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

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Abstract

We exploit the relocation of the NFL's Rams franchise as a natural experiment to estimate the effect of residential proximity to sports amenities using difference-in-differences hedonics. For a sample of single-family homes transacted in St. Louis between 2012 and 2019, we reveal that the relocation has provoked a significant relative price depreciation of 7.52% in housing values within a three-mile impact area. Subsequent distance ring analyses show that the effect is dispersed heterogeneously across space and declines in a non-linear distance-decaying pattern from the former host stadium. An approximation of the aggregate relative housing value depreciation suggests that the Rams generated substantial intangible amenity value in St. Louis. However, this magnitude effect may only justify partial subsidies for sports facilities and cannot provide a broader economic rationale for the generous public subsidization seen over the past decades. These results withstand a wide range of robustness checks, although they are somewhat mitigated considering general equilibrium effects.

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1 Introduction

Between 1990 and 2009, 91 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 primarily driven by a combination of team relocations, league expansions, and the replacement of aging facilities. It was catalyzed by municipalities' desires of becoming major league host cities, ubiquitously considered a pivotal status criterion distinguishing top-tier cities. Today, there still prevails an excess demand for major league teams, resulting in intense inter-city competitions among large municipalities in the US, similar to the bidding 'wars' surrounding major industrial plants (Greenstone et al. (2010), Slattery (2023)). Aiming to lure in a franchise, public entities often provide massive public subsidies of several hundred millions of dollars for the construction, renovation, or maintenance of professional sports facilities. Similarly, cities that are already hosting a major league team, commonly encounter relocation threats leveraged by franchises to bolster their bargaining power and secure larger subsidies (Humphreys and Zhou (2015)).

In this context, stadium proponents typically argue that sports facilities generate considerable economic spillover effects within local economies, for example in terms of income revenue streams and employment opportunities. However, a plethora of ex-post evaluation studies comes to the unanimous conclusion that the direct, i.e. tangible, economic impact of sports facilities is at best non-significant as a result of crowding-out and substitution effects (e.g. Baade and Dye (1988), Baade and Dye (1990), Coates and Humphreys (1999), Coates (2023)). Intriguingly, despite the overwhelming evidence of the economic impotence of sports facilities, public funding for stadium projects has increased in magnitude, as stadium costs constantly evolve in light of new sophisticated stadium features. In total, a substantial sum of $33bn in public funds have been provided over the past fifty years for stadium projects (Bradbury et al. (2023)). Not only does this sum reflect immense opportunity costs, it also raises distributional concerns, as the true winners may be above all team owners benefiting from large increases in team values upon moving to a new facility.[1] 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.[2] 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 emphasizes the lack of a direct economic rationale justifying public subsidization, it may however be that hosting a major league franchise yields substantial positive externalities, that are intangible, i.e. non-pecuniary, amenity benefits. If sufficiently large, such amenity benefits might justify public subsidies for sports facilities. Concretely, sports facilities as urban amenities provide numerous perennial consumption opportunities to local residents (Glaeser et al. (2001), Brueckner et al. (1999)), not only in terms of the hosted sports- and non-sports events, i.e. concerts and conventions, but equally in terms of their sports-related surrounding environment of shops, bars, and restaurants (Abbiasov and Sedov (2023)), tailored to enhance the overall fan experience. Moreover, well-designed sports facilities that neatly blend in the urban fabric may serve as important urban landmarks and catalysts driving and consolidating urban development, in particular in deserted downtown areas (Bachelor (1998), Chapin (2004), Holm (2019)). In this vein, Rosentraub (2006) argues that public investments in the sports sector, aimed at revitalizing or fostering the city core, may act as important signals and enhance a city's overall appeal. Consequently, they implicitly alleviate urban flight of citizens and firms.

[1] For instance, the value of the Rams has doubled shortly after moving to Los Angeles (Click (2016)).

[2] The recently secured record-breaking public contribution of $1.26 billion for a new NFL stadium in Nashville is one of many examples that Humphrey's prediction seems to become reality (Kaplan (2023).)

