006), pp. 132–138.

— "Compensating Differentials and the Social Benefits of the NFL". In: *Journal of Urban Economics* 56.1 (2004), pp. 25–50.

Chapin, Timothy S. "Sports Facilities as Urban Redevelopment Catalysts: Baltimore's Camden Yards and Cleveland's Gateway". In: *Journal of the American Planning Association* 70.2 (2004), pp. 193–209.

Chikish, Yulia, Brad R. Humphreys, and Adam Nowak. "Sports Arenas, Teams and Property Values: Temporary and Permanent Shocks to Local Amenity Flows". In: *Journal of Regional Analysis & Policy* 49.1 (2019), pp. 1–12.

Clapp, John M., Anupam Nanda, and Stephen L. Ross. “Which School Attributes Matter? The Influence of School District Performance and Demographic Composition on Property Values”. In: *Journal of Urban Economics* 63.2 (2008), pp. 451–466.

Clapp, John M. and Yazhen Wang. “Defining Neighborhood Boundaries: Are Census Tracts Obsolete?” In: *Journal of Urban Economics* 59.2 (2006), pp. 259–284.

Clark, David E. and William E. Herrin. “Historical Preservation Districts and Home Sale Prices: Evidence from the Sacramento Housing Market”. In: *Review of Regional Studies* 27.1 (1997).

Click, Eric. “One Development Project, Two Economic Tales: The St. Louis Cardinals’ Busch Stadium and Ballpark Village”. In: *Missouri Policy Journal* 21 (2014), pp. 21–34.

— “The St. Louis Rams: The Greatest Public Financing Show on Earth”. In: *Missouri Policy Journal* 4 (2016), pp. 24–50.

Coates, Dennis. “Stadiums and Arenas: Economic Development or Economic Redistribution?” In: *Contemporary Economic Policy* 25.4 (2007), pp. 565–577.

Coates, Dennis and Brad R. Humphreys. “The Effect of Professional Sports on Earnings and Employment in the Services and Retail Sectors in Us Cities”. In: *Regional Science and Urban Economics* 33.2 (2003), pp. 175–198.

— “Proximity Benefits and Voting on Stadium and Arena Subsidies”. In: *Journal of Urban Economics* 59.2 (2006), pp. 285–299.

— “The Effect of Professional Sports on the Earnings of Individuals: Evidence from Microeconomic Data”. In: *Applied Economics* 43.29 (2011), pp. 4449–4459.

Coates, Dennis, Brad R. Humphreys, and Andrew Zimbalist. “Compensating Differential and the Social Benefits of the NFL: A Comment”. In: *Journal of Urban Economics* 60 (2006), pp. 124–131.

Cohen, Mark A. “A Note on the Cost of Crime to Victims”. In: *Urban Studies* 27.1 (1990), pp. 139–146.

Cooperman, Jeannette. “The Story of Segregation in St. Louis”. In: *St. Louis Magazine* (2014).

Coulson, N Edward and Robin M Leichenko. “The Internal and External Impact of Historical Designation on Property Values”. In: *Journal of Real Estate Finance and Economics* 23.1 (2001), pp. 113–124.

Crompton, John L. “The Impact of Parks on Property Values: Empirical Evidence from the Past Two Decades in the United States”. In: *Managing Leisure* 10.4 (2005), pp. 203–218.

Cullen, Julie B. and Steven D. Levitt. “Crime, Urban Flight, and the Consequences for Cities”. In: *The Review of Economics and Statistics* 81.2 (1999), pp. 159–169.

Daniel, Vanessa E., Raymond Florax, and Piet Rietveld. “Floods and Residential Property Values: A Hedonic Price Analysis for the Netherlands”. In: *Built Environment* 35.4 (2009), pp. 563–576.

Dehring, Carolyn A., Craig Depken, and Michael R. Ward. “A Direct Test of the Homevoter Hypothesis”. In: *Journal of Urban Economics* 64 (2012), pp. 155–170.

Dehring, Carolyn A., Craig A. Depken, and Michael R. Ward. “The Impact of Stadium Announcements on Residential Property Values: Evidence From a Natural Experiment in Dallas-Fort Worth”. In: *Contemporary Economic Policy* 25.4 (2007), pp. 627–638.

Dickson, Tamara. *Residential Report: 2020 Annual Review*. Tech. rep. Nashville Downtown Partnership, 2020.

Eves, Chris. “The Long-Term Impact of Flooding on Residential Property Values”. In: *Property Management* 20.4 (2002), pp. 214–227.

Fama, Eugene F. "Efficient Capital Markets: A Review of Theory and Empirical Work". In: *The Journal of Finance* 25.2 (1970), pp. 383–417.

Farley, John E. "Race, Not Class: Explaining Racial Housing Segregation in the St. Louis Metropolitan Area, 2000". In: *Sociological Focus* 38.2 (2005), pp. 133–150.

Farmer, Sam and Roger Vincent. "Owner of St. Louis Rams Plans to Build NFL Stadium in Inglewood". In: *Los Angeles Times* (2015).

Feng, Xia and Brad R. Humphreys. "The Impact of Professional Sports Facilities on Housing Values: Evidence from Census Block Group Data". In: *City, Culture and Society* 3.3 (2012), pp. 189–200.

— "Assessing the Economic Impact of Sports Facilities on Residential Property Values: A Spatial Hedonic Approach". In: *Journal of Sports Economics* 19.2 (2018), pp. 188–210.

Fenn, Aju J. and John R. Crooker. "Estimating Local Welfare Generated by an NFL Team under Credible Threat of Relocation". In: *Southern Economic Journal* 76.1 (2009), pp. 198–223.

Fischel, William A. *The Homevoter Hypothesis: How Home Values Influence Local Government Taxation, School Finance, and Land-Use Policies*. Harvard University Press, 2001.

Ford, Deborah Ann. "The Effect of Historic District Designation on Single-Family Home Prices". In: *Real Estate Economics* 17.3 (1989), pp. 353–362.

Fujita, Masahisa. *Urban Economic Theory: Land Use and City Size*. Cambridge: Cambridge University Press, 1989.

Gayant, Jean-Pascal. *L'Économie du Sport*. 1st ed. Dunod, 2016.

Glaeser, Edward L. "What's So Great About Skyscrapers?" In: *Triumph of the City*. Macmillan, 2011, pp. 135–163.

Glaeser, Edward L, Jed Kolko, and Albert Saiz. "Consumer City". In: *Journal of Economic Geography* 1 (2001), pp. 27–50.

Goodman, Allen C. and Thomas G. Thibodeau. "Age-Related Heteroskedasticity in Hedonic House Price Equations". In: *Journal of Housing Research* 6.1 (1995), pp. 25–42.

— "Housing Market Segmentation and Hedonic Prediction Accuracy". In: *Journal of Housing Economics* 12.3 (2003), pp. 181–201.

Gordon, Colin and Sarah K. Bruch. "Home Inequity: Race, Wealth, and Housing in St. Louis Since 1940". In: *Housing Studies* 35.7 (2020), pp. 1285–1308.

Gordon, David and Michael Stowe. "Historical Preservation Districts and Local Political Organizations Effects on Real Property Values". In: (2014).

Griswold, Nigel G. and Patricia E. Norris. *Economic Impacts of Residential Property Abandonment and the Genesee County Land Bank in Flint, Michigan*. Report. MSU Land Policy Institute, 2007.

Gullo, Robert. *Report: NFL Had Initial Thoughts of Relocating Raiders or Chargers to St. Louis*. 2022. URL: https://www.sportskeeda.com/nfl/news-nfl-thought-relocating-team-st-louis (visited on 03/31/2023).

Hall, Robert E. "The Measurement of Quality Change from Vintage Price Data". In: *Price Indexes and Quality Change*. Cambridge, Massachusetts: Harvard University Press, 1971, pp. 240–271.

Halvorsen, Robert and Raymond Palmquist. "The Interpretation of Dummy Variables in Semilogarithmic Equations". In: *The American Economic Review* 70.3 (1980), pp. 474–475.

Han, Hye-Sung. "The Impact of Abandoned Properties on Nearby Property Values". In: *Housing Policy Debate* 24.2 (2014), pp. 311–334.

Hanau, Adam B. "NFL Team Relocations in the Age of Modern Stadium Finance: Motivations for a Team to Move and Implications for Smaller Markets". In: *Journal of Law & Business* 13.1 (2016), pp. 235–249.

Heyne, Malte, Bernd Suessmuth, and Wolfgang Maennig. "Mega-Sporting Events as Experience Goods". In: *SSRN Electronic Journal* (2010).

Holm, Eric Joseph van. "Minor Stadiums, Major Effects? Patterns and Sources of Redevelopment Surrounding Minor League Baseball Stadiums". In: *Urban Studies* 56.4 (2019), pp. 672–688.

Horn, Brady P., Michael Cantor, and Rodney Fort. "Proximity and Voting for Professional Sporting Stadiums: The Pattern of Support for the Seahawk Stadium Referendum". In: *Contemporary Economic Policy* 33.4 (2015), pp. 678–688.

Huang, Haifang and Brad R. Humphreys. "New Sports Facilities and Residential Housing Markets". In: *Journal of Regional Science* 54.4 (2014), pp. 629–663.

Huber, Peter J. "The Behavior of Maximum Likelihood Estimates Under Nonstandard Conditions". In: *Fifth Berkeley Symposium*. 1967, pp. 221–233.

Huguelet, Augustin, Katie Kull, and Joel Currier. *'Under Cover of Darkness': The Inside Story of How the Rams Worked the NFL and Ditched St. Louis*. 2022. URL: `https://www.stltoday.com/business/local/under-cover-of-darkness-the-inside-story-of-how-the-rams-worked-the-nfl-and/article_0df390b8-40d5-5ead-b78b-779cb5187f9e.html` (visited on 04/04/2023).

Humphreys, Brad R. "Should the Construction of New Professonial Sports Facilities be Subsidized?" In: *Journal of Policy Analysis and Management* 38.1 (2019), pp. 270–288.

Humphreys, Brad R. and Adam Nowak. "Professional Sports Facilities, Teams and Property Values: Evidence from NBA Team Departures". In: *Regional Science and Urban Economics* 66 (2017), pp. 39–51.

Humphreys, Brad R. and Hyunwoong Pyun. "Professional Sporting Events and Traffic: Evidence from US Cities". In: *Journal of Regional Science* 58.5 (2018), pp. 869–886.

Humphreys, Brad R. and Li Zhou. "Reference-Dependent Preferences, Team Relocations, and Major League Expansion". In: *Journal of Economic Behavior & Organization* 109 (2015), pp. 10–25.

Hunn, David. "Creativity and Hope: How St. Louis Will Fund a $985 Million Football Stadium". In: *St. Louis Post Dispatch* (2015).

Hurt, Doug. *Sports Infrastructure, Sports Entertainment, and Reshaping Place in St. Louis*. 2021. URL: `http://www.focusongeography.org/publications/articles/st_louis/index.html` (visited on 03/08/2023).

Hwang, Sungsoon. "Residential Segregation, Housing Submarkets, and Spatial Analysis: St. Louis and Cincinnati as a Case Study". In: *Housing Policy Debate* 25.1 (2015), pp. 91–115.

Johnson, Bruce K., Peter A. Groothuis, and John C. Whitehead. "The Value of Public Goods Generated by a Major League Sports Team: The CVM Approach". In: *Journal of Sports Economics* 2.1 (2001), pp. 6–21.

Johnson, Bruce K., Michael J. Mondello, and John C. Whitehead. "The Value of Public Goods Generated by a National Football League Team". In: *Journal of Sport Management* 21.1 (2007), pp. 123–136.

Johnson, Bruce K. et al. "Willingness to Pay for Downtown Public Goods Generated by Large, Sports-Anchored Development Projects: The CVM Approach". In: *City, Culture and Society* 3.3 (2012), pp. 201–208.

Johnson, Candon and Joshua C. Hall. "The Public Choice of Public Stadium Financing: Evidence from San Diego Referenda". In: *Economies* 7.1 (2019), p. 22.

Joshi, Aakrit, Brady P. Horn, and Robert P. Berrens. "Major League Soccer Expansion and Property Values: Do Sports Franchises Generate Amenities or Disamenities?" In: *Applied Economics* 52.44 (2020), pp. 4881–4899.

Jud, G. Donald. "The Effects of Zoning on Single-Family Residential Property Values: Charlotte, North Carolina". In: *Land Economics* 56.2 (1980), p. 142.

Judd, Dennis R. "The Role of Governmental Policies in Promoting Residential Segregation in the St. Louis Metropolitan Area". In: *The Journal of Negro Education* 66.3 (1997), p. 214.

Kain, John F. and John M. Quigley. "Racial Discrimination in Urban Housing Markets". In: National Bureau of Economic Research, 1975, pp. 56–91.

Kalist, David E. and Daniel Y. Lee. "The National Football League: Does Crime Increase on Game Day?" In: *Journal of Sports Economics* 17.8 (2016), pp. 863–882.

Kavetsos, Georgios. "The Impact of the London Olympics Announcement on Property Prices". In: *Urban Studies* 49.7 (2012), pp. 1453–1470.

Keeler, Zachary T., Heather M. Stephens, and Brad R. Humphreys. "The Amenity Value of Sports Facilities: Evidence From the Staples Center in Los Angeles". In: *Journal of Sports Economics* 22.7 (2021), pp. 799–822.

Kiel, Katherine A, Victor Matheson, and Christopher Sullivan. *The Effect of Sports Franchises on Property Values: The Role of Owners Versus Renters*. Working Paper. College of the Holy Cross, 2010.

King, Gary and Margaret E. Roberts. "How Robust Standard Errors Expose Methodological Problems They Do Not Fix, and What to Do About It". In: *Political Analysis* 23.2 (2015), pp. 159–179.

Leichenko, Robin M., N. Edward Coulson, and David Listokin. "Historic Preservation and Residential Property Values: An Analysis of Texas Cities". In: *Urban Studies* 38.11 (2001), pp. 1973–1987.

Listokin, David, Barbara Listokin, and Michael Lahr. "The Contributions of Historic Preservation to Housing and Economic Development". In: *Housing Policy Debate* 9.3 (1998), pp. 431–478.

Locke, Stephen L. "Estimating the Impact of Major League Baseball Games on Local Air Pollution". In: *Contemporary Economic Policy* 37.2 (2019), pp. 236–244.

Lynch, Allen K. and David W. Rasmussen. "Measuring the impact of crime on house prices". In: *Applied Economics* 33.15 (2001), pp. 1981–1989.

Mares, Dennis and Emily Blackburn. "Major League Baseball and Crime: Opportunity, Spatial Patterns, and Team Rivalry at St. Louis Cardinal Games". In: *Journal of Sports Economics* 20.7 (2019), pp. 875–902.

Mason, Randall. *Economics and Historic Preservation: A Guide and Review of the Literature*. Discussion Paper. The Brookings Institution Metropolitan Policy Program, 2005.

Matheson, Victor A. and Robert A. Baade. "Mega-Sporting Events in Developing Nations: Playing the Way to Prosperity?" In: *South African Journal of Economics* 72.5 (2005), pp. 1085–1096.

Mckenzie, David. *When Should You Cluster Standard Errors? New Wisdom from the Econometrics Oracle*. 2017. URL: https://blogs.worldbank.org/impactevaluations/when-should-you-cluster-standard-errors-new-wisdom-econometrics-oracle (visited on 02/22/2023).

Metzger, Molly W., Patrick J. Fowler, and Todd Swanstrom. "Hypermobility and Educational Outcomes: The Case of St. Louis". In: *Urban Education* 53.6 (2018), pp. 774–805.

Miller, Phillip A. "The Economic Impact of Sports Stadium Construction: The Case of the Construction Industry in St. Louis, Mo". In: *Journal of Urban Affairs* 24.2 (2002), pp. 159–173.

Morancho, Aurelia Bengochea. "A Hedonic Valuation of Urban Green Areas". In: *Landscape and Urban Planning* 66.1 (2003), pp. 35–41.

More, Thomas A., Thomas Stevens, and P.Geoffrey Allen. "Valuation of Urban Parks". In: *Landscape and Urban Planning* 15.1-2 (1988), pp. 139–152.

Moulton, Brent R. "Random Group Effects and the Precision of Regression Estimates". In: *Journal of Econometrics* 32.3 (1986), pp. 385–397.

— "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units". In: *The Review of Economics and Statistics* (1990), pp. 334–338.

Muth, Richard F. "Models of Land-Use, Housing, and Rent: An Evaluation". In: *Journal of Regional Science* 25.4 (1985), pp. 593–606.

Nelson, Arthur C. "Prosperity or Blight? A Question of Major League Stadia Locations". In: *Economic Development Quarterly* 15.3 (2001), pp. 255–265.

Neto, Amir Borges Ferreira and Kayla Whetstone. "The Effect of the Raiders' Relocation to Las Vegas on Residential Property Values". In: *Journal of Housing Research* 31.2 (2022), pp. 181–195.

Ngai, L. Rachel and Silvana Tenreyro. "Hot and Cold Seasons in the Housing Market". In: *The American Economic Review* 104.12 (2014), pp. 3991–4026.

Noll, Roger G. and Andrew Zimbalist. "Sports, Jobs, Taxes: Are New Stadiums Worth the Cost?" In: *The Brookings Review* 15.3 (1997), p. 35.

Nunn, Samuel and Mark S. Rosentraub. "Sports Wars - Suburbs and Center Cities in a Zero-Sum Game". In: *Journal of Sport & Social Issues* 21.1 (1997), pp. 65–82.

O'Brien, Robert M. "A Caution Regarding Rules of Thumb for Variance Inflation Factors". In: *Quality & Quantity* 41.5 (2007), pp. 673–690.

Oates, Wallace E. "The Effects of Property Taxes and Local Public Spending on Property Values: An Empirical Study of Tax Capitalization and the Tiebout Hypothesis". In: *Journal of Political Economy* 77.6 (1969), pp. 957–971.

Oliveri, Rigel C. "Setting the Stage for Ferguson- Housing Discriminiation and Segregation in St. Louis". In: *Missouri Law Review* 80 (2015), pp. 1053–1073.

Panduro, Toke Emil and Kathrine Lausted Veie. "Classification and Valuation of Urban Green Spaces - a Hedonic House Price Valuation". In: *Landscape and Urban Planning* 120 (2013), pp. 119–128.

Porsche, Marcel and Wolfgang Maennig. "The Feel-Good Effect at Mega Sport Events - Recommendations for Public and Private Administration Informed by the Experience of the FIFA World Cup 2006". In: *SSRN Electronic Journal* (2008).

Propheter, Geoffrey. "Sports Facilities and the Local Property Tax Base in Recovery". In: *Regional Science Policy & Practice* 13.5 (2021), pp. 1687–1701.

Pyun, Hyunwoong and Joshua C. Hall. "Does the Presence of Professional Football Cause Crime in a City? Evidence From Pontiac, Michigan". In: *Applied Economics* 51.36 (2019), pp. 3958–3970.

Pyun, Hyunwoong, Brad R. Humphreys, and Umair Khalil. "Professional Sports Events and Public Spending: Evidence from Municipal Police Budgets". In: *Journal of Sports Economics* 24.1 (2023), pp. 73–96.

Randolph, William C. "Estimation of Housing Depreciation: Short-Term Quality Change and Long-Term Vintage Effects". In: *Journal of Urban Economics* 23.2 (1988), pp. 162–178.

Raskin, Alex. "Los Angeles Rams Finalize Relocation Settlement With St. Louis for $820m thanks to $220m from the other Teams". In: *Daily Mail* (2022).

Respaut, Robin. *With NFL Rams Gone, St. Louis Still Stuck with Stadium Debt*. 2016. URL: `https://www.reuters.com/article/us-sports-nfl-stadiums-insight-idUSKCN0VC0EP` (visited on 04/11/2023).

Rosen, Sherwin. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition". In: *Journal of Political Economy* 82.1 (1974), pp. 34–55.

Rosentraub, Mark S. "The Local Context of a Sports Strategy for Economic Development". In: *Economic Development Quarterly* 20.3 (2006), pp. 278–291.

— *Major League Winners: Using Sports and Cultural Centers as Tools for Economic Development*. New York: Routledge, 2009.

Rypkema, Donovan. "The (Economic) Value of National Register Listing". In: *CRM* 1 (2002), pp. 6–7.

Schaeffer, Peter V. and Cecily Ahern Millerick. "The Impact of Historic District Designation on Property Values: An Empirical Study". In: *Economic Development Quarterly* 5.4 (1991), pp. 301–312.

Stephenson, E. Frank. "The Cost of Losing a National Football League Franchise: Evidence from Hotel Occupancy Data". In: *Applied Economics Letters* 28.18 (2021), pp. 1558–1561.

Stoecker, Charles, Nicholas J. Sanders, and Alan Barreca. "Success Is Something to Sneeze At: Influenza Mortality in Cities that Participate in the Super Bowl". In: *American Journal of Health Economics* (2016).

Tiebout, Charles M. "A Pure Theory of Local Expenditures". In: *Journal of Political Economy* 64.5 (1956), pp. 416–424.

Tighe, J. Rosie and Joanna P. Ganning. "The Divergent City: Unequal and Uneven Development in St. Louis". In: *Urban Geography* 36.5 (2015), pp. 654–673.

Tita, George E., Tricia L. Petras, and Robert T. Greenbaum. "Crime and Residential Choice: A Neighborhood Level Analysis of the Impact of Crime on Housing Prices". In: *Journal of Quantitative Criminology* 22.4 (2006), pp. 299–317.

Tu, C. C. "How Does a New Sports Stadium Affect Housing Values? The Case of FedEx Field". In: *Land Economics* 81.3 (2005), pp. 379–395.

Wagoner, Nick. *Stan Kroenke Buys 60 Acres in L.A.* 2014. URL: `https://www.espn.com/nfl/story/_/id/10380150/st-louis-rams-owner-stan-kroenke-buys-60-acres-land-los-angeles` (visited on 01/31/2023).

— *How the Blues' Stanley Cup Run Has Revitalized St. Louis*. 2019. URL: `https://www.espn.com/nhl/story/_/id/26922942/how-blues-stanley-cup-run-revitalized-st-louis` (visited on 03/19/2023).

Watkins, Craig A. "The Definition and Identification of Housing Submarkets". In: *Environment and Planning A: Economy and Space* 33.12 (2001), pp. 2235–2253.

White, Halbert. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity". In: *Econometrica* 48.4 (1980), p. 817.

Wooldridge, Jeffrey M. *Introductory Econometrics: A Modern Approach*. 7th ed. Mason, OH: South Western, Cengage Learning, 2018.

Yiu, Chung-Yim and Ka-Shing Cheung. "The Age–Period–Cohort Problem in Hedonic House Prices Models". In: *Econometrics* 10.1 (2022), p. 4.

Zimbalist, Andrew. "Facility Finance - Measurement, Trends, and Analysis". In: *Circling the Bases: Essays on the Challenges and Prospects of the Sports Industry*. Temple University Press, 2010, pp. 100–116.

Appendix

The Appendix is organized as follows: Appendix A contains robustness checks with respect to the parallel trend assumption and the selection of the sample period. Appendix B presents additional robustness checks related to alternative model specifications. Within Appendix C we present the results of a simple proximity model, which was omitted from the main text body, due to severe multicollinearity. Further, Appendix D presents the plots for the variable transformations that were undertaken. Finally, Appendix E contains supplementary tables and figures. Among others, it contains a summary table and a table containing the definitions of all the additional variables used throughout the Appendix.

Appendix A - Robustness Checks

Testing for the Parallel Trend Assumption

As outlined in Section 4, the adequate use of the difference-in-difference methodology requires that the treatment and control group incorporate decent counterparts. Practically, it needs to be assumed that, in the absence of the treatment, both groups would have followed the same trend. By nature of the logic of empirical research, the parallel trend assumption cannot be purely satisfied ex-ante by choosing an appropriate research design, but needs to be examined ex-post by the researcher, and the severity of a potential deviation in pre-trends needs to be evaluated within the respective research context (Ahlfeldt and Kavetsos (2014)).

Against this backdrop, simply visualizing the pre-trends of both groups can already reveal obvious violations of the common trend assumption. Therefore, we first plot those trends in Figure 4.

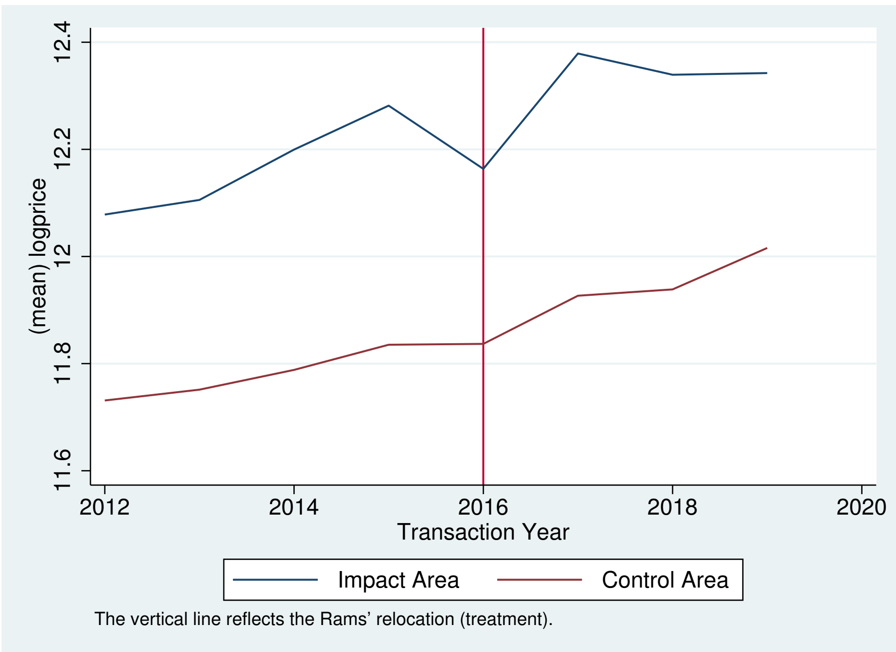


Figure 4: Parallel Trend Plot

The plot shows that both groups followed a fairly similar trajectory until the occurrence of the treatment in 2016, and there are no obvious violations, i.e. reversed trends, of the common trend assumption. Further, 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 and then remained relatively stable for the following two years. In contrast, one can see a relatively constant increase of the average (log-) housing price within the control area. However, it is important 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. Nevertheless, the difference in magnitude is relatively small.