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

Against this background, this paper explores the intangible (dis-)benefits generated by a major league sports franchise. Concretely, we exploit the relocation of the NFL's Rams franchise in 2016 from St. Louis, Missouri, to Los Angeles, California, as a natural experiment enabling us to assess the change in implicit amenity value resulting from the team's departure. St. Louis provides a unique and promising case study as the city constitutes typical characteristics of a Rust-belt city that has experienced a general economic and population decline for more than 70 years (Metzger et al. (2018)). In an effort to counteract this long-term trend, political and economic leaders in St. Louis have incrementally embraced a sports-led urban development strategy since the early 1990s, paralleling the responses made by other former industrial hubs (Rosentraub (2006)). Sports facilities thereby play a crucial role in promoting entertainment and tourism, and revitalizing the urban landscape of the city core as imposing landmarks (Hurt (2021)). Despite of its relatively small 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), and the Blues (NHL).[3] In this light, ESPN designated St. Louis as 'the ultimate sports city'[4] and the residents precede a reputation of being absolutely sports-fanatic. Thus, despite poor performance and low attendance in the last years of their tenure, the Rams' relocation left a deep mark and induced a general drop in social morale (Wagoner (2019)). Fans as well as public officials reacted with disappointment and resentment against the Rams organization, both because of losing the team, but especially due to the way the franchise departed which many citizens perceived as dishonest, disgraceful, and slanderous, (Feldman (2016), Wilson and Eligon (2016)).[5]

In light of the importance that professional sports plays for the city and its residents, we hypothesize that the Rams generated substantial intangible amenity value, which is capitalized in residential property values. Housing markets serve as fruitful ground for empirical analyses because residential property prices 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 sports teams and venues should be discernible in local property values within a certain distance to the stadium. Simply put, if the presence of the Rams induced considerable quality-of-life benefits, the effect of the relocation should be expressed in a relative price discount of properties close to the Edward Jones Dome, the stadium in

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

[4]C.f. ExploreStLouis.com.

[5]While publicly professing a sincere commitment in finding a solution to stay in St. Louis, recent documents revealed that the NFL and Rams organization obscured their long-planned intentions of moving the franchise to Los Angeles, including a devastating relocation statement by the Rams nullifying any future market potential for the NFL in St. Louis (Huguelet et al. (2022)).

which the Rams played from 1995-2015.[6]

Furthermore, we postulate that the relocation can be treated as a natural experiment, since until the filing for relocation on January 4th, 2016, and the ratification by the NFL a few days later, on January 12th, 2016, the Rams ownership has repeatedly publicly declared their intention to remain in St. Louis. Consequently, the franchise engaged in negotiations with the City of St. Louis and the NFL, first regarding upgrades to the Edward Jones Dome, and later on the construction of a new state-of-the-art venue whose financing plan was unveiled and ratified by city officials in late December 2015, only a few days before the Rams officially decided to leave the city (Click (2016)). Conceptually, we exploit the departure as an exogenous shock to estimate the relative change in the valuation of residential proximity to the former host stadium. We analyze a sample of single-family homes transacted between 2012 and 2019, employing difference-in-differences hedonics.

We find that the relocation is associated with a relative price depreciation of single-family homes of 7.52% within a three-mile distance from the Edward Jones Dome. Our distance ring models suggest that the effect is dispersed heterogeneously across space and declines in a non-linear distance decaying fashion from the former host stadium. Finally, we approximate the foregone intangible amenity value through the aggregate relative depreciation of the residential housing stock. Our estimated range of $155 to $275 million, expressed in 2024 dollars, highlights that major league teams bear the potential to generate substantial amenity benefits. This finding may be particularly relevant for cities facing challenges similar to those experienced by St. Louis. Nevertheless, the cumulative intangible amenity value that the Rams generated in St. Louis is insufficient to justify the large public subsidies typically demanded by stadium proponents from state and local governments.

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

2 Related Literature

The economists' toolkit provides three empirical approaches to unveil the intangible benefits associated with sports amenities. Firstly, the contingent valuation method (CVM) relies on surveys in which participants are directly asked about their willingness-to-pay (WTP) for keeping a specific franchise in town. Within their comprehensive review, Bradbury et al. (2023) conclude that the overall findings of the CVM examinations indicate considerable non-use values in terms of quality of life and civic pride benefits. However, the magnitude of those benefits is often small relative to facility costs. Nonetheless, the method is often criticized for its lack of credibility due to the hypothetical nature of the relocation scenarios it presents. In a related instance to St. Louis, Fenn and Crooker (2009) address this concern and examine the credible relocation threat faced by the Vikings (NFL) in Minnesota if the city did not provide them with a new stadium. The authors estimate an aggregate $700 million welfare value for the Vikings franchise; however, they also conclude that Minnesotans were nevertheless opposed to the construction of a new stadium.