In summary, while the parallel trend plot suggests that the trends are approximately similar, it also warrants further statistical investigation to confirm the validity of the parallel trend assumption. Hence, we estimate a hedonic leads- and lags model to statistically examine potential deviations in pre-trends between both groups. Based on Equation 2, the model is specified as follows:

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

whereby the model incorporates $m = 4$ leads (δ_{-1}, ... , δ_{-4}) capturing the pre-treatment-, i.e. anticipatory effects, and $q = 4$ lags (δ_1, ... , δ_4) capturing the post-treatment effects. The other model components are as defined before.

Table 9 presents the regression estimates for the leads and lags. In Column (1), the model is estimated on the full sample period from 2012-2019. The results show that none of the coefficients are statistically significant when using 2012 as the reference year. This supports the common trend assumption and indicates that there are no statistically significant differences in pre-trends. However, it should be noted that the housing price margins in 2015, the year prior to the relocation, were slightly different between the control and treatment areas, with 0.11 for the control area and 0.2 for the treatment area. Moreover, it is somewhat surprising that, despite the visible shock to the housing market in the impact area in 2016, we do not find statistically significant post-treatment effects when using 2012 as the base year in our leads and lags model.

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

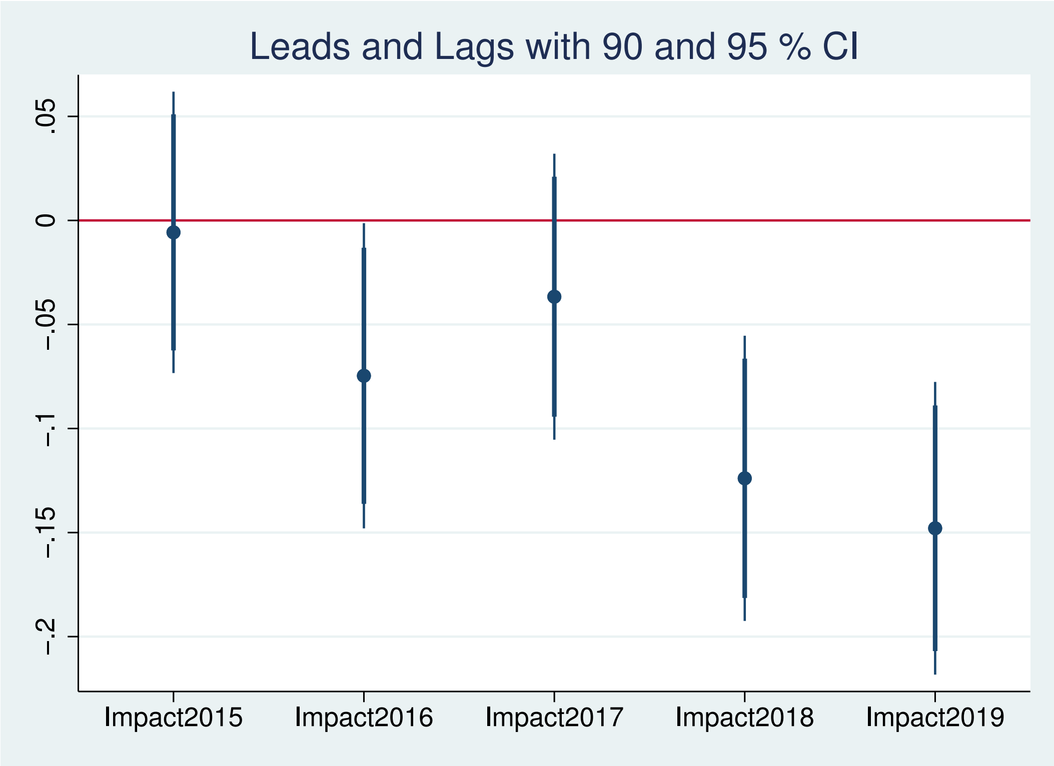
	Full Sample Period	Shortened Sample Period (2014-2019)			
	(1)	(2)	(3)	(4)	(5)
	Robust	Robust	Normal Se	Clustered, Tract	Clustered, Ward
Impact	0.075	0.170***	0.170***	0.170**	0.170*
	(0.072)	(0.043)	(0.037)	(0.076)	(0.087)
Impact2013	0.019				

	(0.074)				
Impact2014	0.090				
	(0.071)				
Impact2015	0.087	-0.006	-0.006	-0.006	-0.006
	(0.069)	(0.037)	(0.034)	(0.041)	(0.024)
Impact2016	0.014	-0.075*	-0.075**	-0.075*	-0.075*
	(0.072)	(0.042)	(0.037)	(0.042)	(0.037)
Impact2017	0.050	-0.037	-0.037	-0.037	-0.037
	(0.068)	(0.036)	(0.035)	(0.025)	(0.033)
Impact2018	-0.037	-0.124***	-0.124***	-0.124***	-0.124***
	(0.070)	(0.039)	(0.035)	(0.036)	(0.034)
Impact2019	-0.059	-0.148***	-0.148***	-0.148***	-0.148***
	(0.070)	(0.039)	(0.036)	(0.041)	(0.048)
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	0.7595	0.7595	0.7595	0.7595
Observations	12695	11048	11048	11048	11048

The coefficients are estimated as ordinary least squares.
The dependent variable is the natural logarithm of the recorded transaction price.
In columns (2) - (5) the sample period is shortened to 2014-2019.
Reference are Impact2012 and Impact2014 respectively.
The full regression results are available from the author.
Standard errors are depicted in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Therefore, we re-estimate Equation 5 using 2014 as a reference year, because Figure 4 indicates a slight difference in trends beginning in 2013. As before, we estimate the model across different error specifications and the results are presented in columns (2) - (5). Essentially, across all specifications, the model suggests there is no statistically significant difference in the pre-trends in 2015, when using 2014 as the base year. Further, the margins of the treatment and control groups are similar in 2015, with 0.053 for the control area and 0.047 for the impact area, further supporting the common trend assumption. Moreover, the results indicate significant post-treatment effects in 2016, 2018, and 2019, regardless of the specification of the error term. However, although we observe the expected negative sign, we cannot reject the null of non-significance for the lag reflecting the effect in 2017. Finally, the model estimates suggest that the treatment effect becomes larger over time. Figure 5 illustrates this evolution by plotting the model coefficients.

Figure 5: Coefplot - Model with Leads and Lags



In conclusion, the results consolidate our identification strategy and provide reasonable support for the parallel trend assumption, suggesting that the treatment and control area constitute appropriate counterparts to assume that they would have followed the same trends in the absence of the treatment. However, given the non-significant coefficients of the leads and lags model for the entire sample period, as well as the slight visible difference in slope of the (log-) average prices between the treatment and control areas beginning in 2013, we test for the robustness of our results by replicating our hedonic analyses for adjusted sample periods. The results are presented below.

Testing for Anticipation Effects - Adjusted Sample Periods

Within this section, we replicate our hedonic analyses by re-estimating Equations 2 & 3, whereby we first embed a third period, i.e. anticipation period, within the model, to test for anticipation effects, and second, adjust the sample period and compare the model findings with the original results for robustness.

Upfront, it is worth noting that adjusting, i.e. shortening, the sample period allows to combine three practical purposes: firstly, it establishes consistency with the results of the leads and lags model outlined in the previous section, which suggested that a shortening of the pre-treatment period to 2014 might be preferable for the sake of causal inference; secondly, we can exclude that the results are mainly driven by some potentially confounding events simultaneously occurring within the sample period; and thirdly, it allows to examine potential anticipation effects of the relocation, which would interfere with the identification strategy of exploiting the relocation as a natural experiment.

With respect to the last point, it might be justly criticized that the relocation of the Rams was to some extent foreseeable, particularly because the Rams have repeatedly communicated their general dissatisfaction with the state of Edward Jones Dome and publicly demanded for upgrades of the facility. We therefore first review the relocation history and elaborate on events which have spurred speculation about a return of the Rams to Los Angeles, and might have therefore provoked anticipatory market reactions. Eventually, we present the adjusted regression estimates for different lengths of the pre-and post treatment period.

The Relocation History of the St. Louis Rams

If not stated otherwise, the information presented in this subsection stem primarily from Click (2016), who provides an excellent account of the full trajectory of football in St. Louis.

After losing the Cardinals (NFL) to Arizona in 1987, St. Louis was without a football team for almost a decade. 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 Edward Jones Dome, formerly known as Trans World Dome,[38] in 1995, intending to bring a new football franchise into town. The Rams, which at the time shared a stadium with a baseball franchise in Los Angeles, were considered the ideal candidate as they were looking for an own sporting venue to better develop their brand. To entice the Rams to leave the more prosperous Los Angeles market, the Rams were offered an exceptionally favorable lease contract valid for the duration of thirty years, which allowed the Rams to keep most of the game-related revenues for themselves. Additionally, as mentioned earlier, the contract included an "escape-hitch" which gave the Rams the possibility to unilaterally break the lease agreement without penalty, should the stadium not be ranked in the top 25% of NFL stadiums, on March 1, 2005, or March 1, 2015, respectively. Upon non-compliance in 2015, the contract would automatically turn into a one-year lease, giving the franchise a successive option to renew the lease. By the first deadline in 2005, Edward Jones

[38]We note that following the Rams' departure, the stadium was again renamed and is currently designated as *The Dome at America's Center*. However, in this thesis, we have chosen to use the Dome's former name for the sake of resonance and readability. Likewise, since the stadium was named as Edward Jones Dome for the majority of the time that the Rams played there, we believe that utilizing its previous nomenclature will enhance clarity.

Dome had already fallen from its top ranking. Despite this, the Rams, under the ownership of Georgia Frontiere, agreed on renovations worth 30 million $, rather than to opt to leave the city. However, it was already evident at the time that the Dome would require a significant overhaul, or the city would risk the Rams exercising their contract clause and departing from St. Louis in 2015.

Therefore, since 2012, city officials and new Rams owner Stan Kroenke, a Missouri native who has expressed his desire to find a mutually agreeable solution, have engaged in negotiations aiming to secure a long-term future for the Rams in St. Louis.[39] The views of both sides eventually drifted too far apart and while the franchise demanded considerable renovations totaling 700 million $, the city could only propose contributions in height of 124 million $ in view of its economically restrained situation. In January 2013, an arbitration tribunal ruled that only the Rams' proposal would allow the contract to be fulfilled. However, city officials initially declared that they did not intend to implement the proposal and announced new rounds of negotiations instead, knowing full well that a departure before March 15, 2015, was contractually impossible anyway. In this context, two events in particular increased speculation about a potential return of the Rams to Los Angeles. First, on January 31, 2014, it became publicly known that franchise owner Sam Kroenke had bought land in Inglewood, California, which he communicated to the NFL, as was required by NFL statutes for franchise owners becoming active in the Los Angeles market.[40] However, it should be noted that NFL Commissioner Goodell publicly stated that no intention had been communicated to build a stadium on the land, and that the NFL has a clear relocation policy that would pose considerable practical and financial hurdles to any relocation, which would have to be overcome first.[41] In addition, the parcel alone was too small for an entire stadium complex, and Kroenke is a real estate businessman and a purchase of land is per se not unusual for him. Thus, it can be plausibly assumed that the purchase of land should not have led to any anticipatory market reaction in St. Louis.

Further, on the day of the contract clause in 2015, the stadium was predictably not ranked among the best quarter of stadiums, so that the contract was converted to a one-year lease with an unilateral annual option of renewal for the Rams. A few months prior, in December 2014, the Rams had already announced that they did not want to make use of their right to move and would stay in St. Louis for the upcoming season. One important reason was probably that NFL Commissioner Goodell had made it clear that the NFL would not agree to any relocation at the time, and that a move would be therefore possible at the earliest in 2016.
Nevertheless, a report in January 2015 has significantly fueled speculation about a return to Los Angeles in the forthcoming season. Specifically, Rams owner Kroenke announced on January 5, 2015, plans to build a new 80,000-seat stadium in Inglewood near Los Angeles, which was expected to be completed in 2018.[42] 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 here that two other NFL teams, the Chargers and Raiders, who were in a similar situation and equally expressed dissatisfaction about their host facilities, also positioned themselves for a move to Los Angeles.

[39] C.f. Stltoday.com.

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

[41] 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)).

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

In addition, as outlined above, 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 not uncommon in the American franchise system.

The tacit threat of relocation seems to have proven fruitful, as only four days later, Missouri Governor Jay Nixon established a stadium task-force. This task force was assigned to develop a concept for a new venue, located near the old one but closer to the water and equipped with a series of sophisticated stadium features that would have made it one of the most modern stadiums in the NFL.[43] Over the course of the year, more concrete financing and construction plans were incrementally revealed to the public. Those plans were equally presented to the NFL in October 2015, in the framework of a conference on the future of the franchise in St. Louis, at which public officials from San Diego and Oakland, the then host cities of the Chargers and Raiders, likewise participated to present their respective future concepts. On the city officials' side, the meeting was described as very productive and insightful, and the new stadium plans were therefore ultimately approved by city committees in early December, and submitted to the NFL in late December 2015. Around the same time, Oakland and San Diego likewise submitted their new stadium plans.
In turn, all three franchises submitted their relocation applications in early January. For the Rams, this was on January 4, 2016, and along with their application, the franchise owners have issued a statement declaring that the new stadiums plans proposed by the city were unacceptable. Additionally, the Rams listed three key reasons for their intention to move to Los Angeles: 1) their contractual right to relocate; 2) the Inglewood project's superiority over the proposals of the other two franchises; and 3) the belief that the relocation would strengthen the league as a whole. 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 relocation of the Rams was approved by the NFL alongside the relocation of the Chargers. It was decided that the two franchises would 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. Ultimately, 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.

Anticipation Effects - Announcement of Stadium Construction in 2015

Against the background of the relocation history, 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. We postulate that, given the ongoing negotiations, the parallel developments in different cities, the new stadium proposal, and the fact that public mudslinging often occurs, no significant anticipatory effects in the market should be discernible. 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 diff-in-diff constellation,

[43] C.f. Stlouistoday.com.

reflecting the last year before relocation. The coefficient of this period should thus indicate whether there was a significant anticipatory market reaction in 2015 relative to the price evolution between the two groups from 2012-2014.

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

	Robust Se	Normal Se	Clustered Se		
	(1)	(2)	(3)	(4)	(5)
	Robust	OLS	Census Tract	Ward	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 is a dummy for the anticipation period taking the value one if a single-family home was transacted between the announcement on the 05.01.2016 and the filing for relocation about one year later on the 04.01.2016. Accordingly, ImpactxInter is the interaction term for properties located in the impact area and sold within the Inter period. As one can see, in neither column, the difference-in-difference coefficient reflecting the interaction term is significantly different from zero, whereas the coefficient of the post treatment effect remains relatively unaffected and is fairly comparable to the previous estimate in terms of direction, sign, and significance. Therefore, the model provides evidence that the announcement of the stadium construction in Los Angeles has not provoked anticipatory market reactions in St. Louis' single-family housing market and generally supports the identification strategy.

Anticipation Effects - Announcement of Land Purchase in 2014 & Deviation in the Pre-Trend Evaluation

Although, we postulate above 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 4 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 taking place between the land purchase on the 31.01.2014, and the filing for relocation on the 04.01.2016. The presence of a significant coefficient for the adjusted Inter-period, would signal that it might be preferable to shorten the pre-treatment period, such that it does not cover this significant price jump.

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 presents the estimation results. As can be seen, the coefficient for ImpactxInter2 is positive and significant across all error specifications, whereas we do not observe a significant coefficient for the interaction term of the post treatment period and impact area, when using 2012 & 2013 as the reference years. The results of this and the previous estimation therefore suggest that there seems to be some significant change in (log-) average prices between the impact and control area occurring in 2014, that is not associated with the treatment in 2016. Taken together with the results of the leads and lags model, it appears essential to check for the robustness of the main conclusions of this paper by shortening the pre-treatment period such that it excludes 2012 and 2013 as reference years. Eventually, we therefore replicate our hedonic analyses for two shortened sample periods, whereby we at first use both 2014 & 2015 as reference years, but also demonstrate the robustness of the findings for when only using 2015 as the sole reference year.
Lastly, it is worth noting that, while it might be more accurate to shorten the pre-treatment period for the sake of causal inference, from a mere econometric perspective, it might not necessarily yield better model results, as it reduces the sample size considerably. There may hence be a trade-off, and by shortening the sample period we may lose some precision of our estimates.

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

Table 12 contains the estimation results for the main coefficients of the base model when shortening the pre-treatment period to 2014 & 2015. As before, we estimate Equation 2 across different error constellations. For the sake of scarcity, we only present the results for the main coefficients of the base model. The regression outputs of the distance ring models are provided in the Supplementary Appendix. 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 & 2015 as reference years, the model suggests an even larger relative price depreciation of 9.23%, which is significant at the highest level across all error specifications. With respect to 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.

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

As we already mentioned in the introduction of this section, shortening the sample period brings about the practical advantage that it allows to exclude spurious transactions, that are transactions of single-family homes which are potentially influenced not only by the treatment, but also by other confounding development or construction projects taking place over the sample period, and that also might have an impact on the building price.

Based on thorough qualitative research, we have identified potentially confounding events taking place at some point within the 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 80000-seat stadium in Inglewood, which fuels speculation about a relocation.

II **Post-Treatment Period**:

- *July 4*, 2018: Re-Opening of 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 $)

Against this background, within this subsection, we first present the results of the base model, when additionally shortening the pre-treatment period to 2015 only. Removing 2014 from the pre-sample period might be desirable in light of the previous findings presented in this section, which indicated that there seems to be a slight but nevertheless visible market reaction occurring between 2013 and 2014. Regarding the identified potential confounding events taking place in that time window, it seems questionable whether the opening of Ballpark Village I alone can explain the significant findings in Table 10. The adjacent "village" offers plenty of new consumption benefits to consumers, however, it seems doubtful whether the intangible benefits associated with the opening of the first phase emanate such strong spatial externalities. Besides, we posited above that the purchase of land in Inglewood should not have had a visible impact on the market.

It might rather be that the observed price increase in the housing market reflects the overall economic recovery of the city after the sublime crisis of 2008. This may especially be, as downtown areas were hit particularly hard during the crisis, because that is were most financial establishments are located. In view of this point, Metzger et al. (2018) affirms that the foreclosure crisis has largely impacted St. Louis and reports that almost 10% of all owner-occupied homes were foreclosed in between 2007 and 2014. Against this background, it may be that the housing market was still somewhat impaired in its functioning between 2012-2014. Hence, the estimates of the base model with only 2015 as a reference year may better reflect the "pure" market reaction following the relocation of the Rams, however, it is at the expense of smaller sample size.

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

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) 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

Table 13 presents the estimation results of the base model, when shortening the sample period to 2015 only. As before, the results for the distance ring models are provided in the Supplementary Appendix. As can be seen, the qualitative conclusions are again unaffected by the shortening of the pre-treatment period by one additional year, stressing the consistency and robustness of the results. The relative price discount is estimated to be even larger than with a significant point estimate of 9.33 %. Regarding the results of the distance ring models, we constate that there are again no visible differences compared to the main findings of this thesis.

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

As listed above, several potentially price-impacting events occur in the post-treatment period after July 4th, 2018. Therefore, we finally re-estimate the model with a shortened sample only consisting of transactions taking place between 01.01.2014 - 04.07.2018. The results of the base model are presented in Table 14, whereas the estimation results of the distance ring models are again provided in the Supplementary Appendix. Despite the considerable reduction of the sample period and the smaller sample size, the model findings are almost identical to those of the full sample period in terms of direction, significance, and magnitude. Furthermore, the qualitative results of the distance ring models remain unchanged, but we note that the distance-decaying pattern of the treatment effect is less discernible than for the full sample period.

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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix B - Additional Robustness Checks - Alternative Model Specifications

Is the Model Overspecified? - Examining Multicollinearity and the Endogeneity of Regressors

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 lead to multicollinearity concerns) and including fewer covariates (which can result in omitted-variable bias). Moreover, endogenous relationships among covariates can threaten the causal inference of the treatment effect. In this section, we address these concerns by re-estimating the base model, specifically by removing potentially endogenous and highly correlated independent variables, to test the robustness of our results.

One potential criticism of our base model is the inclusion of a large number of covariates, which may artificially inflate the standard errors of individual coefficients due to the presence of structural relationships among independent variables (Bayoh et al. (2004)). Despite this concern, we chose to control for a rich set of covariates as it is methodologically desirable to isolate the treatment effect by controlling for as many relevant housing and local characteristics as possible (Tu (2005)). However, as previously noted, this approach may introduce severe collinearity, which poses two challenges: first, it may decrease the precision of individual coefficients and render them insignificant, and second, it may impair the interpretability of concerned coefficients since collinear relationships among covariates impede the ceteris paribus interpretation of the estimate. Nonetheless, given the highly significant results of our findings, we argue that our model is appropriately specified and posit that the concern of multicollinearity is negligible.
However, Table 15 indicates that the variance inflation factors (VIFs) for several independent variables in our base model exceed the typical threshold value of 10, raising concerns about multicollinearity. Particularly, the controls for proximity to the other two major league stadiums have exorbitantly high VIFs. Furthermore, some neighborhood controls seem to be structurally related, as was 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 1. While this observation is concerning from an econometric perspective, 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. This strengthens its interpretation as the isolated treatment effect of the relocation.

In this context, it is noteworthy 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 performance as controls. The slightly inflated VIFs of the difference-in-difference coefficients also seem to occur naturally through the structural relation of the interaction term (Allison 2012). Moreover, O'Brien (2007) argues that rules of thumb for VIFs need to be interpreted jointly with

Table 15: VIFs of the Base and Slim Model

	(1) Base Model vif	(2) Slim Model 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

other factors that influence the stability of the estimates.[44] Consequently, VIFs over 40 are not necessarily problematic, and the model is not unusable. Nonetheless, they should be viewed with skepticism.

In practice, the most common approach to address multicollinearity within a model is to exclude correlated variables. However, O'Brien (2007) cautions that doing so may shift the model and change the underlying theory to be tested. Therefore, the dropping of independent variables 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' peculiar socio-demographic and economic situation, 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 and robustness of our results. In this vein, we present Table 17, which shows the estimation 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. 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.

Column (2) shows that the exclusion of controls for the other two stadiums has no visible effect on our findings. Column (3) suggests the same overall conclusions as before, although the estimated relative price depreciation of single-family homes within the impact area is slightly smaller with a point estimate of 6.03%. Otherwise, there are no significant differences relative to our preferred model specification. Therefore, we conclude that our preferred model specification is adequate, and we emphasize that multicollinearity does not significantly impair the estimation results.

Table 17: Regression Estimates - Removing Highly Correlated Covariates

	(1) Base Model	(2) No Distance Controls	(3) 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***

[44]From a more technical perspective, it may be remarked that a high VIF does not necessarily coerce a large standard deviation, as the standard deviation of a coefficient j is simultaneously determined by its error variance σ_j, and the total sample variation in x_j: SST_j (Wooldridge (2018)).

	(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)
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, the findings also provide evidence that potentially endogenous relationships among some of the covariates have not led to spurious regression estimates. Specifically, we observe that the inclusion or exclusion of most of the neighborhood characteristics does not significantly alter the estimation results. We interpret this as supporting our identification strategy that the relocation constitutes an exogenous shock that is unrelated to local changes in neighborhood features.

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

As discussed in Section 4, the selection of covariates for hedonic modeling is not predetermined and depends on both theoretical considerations and contextual factors. Although we control for a wide range of covariates, there are still some control variables commonly used in previous hedonic studies that we did not include, either by choice, or due to data limitations. In this section, we examine the potential impact of these variables on the estimation results and present an intentionally "oversaturated" model to test the robustness of our findings.

Generally, the omission of a control variable in any econometric model is only then a problem for causal inference if the omitted variable is at least moderately correlated with any of the independent variables and the dependent variable simultaneously. As a result, this would induce heteroskedastic error terms, or to put differently, one would recognize a conditional structure within the errors. In such a case, the model would suffer from the well-known *omitted variable bias* (OVB). Eventually, as in practice, the plausibility of omitted variables can never be fully excluded, it remains to the researcher to contemplate on the impact of potentially unobserved characteristics on the findings.

Despite the fact that we are already controlling for a generous amount of covariates and the adjusted R^2 values are relatively high across the presented models, it might also be that the findings suffer from OVB, especially due to the integration of the stadium into St. Louis Downtown. If there are any other unobserved factors that are equally related to proximity to the stadium and have a significant impact on housing values, and if these factors have also changed alongside the treatment, the findings may be biased. By shortening the pre-and post-treatment periods, as shown in the Appendix A, we have already demonstrated that other construction projects and sports-related events that occurred throughout the sample period did not significantly bias the findings. To the best of the authors' knowledge, we are not aware of any other potential confounding changes taking place within either the impact or control area that might explain the observed findings.

Notwithstanding, there are two potentially relevant omitted covariates for which information was restricted or not available, namely the proximity of a property to transport infrastructure, i.e. the nearest bus or train station, or the closest highway interchange, as well as the quality of local public and private schools. Both have been shown to significantly shape housing values.[45] While the latter is presumably less problematic, as the quality of local schools is likely to be mostly captured by the included neighborhood controls,[46] the omission of transport amenities needs to be contemplated.
Transport infrastructure is essential insofar as urban economic theory posits that a large variation in land prices and the composition of a city can be explained by the *Monocentric-City Model* (C.f. Alonso (1964); Muth (1985); Fujita (1989)). The model suggests that the land and consequently house price gradient decreases proportionally in average commuting time - and thus also with proximity - to the CBD where most of the jobs are located. If there occurred any sports- or non-sports-related changes affecting the transport infrastructure that are simultaneously correlated

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

[46] C.f. Metzger et al. (2018) who discern that lower educational outcomes in St. Louis' schools are particularly concentrated in low-income neighborhoods.

with proximity to the downtown area and thus to the stadium, our models might not properly capture this effect. As a result, one would mistakenly attribute the observed depreciation in housing prices to the foregone amenity benefits from hosting a sports franchise, whereas in reality, the main channel explaining the results would be changes in transport amenities.

In this light, it is noted that in terms of non-sports-related changes, to the best of our knowledge, no large transport construction project took place over the course of the sample period that would explain the observed findings. Regarding sports-related changes in urban transportation, Humphreys and Pyun (2018) find that MLB home matches are positively associated with traffic congestion as a large number of people concentrate in one and the same location. Besides, Humphreys and Nowak (2017) find that professional sports teams might generate substantial disamenities in local markets, largely explained by nuisance. Accordingly, the authors reveal that the departure of two NBA franchises has led to a price appreciation of residential properties in Charlotte and Seattle, respectively. However, the findings for St. Louis suggest differently and it was shown that local housing values fell relative to the projected trend without relocation. Importantly, as discussed in Section 7, one reason for those contrasting findings might be differences in the fan base and the number of matches among the NFL, MLB and NBA. While an average NFL team plays only about 8 home games per season, attracting many out-of-town spectators who arrive and leave before and after the match and potentially dispersing traffic congestion, the MLB and NBA seasons are considerably longer, with about 79 and 45 home games respectively on average, and a typical match primarily attracts local spectators (Abbiasov and Sedov (2023)).