Secondly, voting behavior in referendums may offer more accurate assessments of the anticipated benefits of new stadiums as voters face immediate real outcomes. Additionally, referendums allow to uncover spatial patterns in support levels related to proximity to the facility. Overall, while the literature generally suggests electoral support for sports facilities, evidence on the spatial distribution of support levels is somewhat discordant. On the one hand, Dehring et al. (2008) find that support for a new stadium for the Cowboys (NFL) in Arlington, Texas was positively associated with expected increases in property values, aligning with the homevoter hypothesis by Fischel (2001). Similarly, Coates and Humphreys (2006) observe a positive association between proximity to the stadium and the WTP for the renovation of a facility in Green Bay, Wisconsin. On the other hand, Ahlfeldt and Maennig (2012) and Horn et al. (2015) observe NIMBY ('Not In My Backyard') behavior during referendums in Munich and Seattle respectively, indicating that while there was general support for the new facilities, residents living close to the proposed sites exhibited the lowest levels of support.

Thirdly, this paper follows the footsteps of a relatively rich and predominantly hedonic literature exploring the effects of sports facilities and teams on local housing markets via cross-city comparisons or local case studies. While the vast majority of these papers examine the associated amenity benefits through housing prices and land values (Tu (2005), Ahlfeldt and Maennig (2009), Ahlfeldt and Maennig (2010), Feng and Humphreys (2012), Ahlfeldt and Kavetsos (2014), Feng and Humphreys (2018)), Keeler et al. (2021)), the question has also been studied from various other perspectives, including tax assessment values (Propheter (2021), Bradbury (2022)), monthly rents (Carlino and Coulson (2004), Agha and Coates (2015)), as well as mortgage applications (Huang and Humphreys (2014)). The majority of these papers focus on either American or European contexts and emphasize that sports facilities emanate significant intangible benefits, which are concentrated within a few miles around the facility and typically diminish nonlinearly with distance. Concerning the prior literature on housing prices and rents, estimates of average appreciation rates typically range from 2% to 15%. However, some studies also report negative (Dehring et al. (2007), Humphreys and Nowak (2017)) or null (Kiel et al. (2010), Bradbury (2022)) effects. Notably, these findings are not confined solely to the opening of a new facility, as several papers document that binding or credible announcements evoke comparable market reactions (Dehring et al. (2007), Kavetsos (2012), Keeler et al. (2021), Neto and Whetstone (2022)).

Overall, while several papers report that teams and stadiums generate substantial implicit amenity value, the prior literature still provides inconclusive evidence as to what extent the aggregate social gains stand in relation to the generous public subsidization. In this regard, Bradbury et al. (2023) draw a rather skeptical conclusion. Nevertheless, it should be noted that some papers on the higher end of the spectrum also report remarkably large effects, such as an aggregate housing appreciation of £1.9bn associated with the construction of the New Wembley Stadium in London (Ahlfeldt and Kavetsos (2014)).

Generally though, while rich in essence, the prior literature has hitherto laid little emphasis on the underlying urban and economic mechanisms driving both direction and magnitude of the impact of sports amenities on local housing markets. In this light, this paper aims to better carve out the urban and economic context in which the Rams operated and to contextualize the findings to provide complementary evidence on the interplay of sports facilities and their idiosyncratic urban environments. Specifically, we enrich our set of covariates with urban and geographical characteristics, such as historical designation, floodzones, or proximity to parks, that have been vastly ignored within prior hedonic studies on sports amenities, despite their well-documented impact on housing markets. In addition, we exploit a unique geospatial dataset to obtain information on the urban composition of St. Louis. In this context, the integration of the Edward Jones Dome within downtown St. Louis and its predominantly commercial and industrial surroundings allows us to implicitly examine arguments that sports facilities generate larger spatial externalities and enhance location desirability most when they are built in central locations and seamlessly integrated into the urban fabric (Nelson (2001), Rosentraub (2009), Ahlfeldt and Maennig (2009)). This supports the notion that 'a moat of parking' may hinder the realization of positive amenity benefits (Nelson (2001)). Intriguingly though, Propheter (2021) mirrors this logic by positing that the 'island-like' design of Dodgers Stadium in Los Angeles might act as a buffer, separating residential living quarters also from sports-related congestion externalities.[7] Equally, the Dome's surrounding area in St. Louis may yield a comparable effect.
Further, by nature of the location of most major league teams, prior studies primarily examine the effect of sports facilities in large metropolitan areas. However, Agha and Coates (2015) find that the impact of minor league teams on rents is largest in mid-sized cities like St. Louis, whereas it is less pronounced in larger, potentially more saturated markets. Hence, St. Louis' economic framework and reliance on the sports industry promises new evidence on this matter.