Lastly, in an attempt to capture residential proximity to major transport infrastructure, we also included the average commuting time to work as a control variable, which was obtained at the zip-code level from the ACS. Similarly, to account for school quality, we added the share of the population with a high-school or academic degree, which was also available at the zip-code level. Additionally, we tested the results by including a set of other local controls commonly used in previous studies, such as 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.[47] We also examined the impact of being located within an Empowerment Zone.[48] Table 18 displays the estimation results of this deliberately oversaturated model.

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

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) Neighborhood
Target Variables					
Impact	0.1331***	0.1331***	0.1331	0.1331	0.1331*

[47] A summary table of the descriptive statistics for these additional covariates is provided in the Supplementary Appendix.

[48] Empowerment Zones are distressed urban areas that provide businesses with federal tax credits.

	(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

The results suggest that including these additional covariates did not have a visible impact on the main conclusions, supporting the robustness of our findings and indicating that none of the additional covariates led to a considerable OVB relative to our preferred model specification. However, it is worth noting that some variables, such as the share of the population holding an academic degree, introduces severe multicollinearity into the model, as expected due to the structural dependencies among the 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. Lastly, we find that the coefficient for average commuting time is insignificant across all model specifications, potentially because the scale level was too large to adequately account for proximity to transport infrastructure.

As a final note, we would like to mention that we have also tested the specification across the ring models and find similar results as before. The results are available from the author upon request.

Estimation Results With Neighborhood Fixed Effects

In the framework of an additional robustness check, we re-estimate Equation 2 to test the degree to which the selection of the scale level of the local fixed effects impacts the model estimates. As discussed earlier in Section 5, we opted to include census tract fixed effects in the model 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 perspective, it is not clear on which scale level the fixed effects should be measured. We prefer census tract fixed effects as they constitute the smallest geographical scale level for which data was available. Nevertheless, neighborhood boundaries have evolved more naturally and may represent more intuitive geographical clusters. Therefore, we present the results of the base model when using neighborhood fixed effects instead of census tract fixed effects. The estimation results are displayed in Table 19.

Table 19: 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

The estimation results suggest that the overall conclusions remain unchanged, indicating the consistency of the findings. However, 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 on any of the indicated scale levels.

Regarding the impact on the covariates, there are no significant differences observed. If anything, it is worth noting the non-significant but negative estimates for Crime and Youth, which were previously reported as highly significant in Table 5. However, the non-significance is likely a result of the multicollinearity introduced by the neighborhood fixed effects. Table 20 shows that the use of neighborhood fixed effects significantly increases the VIFs of the neighborhood coefficients.

Lastly, we have also re-estimated Equation 3 using neighborhood fixed effects, and find that the results are similar to the distance ring models with census tract fixed effects. The results are available from the author upon request.

Table 20: 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 relates to the issue that the simultaneous inclusion of a building's age, transaction year, and construction year, induces perfect multicollinearity in the model. In response, most empiricists tend to omit the latter variable. Yet, Yiu and Cheung (2022) argue that this omission might cause an omitted variable bias if consumers value structural or physical building characteristics attached to a certain cohort, leading them to pay a premium for those features. This premium, as Hall (1971) coins 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 might be correlated with a property's construction year. Similarly, Hall (1971) suggests that cohort effects may equally exist for new buildings, if consumers have a pure taste for newer houses.

Yiu and Cheung (2022) propose to deal with the APC problem by including external information on the quality and renovation status of a house, such as appraised-improvement values of housing structures. Unfortunately, we could not replicate their approach as we are lacking reliable information on assessment values of individual properties in our sample. Besides, as mentioned before, we are employing structural and time-invariant housing characteristics as covariates within our hedonic price regression models, which reflect a snapshot in time. We argue that this is rather unproblematic as our sample period took place quite recently, and most of the structural characteristics typically do not vary over time, i.e. parcel size, and if they do, i.e. the number of carports, the estimation bias should be rather marginal. Additionally, the regression coefficients of the housing controls all exhibit the expected signs.

Notwithstanding, since the housing stock in St. Louis is relatively old, and the range of building ages is somewhat vast, it might be possible that our error terms include dwelling age-heteroskedasticity. This is because the likelihood of significant upgrades and renovations, and thus the size of the error term, are both likely to increase in dwelling age (Goodman and Thibodeau (1995)). For a sample of single-family homes in Dallas, the authors show that housing values depreciate non-linearly in age and that there exists a positive age effect for houses aged between 20 and 40. In a similar vein, Cannaday and Sunderman (1986) provide evidence that the depreciation path of single-family homes may indeed be rather concave than linear.
We adopt two approaches to address the Age-Period-Cohort-Problem and non-linearity in our sample. Firstly, we include control dummy variables indicating the listing of a property within the local, local certified, or national historic register. This is expected to largely account for variance in housing prices induced by certain physical housing features. St. Louis has a relatively large share of historic districts, as depicted in Figure 6, due to its historical significance in the Westward Expansion of the United States.

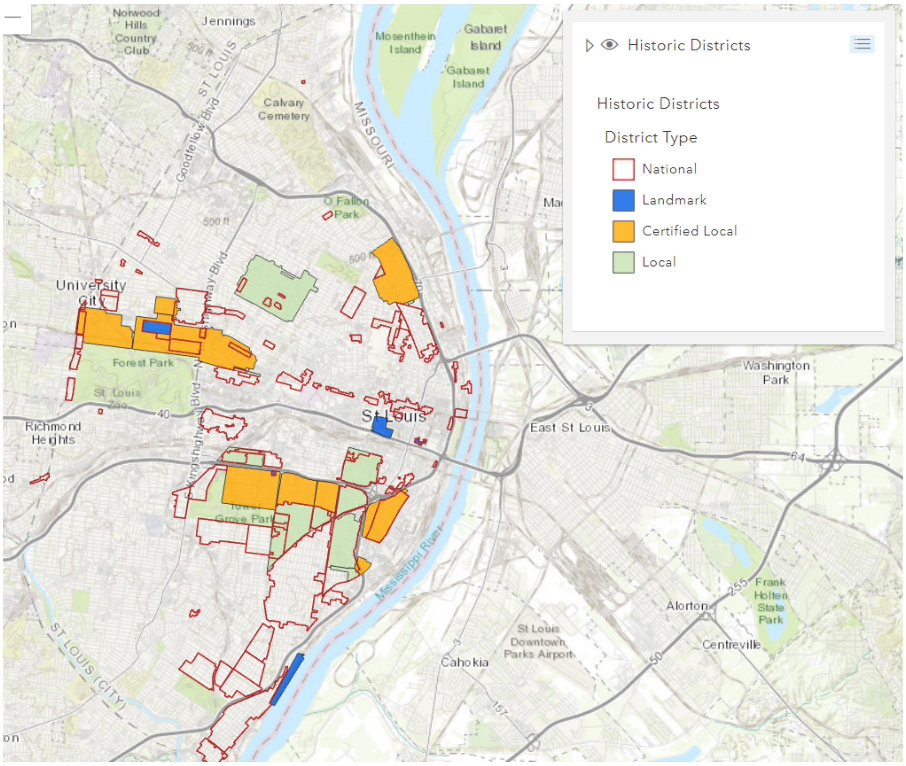


Figure 6: Map of the Local and National Historic Districts in St. Louis
Source: www.stlouis-mo.gov.

In total, the City of St. Louis lists 18 local historic districts and 10 certified local historic districts, whereby the latter are eligible for registration within the National Register of Historic Places (NRHP). It is important to note that these districts require approval by political ordinance and are subject to strict regulations upon admission. For example, any changes made to the exterior or core structure of a property located in a historical district must be ratified by the Cultural Resources Office.[49] In exchange for the stringent regulation, these properties are eligible for federal historic preservation tax credits for rehabilitation efforts.[50]
Further, the criteria for eligibility of listing into the NRHP were first designated in the *National Historic Preservation Act of 1966* and synthesized by the City of St. Louis as follows: *"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"*.[51] 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.

In addition to the historic designation of neighborhoods, the City of St. Louis has set the preservation and conservation of historic buildings and landmarks as a central target within the city's Strategic Land Use Plan.[52] Concretely, St. Louis has a) defined Preservation Review Areas, as

[49] C.f. Stlouis-mo.gov.
[50] C.f. Stlouis-mo.gov.
[51] C.f. Stlouis-mo.gov.
[52] The Strategic Land Use Plan was adopted in 2005 and subsequently amended incrementally. Inherently, the plan assigns land use designations to each block in the city and thereby serves as a guideline for residents and investors by identifying urban areas for maintenance, enhancement, and development.

depicted in Figure 7, in which, due to the significance of a specific urban area on its immediate and surrounding neighborhood, each demolition application needs to be reviewed,[53] and b) set in place a Housing Conservation Program to assure that houses abide by specific building standards, and prevent obsolescence and blight.[54]

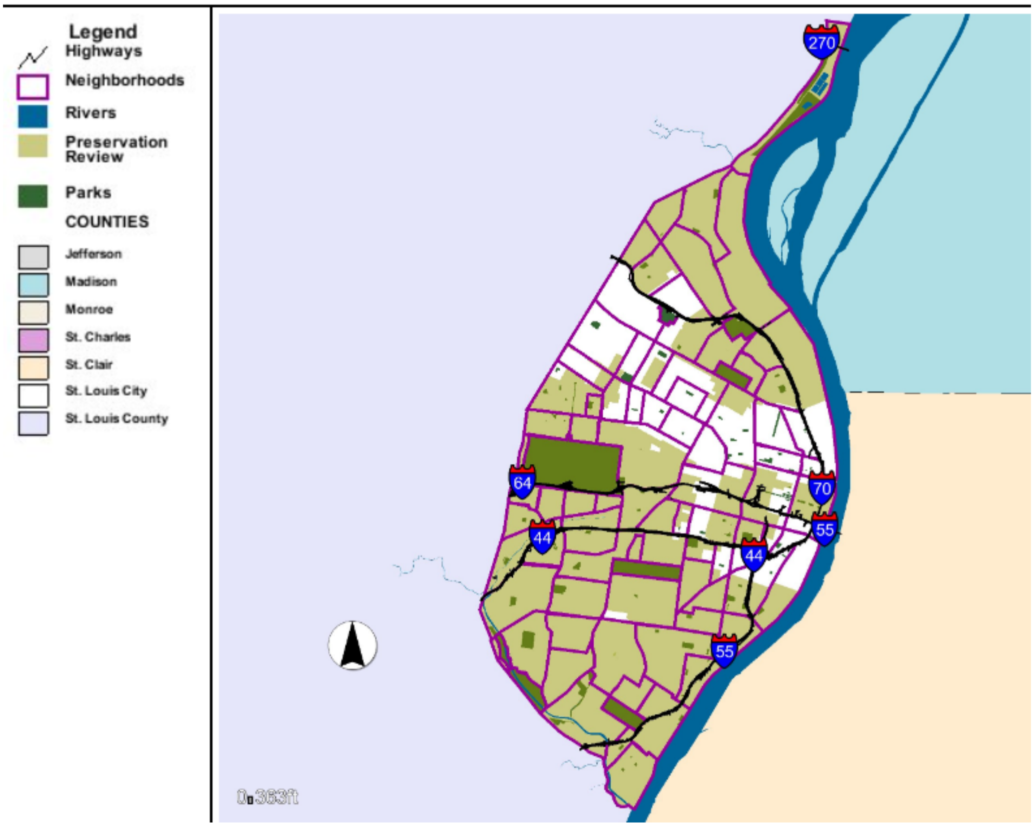


Figure 7: Map of the Preservation Review Areas in St. Louis
Source: Created via Geo St. Louis

Against this backdrop, we postulate that the dummy control variables indicating a property's belonging to any historic district, a Preservation Review Area, or the Housing Conservation Program, should serve as a proxy for potential unobserved building features in terms of exterior architectural design, idiosyncratic structural elements characteristic of a certain building period, as well as potential unobserved differences in building quality. Nevertheless, this approach remains somewhat limited in case of the presence of cohort effects related to particularly modern building styles.

Our estimations reveal that the coefficients for these urban control dummies are highly significant and consistent across all our models and have the expected signs. Concerning the estimation results of the base model, as presented in Table 4, it is estimated that, holding all other variables constant, a single-family home located in a local, national, or certified local historic district, sells on average for about 12.52, 8.85, and 28.15% higher, respectively. Similarly, houses that take part in the Housing Conservation Program sell on average for 21.53% higher, and houses located in a

[53] C.f. Stlouis-mo.gov.
[54] C.f. Stlouis-mo.gov.

preservation review area for approximately 11,51% more.[55]

To put those results into perspective, we briefly review the existing empirical evidence related to historical designation, conservation, and preservation. Within a comprehensive survey of the hitherto existing literature, Mason (2005) shows that despite some mixed evidence, i.e. Coulson and Leichenko (2001), there is a general consensus about the explicit and tacit benefits of historical designation and preservation. In this light, while onerous rules and regulations might be considered a negative externality, the positive externalities generated by historical designation seem to be predominant, as Clark and Herrin (1997) demonstrate for a sample of properties in Sacramento, for which they find an average appreciation rate of 17%. About a decade earlier, Ford (1989) found increases in property values in Baltimore upon historical designation, and argues that the listing in a historic register acts as an insurance mechanism, guaranteeing property owners that their adjacent neighborhood prevails intact. An alternative explanation is given by Gordon and Stowe (2014), who argue that the historical designation of properties might eliminate informational asymmetries and additionally generates spatial spillovers to adjacent neighborhoods.
Further, in terms of magnitude, Leichenko et al. (2001) compare the effects of national and local register listing across nine different cities in Texas and find overall price increases for historic districts varying between 5 and 20 %. In line with our findings, the authors detect larger estimates for national historic districts and argue that this premium might be associated with higher prestige of nationally designated districts, as well as typically more stringent local zoning laws for local historic districts. Moreover, Schaeffer and Millerick (1991) find 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 seen in the case of height regulations in New York (Glaeser (2011)). Similarly, Listokin et al. (1998) warn about the potentially adverse effects of historical designation in terms of displacement effects, increased gentrification, and thwarted growth.

Eventually, while the latter discussion on the potential beneficial or adverse effects of historic designation, conservation, or preservation exceeds the scope of this thesis and might be considered a pertinent question for future research, the general findings in terms of a price appreciation for historically preserved properties are very much consistent with the prior literature on historic designation and preservationist policies. While this supports the overall robustness of our findings, it does not fully exclude the possibility of the presence of age-related heteroskedasticity of the error term, which is why we additionally test for it.

Regarding our second approach, Goodman and Thibodeau (1995) suggest that the age-induced heteroskedasticity of the error term might be dealt with by simply including the square of age into the hedonic price function and thereby allowing non-linear depreciation effects. Hence, we have also tested our models by additionally regressing on the square of age in our models. The results are presented in Table 21.

[55] The percentage effect of the respective dummy coefficient j is calculated as $(\exp(\beta_j) - 1) * 100$ (Halvorsen and Palmquist (1980)).

Table 21: 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

As can be seen, the main results of our base model are unaffected when allowing for non-linear age depreciation and the main coefficient of interest, ImpactxPost, has only changed marginally. As before, age remains highly significant and negative, though, its absolute estimate is slightly larger: $\mid -0.0078 \mid > \mid -0.00364 \mid$. Concerning the coefficient for the square of building age, the estimates are highly significant and positive across the different error specifications, indicating that the effect of age on the price may indeed be best described by a concave relationship. Although the point estimate is relatively low in magnitude, holding all other things constant, the model suggests that a 100-year old building sells on average for about 38% less than a completely new property, which equals a difference of about 8 percentage points relative to our preferred model specification.[56] For a 30 year old building, the difference between the models is similar and estimated to be about 8.5% higher when including the square of age as a regressor. When including AgeSquared, the model suggests that a 30 year old house sells on average for about 18% less than a new house,

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

ceteris paribus, while our preferred specification suggests a discount of only about 10%.[57] Due to the positive sign of AgeSquared, the estimated difference between the two model specifications in terms of the price depreciation in building age, is more pronounced for newer houses, while it converges to zero for very old houses. Accordingly, the difference in the depreciation rate of a 150 year old single-family home is only about 1%.[58]

In conclusion, while, on the one hand, the results suggest that housing depreciation seems to follow a non-linear trend, on the other hand, allowing for non-linear age effects across the different models does not alter the main conclusions, nor does it have any visible impact on the sign, significance and magnitude of the covariates other than age.[59] Therefore, we regard the results as additional support of our main conclusions.

[57] $\exp(-0.00769 * 30 + 0.0000278 * 30^2) - 1 = -0.1859$ & $\exp(-0.00364 * 30) - 1 = -0.1034$.

[58] $\exp(-0.00769 * 150 + 0.0000278 * 150^2) - 1 = -0.4102$ & $\exp(-0.00364 * 150) - 1 = -0.4207$.

[59] For the sake of brevity, we only present the results of the base model and the estimates of the main independent variables. We note that the inclusion of a quadratic term for age was also tested across our distance rings models, but did not have any visible impact on the results. The results are available from the author.

Is Proximity to Parks a Potential Confounding Variable?

As discussed in Section 5, the inclusion of a covariate capturing the distance to the closest urban park might lead to spurious regression estimates if the WTP for proximity to urban parks is an endogenous function of the WTP for proximity to sports facilities. Therefore, we re-estimate Equation 4 without this regressor to test the robustness of the results. In addition, we also re-estimate the base model using a 600-meter distance control ring, and including a squared coefficient to examine potential non-linearity of the effect, as the hedonic literature on parks as urban amenities provides mixed evidence on how the effects of parks are spatially patterned (More et al. (1988)).

Table 22: 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 22 presents the regression estimates, where Column (1) presents the results of the preferred model specification of the base model for ease of comparability. In Column (2), we estimate the model without DistancePark, while in Column (3) we present the estimation results of the main model coefficients using a distance ring dummy that takes the value one if a single-family home lies within a 600-meter distance to any of the selected urban parks or green spaces depicted in Table 23. Finally, in Column 4, we introduce a regressor for the squared distance to the closest park to the model.

Comparing column (1) and (2) of Table 22, we can see that the inclusion or exclusion of the covariate for proximity to the closest park has only a marginal impact on the magnitude of the point estimate, which is estimated to be 7.27%. In terms of direction and significance, there are no differences between the two specifications. Furthermore, column (3) reveals no discernible difference, when specifying the covariate for residential proximity to parks as a 600-meter distance ring. Taken together, these results suggest that there does not seem to exist an observable endogenous relationship between the WTP for residing close to Edward Jones Dome and the WTP to live close to urban parks or green spaces. Therefore, we can conclude that there is no evidence of interference that could potentially affect the detection of the treatment effect.

Furthermore, prior evidence of the intangible benefits of natural urban amenities, such as parks and green spaces, is much more ambiguous, compared to the relatively conclusive literature on sports amenities. While the positive effect of parks on property prices is well-documented, there are still empirical puzzles regarding which types of green spaces matter the most (Panduro and Veie (2013)), which features have the largest price effects (Morancho (2003)), and how this effect is spatially shaped. Although this thesis cannot provide concrete answers to all of these questions, the regression estimates presented in Table 22 shed some valuable light on the magnitude and spatial impact of parks. Specifically, column (1) indicates that each additional mile away from the closest urban park decreases the value of a single-family home by about 18.3% in our sample.[60] Further, column (4) reveals a positive and significant coefficient for the squared distance, suggesting that the effect is non-linear and decreases in a concave fashion. This means that the effect is most pronounced in direct proximity to parks and decreases over-proportionally in distance until it completely vanishes at a distance of 2.93 miles.[61]
When using a distance ring specification instead (column (3)), the point estimate suggests a price premium of approximately 12.75%,[62] on average, for single-family homes located within 600 meters of any of the selected urban parks or green spaces. This finding is consistent with prior literature on the positive effects of green spaces on property prices.

Finally, there are some caveats to consider regarding our approach, which is why we advise to regard the results with some caution. Firstly, our findings might be affected by selectivity bias since we only included the most important parks based on qualitative criteria. This assumption implies that only parks of a certain size, name, or reputation have a considerable impact on the price of a single-family home. However, in reality, small playgrounds may also benefit residents, particularly families, yet, the effect would be expected to be rather low in magnitude and probably highly localized. Additionally, another reason why we were not able to include all 108 parks in St. Louis is that we lack substantial

[60] $(\exp(-0.2) - 1) * 100 = -18,2$.
[61] $\exp(-0.479 * 2.9386 + 0.163 * 2.9386^2) - 1 \approx 0$.
[62] $(\exp(0.12) - 1) * 100 = 12.75$.

information to map the parks within a geographical information system. Secondly, we assumed that the proximity to each park is valued equally. Accordingly, the coefficient that we report reflects an average over all of the effects of proximity to any of the 17 parks and green spaces considered. However, in reality, there are likely considerable differences in effects, depending on the inherent features of each park. Unfortunately, we lack sufficient information on these individual features for a deeper analysis. As a last caveat, it is relevant to mention that our findings might exhibit a slight measurement bias. Concretely, except for the two largest parks, we measured the distance to each park as the distance to the center of each park, because we lacked information on concrete entry points of the included parks.[63]

Table 23: List of Urban Parks and Green Spaces in St. Louis

No.	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

[63] For the two largest parks - Forrest Park & Tower Grove Park - we determined eight coordinates reflecting the corners of the rectangular-shaped parks and the middle points between them, respectively.

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 % living South of the Boulevard are white (Cooperman (2014)), as displayed in Figure 8. This racial segregation is anchored 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)).[64]

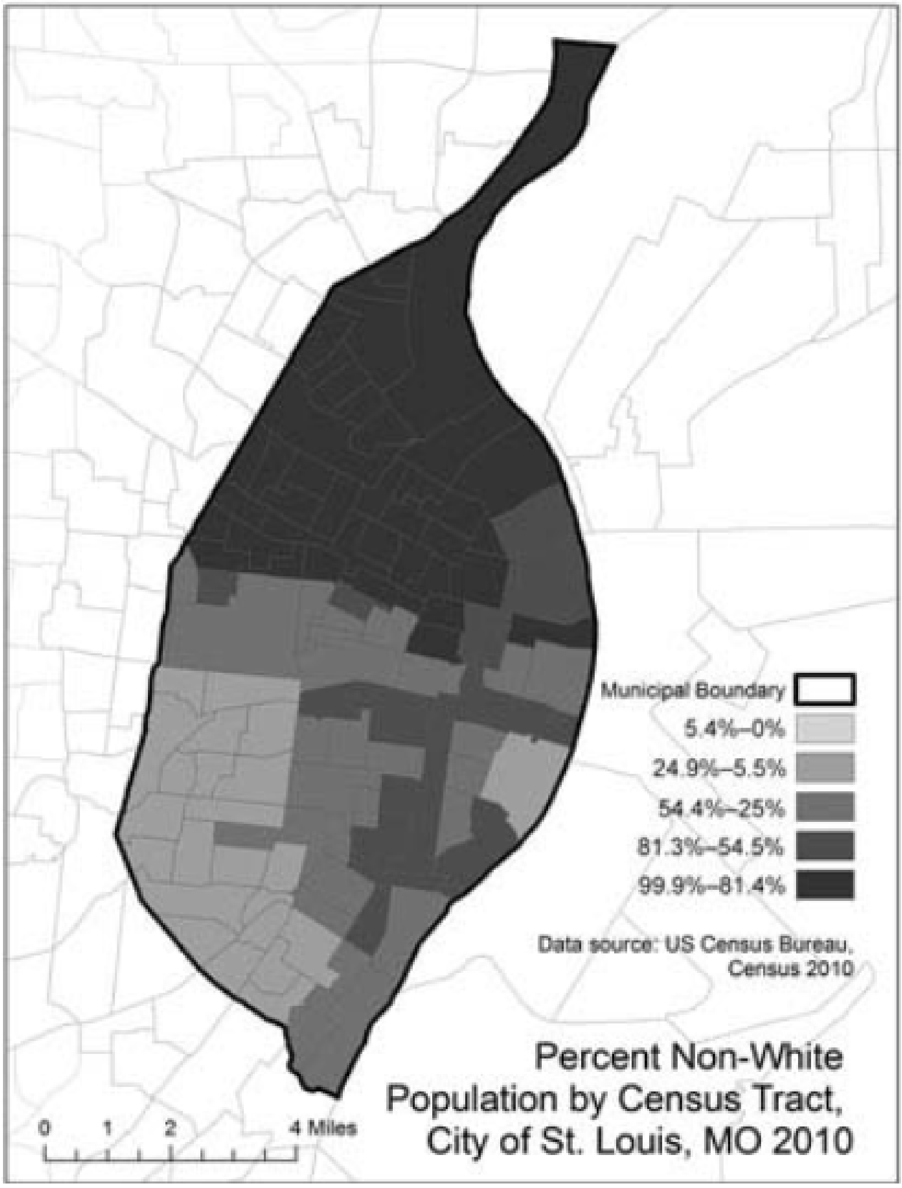


Figure 8: Racial Segregation in St. Louis
Source: Tighe and Ganning (2015), p.658

[64]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, which is why we also tested for these population groups within our robustness check for omitted variable bias, accessible via this link.

St. Louis, as depicted by Metzger et al. (2018), incorporates an extreme case of urban decay, characterized by a 70-year long trend of economic and population decline, reflecting the broader decline 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 fallen by over half to approximately 350.000 in 2000. In particular affluent and predominantly white families have fled to the suburbs, leaving the central city relatively poor and somewhat vacant. This overall trend of decline and growth is also reflected in residential neighborhoods as spatial inequality, leading Tighe and Ganning (2015) to designate St. Louis as a "divergent city".[65] According to the authors, St. Louis is a city with clear patterns of racial segregation, where the North is predominantly black with high crime and vacancy rates, while the South is mostly white, with vibrant commercial areas and stable real estate markets.[66]

The strong demographic divide in St. Louis also potentially carries over important consequences for the housing market. Specifically, housing values in the Northern neighborhoods are on average considerably lower than in the South, as housing values are not purely 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. This has implications for hedonic price functions, as they may differ across submarkets (Watkins (2001)).

Against this background, we argue that controlling for annual neighborhood characteristics and local fixed effects, while clustering standard errors on different geographic scales, should account and capture most of the variation in housing prices associated with changes along demographic lines across neighborhoods. However, given that St. Louis is an extreme case of spatial inequality, we consider three alternative approaches to account for it:

a) Following Jud (1980), we run the same regressions on a "ghetto" sample by eliminating all transactions taking place in a neighborhood which is more than 50 % Black.

b) We include a simple dummy variable within our model, taking the value one if a house is located North of Delmar Boulevard.[67]

c) We omit our lower price bound of 30.000$ to check for selectivity bias resulting from our data cleansing process.

The results are presented below. For the sake of brevity, we only present the regression estimates

[65] It is worth noting that while there are clear patterns of racial segregation in the city as a whole (as shown in Figure 8), downtown and adjacent neighborhoods are relatively mixed. This is good news as it suggests that any price reactions upon relocation are less likely to be influenced by unobserved spatial clustering concentrated in the impact area.

[66] Within an early work on St. Louis residential housing market, Kain and Quigley (1975) already discerned racial stratification in St. Louis about 50 years ago.

[67] We consider all properties with a latitude larger than 38.64351 being located approximately North of Delmar Boulevard. The coordinate corresponds to the southernmost intersection of Delmar Boulevard with Vandeventer Avenue.

of the adjusted base models, respectively. Albeit, we have also tested the three approaches across our ring models and find consistent results, which are available from the author.

Approach a) - Ghetto Sample

Table 24 presents the regression results of the base model for the ghetto sample. The findings suggest that the relocation has induced a relative price depreciation of single-family homes within a three-mile impact area around the stadium. However, the estimated effect is smaller at 4.71%. Additionally, clustering the error term on any of the three scale levels renders the coefficient largely insignificant. These results indicate that the relocation has caused a stronger market reaction in predominantly black neighborhoods, and excluding them from the sample mitigates the observed effect. While these findings suggest that the treatment effect is conditional on socio-demographic characteristics, they do not contradict our conclusions and support the overall consistency of the results.

Table 24: Regression Estimates - Ghetto Sample - Base Model

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) 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 with a share of more than 50 percent 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 25 shows that including a dummy variable for houses located North of Delmar Boulevard does not have a visible impact on the main coefficients of interest in terms of direction, efficiency, or magnitude. The coefficient of the dummy variable is negative as expected, but it is insignificant across all five model specifications. This insignificance may result from multicollinearity among the covariates, as the VIF for North is quite high at 19.38, and North shows moderately high correlations with the neighborhood covariates, especially the percentage of black population ($r = 0.44$). However, these results do not necessarily contradict the existence of the Delmar Divide, as we observe the expected sign, and the insignificance is likely due to artificially inflated errors. Thus, we argue that these findings support the robustness of our results and the selection of our model covariates, as the variation in prices due to geographical location for single-family homes within our sample seems to be already sufficiently accounted for.

Table 25: Regression Estimates Allowing for a North-South-Divide - Base Model

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) 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 excluded non-arms length transactions and properties with potentially poor conditions by removing transactions below a market price of 30.000$. However, to examine potential selectivity bias, we deliberately include all transactions below this threshold in our updated sample, which contains an additional 734 sales. Of these, 92.23% (677) took place North of Delmar Boulevard, as was expected.

If residential proximity to sports venues is valued differently across demographic clusters, the results of our analysis might be biased due to sample selection. For example, it is possible that higher-skilled and more affluent individuals have preferences for cultural amenities, while lower-skilled and less affluent individuals prefer residing close to sports and natural amenities.[68] To address this potential bias, we re-estimate our models using the full sample without any price restrictions. The results of the base model for this unrestricted sample are presented in Table 26.

Table 26: 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 30000 Dollars were 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

The regression results confirm our previous findings and lead to the same qualitative conclusions, indicating that the exclusion of single-family home transactions below the price threshold of 30.000$ has not significantly affected or biased the results. However, it is worth noting that the coefficient of the diff-in-diff estimator is slightly larger when including the low-value transactions, suggesting that homes within the three-mile impact area sold post-relocation at a discount of approximately 9.26% relative to comparable housing units in the control area. This larger coefficient could potentially be

[68] For instance, Brueckner et al. (1999) describe the housing market of Paris, which has a high demand for central housing from the higher-skilled population due to the abundance of historical and cultural institutions.

due to larger and positive effects of sports 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, as observed by Neto and Whetstone (2022) in the Las Vegas single-family residential housing market following the announcement of the construction of a new stadium for the Raiders franchise relocating from Oakland to Las Vegas in 2017.

In summary, three different model specifications were tested to check for the robustness of the main findings in light of the idiosyncratic degree of spatial inequality within St. Louis' residential housing market. All three approaches provide additional evidence that the relocation of the Rams franchise to Los Angeles in 2016 has led to a significant decline in housing prices within proximity to the stadium, implying that the team generated substantial amenity benefits in the market. Further, the robustness checks hint at a potential difference in valuation of proximity to sports amenities by demographic clusters, i.e. with respect to income or race. Due to its relatively clear pattern of spatial segregation, as depicted in Figure 8, St. Louis promises to provide a fertile ground for future research to examine this association in more depth. Similarly, because of low sample size, particularly due to to fewer transactions within St. Louis' Northern neighborhoods, we were unfortunately not able to estimate separate hedonic price functions for potentially different housing submarkets as suggested by Hwang (2015). This may also be an interesting puzzle for future research.

Appendix C - Proximity Model

It is relatively common among the hedonic literature examining sports amenities to test for the presence of heterogeneous treatment effects across space, typically hypothesizing non-linear and distance decaying effects. While this thesis uses distance-rings to capture the non-linearity of the treatment effects, a commonly used alternative would be to specify a simple proximity model in which the price of a property is regressed on the property's distance to the facility and this distance is additionally interacted with the treatment. In a further step, empiricists often account for potential non-linear treatment effects with respect to distance, by including the square value of distance in the model and interacting it with the treatment as well. Such a model might already shed some light on the spatial dispersion of the treatment effects and allow to assess whether the treatment has a potentially heterogeneous impact across space, and if so, reveal which type of spatial pattern it follows.

Against this backdrop, similar to Kavetsos (2012), we have constructed a simple proximity model specified as follows:

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

whereby Distance_i refers to the distance in miles of property i to Edward Jones Dome, and Post $\times$ Distance interacts this term with the dummy for the post-treatment period. The remaining model components are defined as before. Table 27 presents the estimation results of Equation 6. Column (1) displays our preferred model specification with robust standard errors. Additionally, selected model specifications are presented in columns (2) - (5), in which standard errors are clustered on the census tract levels - columns (2) & (4), respectively - and the distance controls for the other two stadiums in St. Louis, Busch Stadium & Enterprise Center, are excluded from the model - columns (3) & (4), respectively - because due to the proximity of the three stadiums, as shown in Figure 1, the distance variables are naturally highly correlated and might thus be a plausible source of multicollinearity. Lastly, column (5) presents the regression estimates without any model controls, mainly to demonstrate the inherently high VIFs induced by the interaction terms, as further discussed below.

Table 27: Regression Estimates of the Proximity Model

	Distance Controls Included		Distance Controls Excluded		No Controls
	(1)	(2)	(3)	(4)	(5)
	Robust	Clustered	Robust	Clustered	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

We observe that the difference-in-difference estimate PostxDistance is highly significant across columns (1) - (4) and has the expected positive sign, indicating that, after the relocation of the Rams to Los Angeles, each additional mile away from the stadium, increases the value of a single-family home by about 1.38% on average, relative to the pre-relocation period. Importantly, those results are consistent in sign, magnitude, and significance, irrespective of the inclusion of the additional distance controls for the other two stadiums in downtown. Hence, the observed results are in line with the findings presented in the main body of this thesis and provide additional support to infer that residing closer to the stadium is relatively less attractive after the team's departure. However, despite being significant in our preferred model, the estimates for the pooled linear distance, depicted by *Distance*, should be interpreted with caution, as we can see that its sign switches from positive to negative, when removing the other distance control variables, and is even highly significant and negative when only including the difference-in-difference estimates in our model, as visible in the last column. These results invite to test for the presence of multicollinearity.

In this vein, Table 28 presents the VIFs for selected regression estimates. As one can clearly see, the model suffers from severe multicollinearity and the diverging results upon the inclusion or exclusion of the distance controls for the other two stadiums are likely resulting from high correlations between *Distance*, *DistanceBusch*, & *DistanceEC*. Effectively, the pairwise correlation coefficients among these variables, as shown in Table 29, are all larger than 0.99 and the relationships among the three variables are thus almost perfectly collinear.[69]

[69] In contrast, the main coefficient of interest, PostxDistance, only exhibits moderate correlations with the three distance covariates of about $r = 0.3$, which should typically not be reason for concern, especially in view of the consistent and significant results across the different model specifications.

Table 28: VIFs of the Proximity Model

	Distance Controls Included		Distance Controls Excluded		No Controls
	(1) Robust vif	(2) Clustered vif	(3) Robust vif	(4) Clustered vif	(5) Robust 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			

The full VIF table can be found in the Supplementary Appendix.

Table 29: 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

What is more, Table 28 also indicates that PostxDistance is unaffected by the multicollinearity induced by the three distance covariates, as its VIF is relatively constant across the model specifications. Despite the fact that it has a VIF exceeding the typical threshold value of 10, column (5) suggests that the high VIF stems primarily from the interaction of the variables and is therefore no reason for concern (C.f. Allison (2012)).

All in all, since the model suffers from severe multicollinearity, we opted to analyze the spatial distribution of the treatment effect through distance rings instead, and to present the results of the proximity model in the Appendix. Although the results of the proximity model should be regarded with some caution, the model provides additional evidence of the relative price depreciation associated with the foregone proximity benefit of residing close to the stadium post-relocation, and thus support the overall conclusions made within this thesis.

As a final note, we would like to mention that we have also tested other model specifications based on prior literature. For example, we interacted the distance variables with a dummy for either period, pre and post, following Bieze (2021); we 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); and we included quadratic distance terms, following Tu (2005); however, all of these specifications encountered multicollinearity issues of similar severity or even exacerbated the issue. The results are available from the author.

Appendix D - Variable Transformations

Figure 9: Log-Transformation of Price

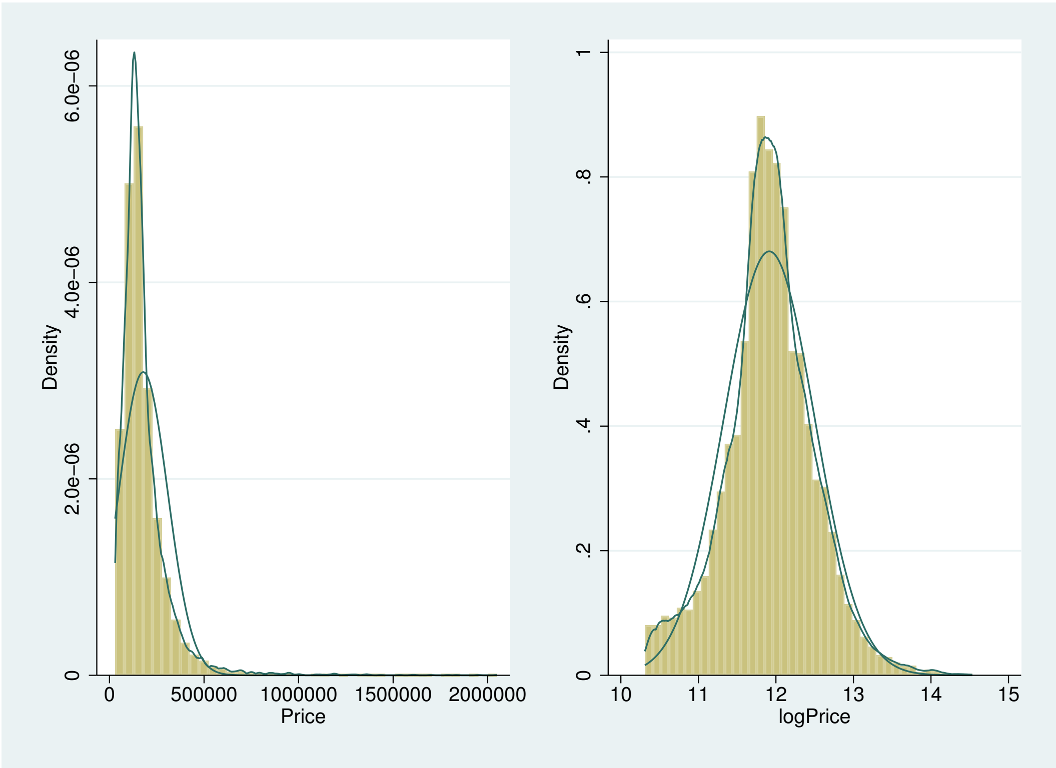


Figure 10: Log-Transformation of Floorsize

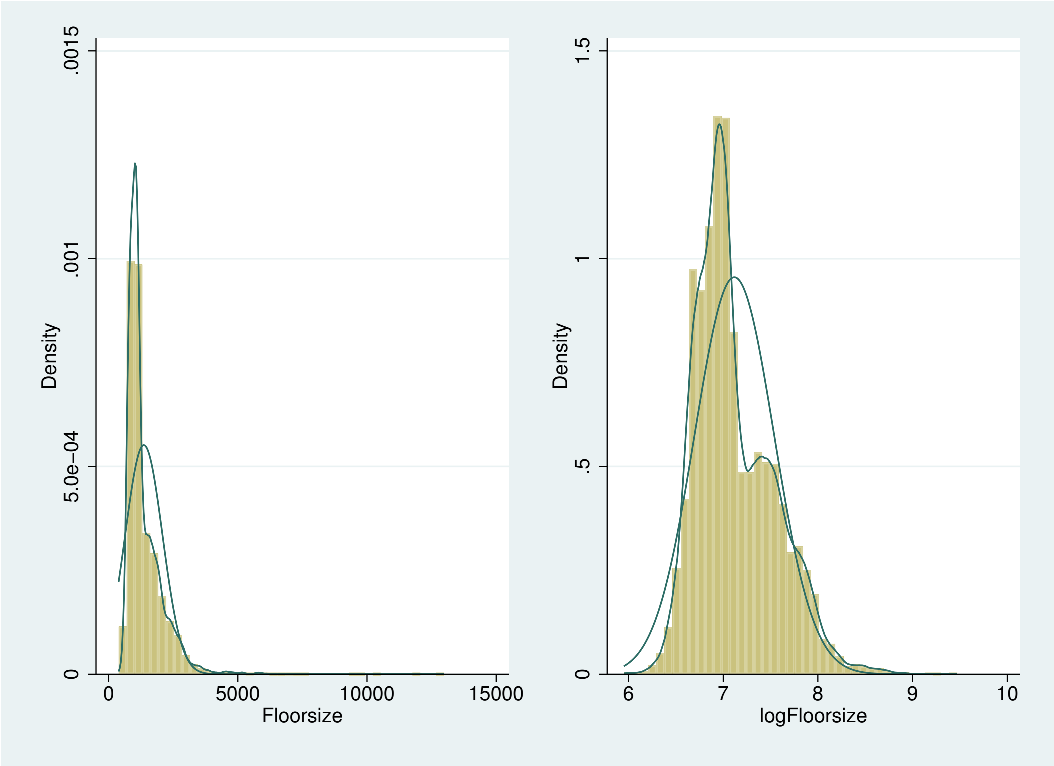
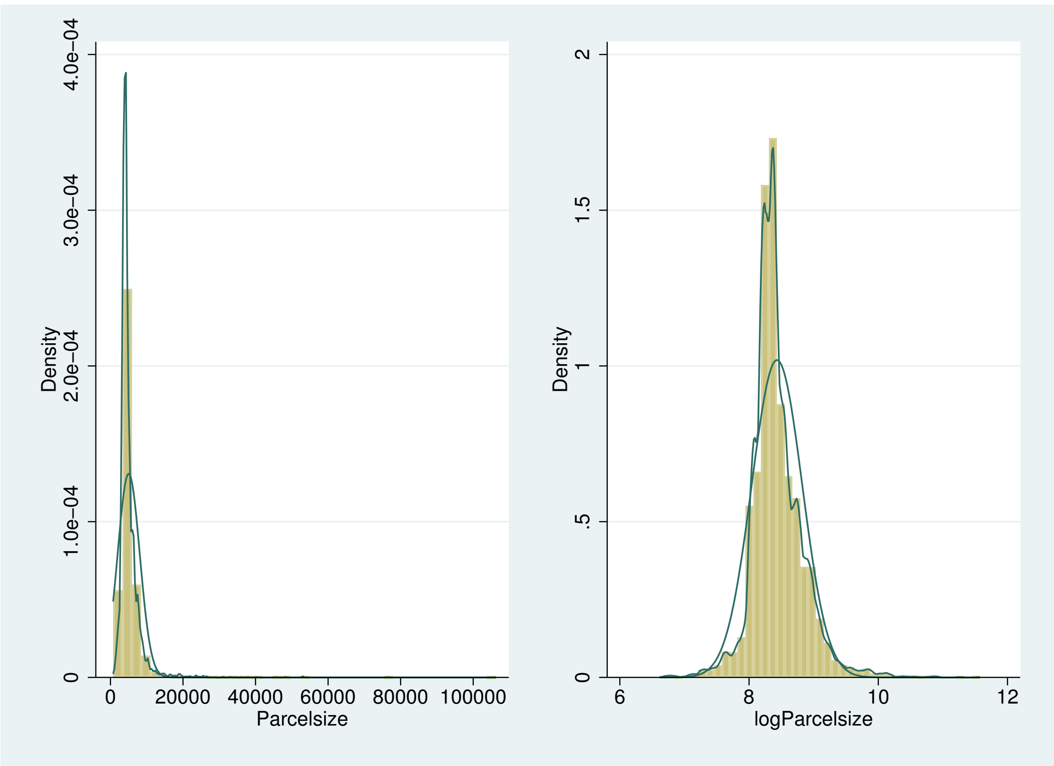


Figure 11: Log-Transformation of Parcelsize



Appendix E - Supplementary Appendix

Supplementary Regression Outputs

Main Body

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

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) 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)	(2)	(3)	(4)	(5)
	Robust	OLS	Census Tract	Ward	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) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) 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)	(2)	(3)	(4)	(5)
	Robust	OLS	Census Tract	Ward	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)	(2)	(3)	(4)	(5)
	Robust	OLS	Census Tract	Ward	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)	(2)	(3)	(4)	(5)
	Robust	OLS	Census Tract	Ward	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) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) 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 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 properties located within 600 feet distance to a park ($1=$ Yes)
DistancePark2	Squared Distance to the closest urban park in miles
North	Dummy for hoses 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.

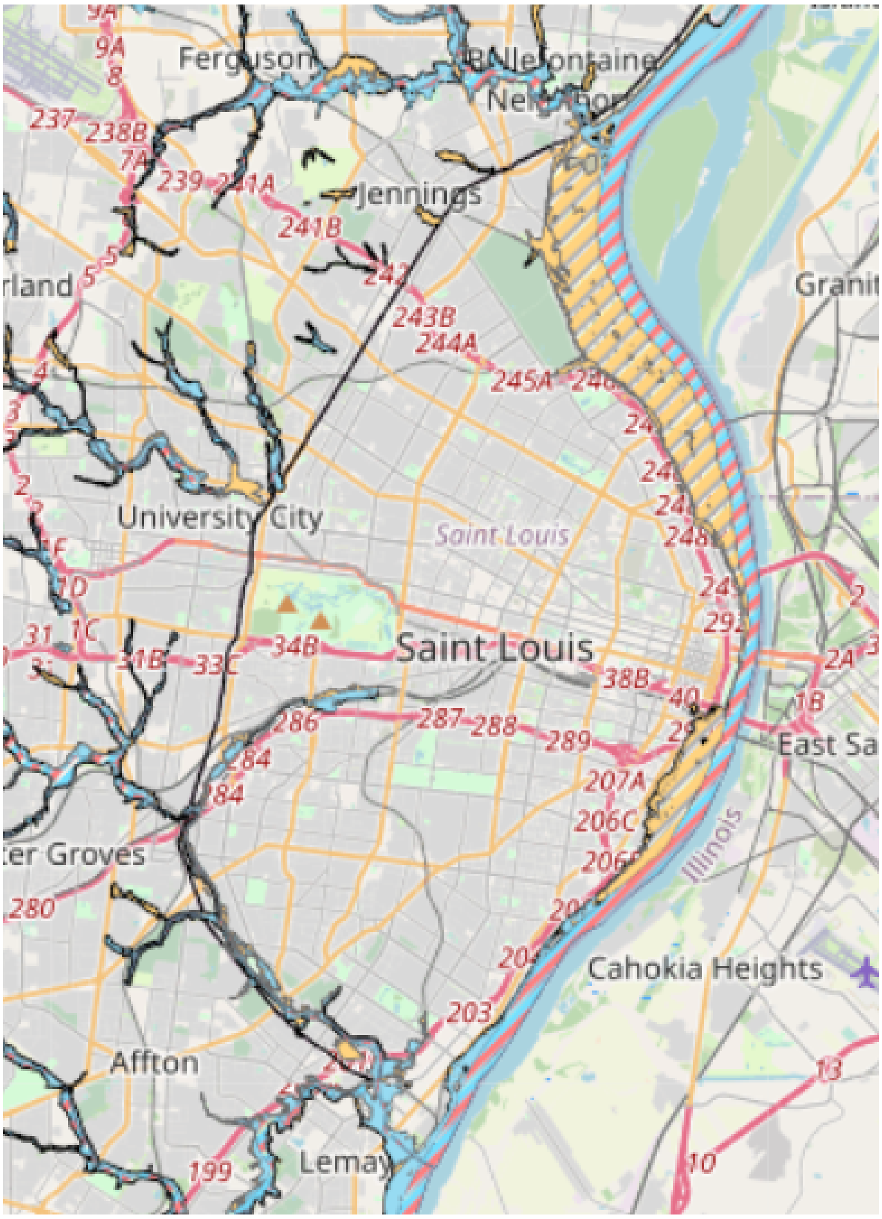
Table 45: VIFs of the Proximity Model

	Distance Controls Included		Distance Controls Excluded		No Controls
	(1) Robust vif	(2) Clustered vif	(3) Robust vif	(4) Clustered vif	(5) Robust 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
logFloorsize	4.01	4.01	4.01	4.01	
logParcelsize	1.88	1.88	1.87	1.87	
Age	1.79	1.79	1.78	1.78	
Frame	1.72	1.72	1.71	1.71	
Stone	1.05	1.05	1.05	1.05	
Stories	3.69	3.69	3.69	3.69	
Garages	1.27	1.27	1.27	1.27	
Carports	1.08	1.08	1.08	1.08	
Attic	1.25	1.25	1.25	1.25	
PopDensity	5.01	5.01	4.82	4.82	
Crime	8.40	8.40	8.34	8.34	
Black	29.21	29.21	28.57	28.57	
Vacancy	15.30	15.30	15.22	15.22	
Youth	14.71	14.71	14.37	14.37	
MedianIncome	13.01	13.01	12.85	12.85	
AccFood	9.70	9.70	9.68	9.68	
Finance	5.25	5.25	5.13	5.13	
Retail	6.59	6.59	6.56	6.56	
DistancePark	5.12	5.12	5.01	5.01	
Local	7.37	7.37	7.14	7.14	
National	4.90	4.90	4.87	4.87	
CertifiedLocal	9.12	9.12	9.11	9.11	
Conservation	1.97	1.97	1.95	1.95	
Preservation	3.31	3.31	3.17	3.17	
Enterprise	2.67	2.67	2.67	2.67	
Flood100	1.13	1.13	1.13	1.13	
Flood500	1.21	1.21	1.21	1.21	
DistanceBusch	4336.14	4336.14			
DistanceEC	6553.68	6553.68			

Standard errors in columns (2) & (4) are clustered on the census tract level.

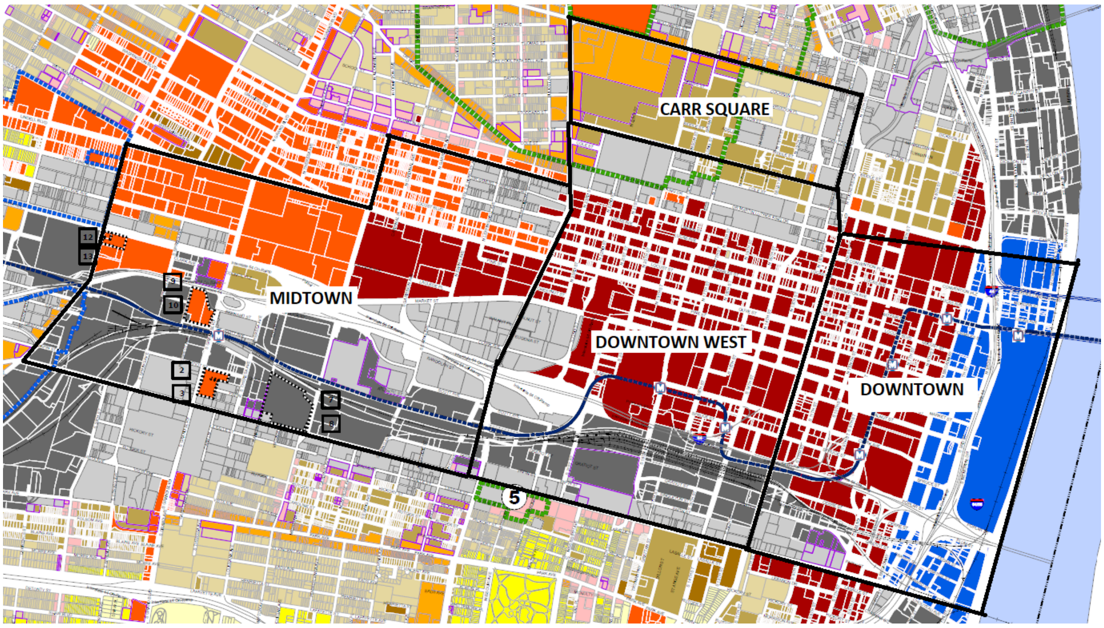
Supplementary Figures

Figure 12: St. Louis - Floodplains



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

Figure 13: 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.

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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

Froch, Jonas

Abstract

We exploit the relocation of the NFL's Rams franchise as a natural experiment to estimate the effect of proximity on residential property values 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 total welfare loss suggest that the intangible benefits emanated by a major league sports franchise may be large enough to justify generous public subsidies for the construction or maintenance of professional sports facilities.

Key Words

Hedonic Price Models; Sports Facility; Property Values; Spatial Externalities; NFL; St. Louis