Ultimately, while the prior literature almost exclusively leverages stadium constructions and team arrivals, surprisingly little is known about the impact of team departures on the local housing market. On the one hand, a team departure may simply induce a symmetrical effect, reflecting the change in amenities. On the other hand, it seems reasonable to assume that team departures may trigger additional effects due to path-dependency and sunk costs nested in sports venues. This may be particularly so in contexts where facilities turn into 'white elephants'.
To our knowledge, this paper constitutes the first case study exploring the effect of the departure of an NFL franchise on residential property values. Simultaneously, a current working paper by Humphreys and Propheter (2024) provides mixed evidence: the 49ers' departure from San Francisco led to a distance-decaying price depreciation, while the Chargers' move from San Diego had no significant effect on housing prices. Prior, only one paper by Humphreys and Nowak (2017) has analyzed the relocation of two NBA franchises from Seattle and Charlotte. The authors find that residential property values respectively appreciated about 6-7% & 7.5-14% within a one- and two-mile impact area after the relocation, suggesting that the franchises constituted considerable urban disamenities in the local market. However, an NFL franchise may have a differing impact because the NFL is by far the most important league, both in terms of revenue and popularity, and congestion effects may be substantially smaller as an average season consists of only eight home matches, as opposed to over forty games played per NBA, MLB, & NHL home season.

[7]This reasoning aligns with the observation that support levels for a new stadium in Seattle were highest in areas within commutable distance to the proposed site, close enough to conveniently experience amenity benefits but far enough away to avoid negative congestion externalities (Horn et al. (2015)). Bradbury et al. (2023) refer to the notion of a *'Goldilocks Zone'*.

In addition, we are able to disentangle the team from the facility effect due to the continuous use of the Edward Jones Dome as a venue for concerts and conventions throughout the sample period. Our case study thus also contributes to a scarce literature investigating pure team effects. First, Joshi et al. (2020) examine the effect of the promotion of an MLS (Soccer) franchise in Seattle in 2009 and observe a depreciation of 5-15% in the value of condominiums within one mile of the stadium. Second, Chikish et al. (2019) study three consecutive sports-related shocks in Oklahoma: the opening of a new stadium in 2002, the unexpected arrival of an NBA franchise playing in the stadium from 2005-2007, and the eventual relocation of another permanent NBA franchise to Oklahoma in 2008. The authors find positive impacts on local property values up to four miles from the arena after all three events in a repeated sales specification. However, only the positive stadium effect remains significant in a conventional hedonic model. They conclude that facilities alone play a considerable role as urban amenities, contributing not only through hosting non-sports-related events but also by shaping the surrounding environment, such as bars and shops.

Finally, to the author's knowledge, no paper has yet examined the impact of sports teams on the residential real-estate market in St. Louis. While previous papers suggest that the sports industry has a significant impact on St. Louis, which is found to be positive in the realm of hotel occupancy rates (Stephenson (2021)), (predominantly) null with respect to employment effects in the construction sector (Miller (2002)) and hospitality industry (Humphreys (2023)), and negative in the context of crime (Mares and Blackburn (2019)), the total expected impact of the sports-led urban revitalization strategy on property values remains ambiguous a priori. This paper aims to partially close this research gap.

3 The Rams Relocation History

After losing the Cardinals (NFL) to Arizona in 1987, St. Louis was without a football team for almost a decade.[8] Aiming to fill this void, the City of St. Louis, St. Louis County, and the state of Missouri, joined forces and jointly provided $258 million for the construction of the Edward Jones Dome in 1995. To entice the Rams away from the more lucrative Los Angeles market, the franchise was offered an exceptionally favorable lease contract lasting thirty years. This lease included an 'escape-hatch‘ clause, allowing the Rams to unilaterally terminate the agreement without penalty if, by March 1, 2005, or March 1, 2015, respectively, the stadium failed to rank among the top 25% of NFL stadiums. While the stadium already fell short of meeting the benchmark by 2005, the franchise chose to stay after agreeing to $30 million worth of renovations. This decision signified not only their intent to stay in St. Louis but also their commitment to honoring their contractual obligations until at least 2015. Nevertheless, in the years leading up to 2015, it became apparent that the Edward Jones Dome would require a significant overhaul. This need raised the possibility of the Rams invoking their contract clause and departing from St. Louis. In response, city officials and Rams owner Stan Kroenke, a Missouri native who openly expressed his intent to seek a mutually agreeable solution, initiated negotiations in 2012. Their objective was to secure a long-term future for the Rams in St. Louis.[9] Though, as no mutual agreement could be found,[10] two events particularly fueled speculations about a return of the Rams to Los Angeles:

(i) On January 31, 2014, it was publicly disclosed that Kroenke had acquired land in Inglewood, California. This information was communicated to the NFL, in accordance with the league's regulations mandating franchise owners to report their involvement in the Los Angeles market.[11] Nevertheless, NFL Commissioner Goodell publicly stated that there had been no communication of intent to construct a stadium on the purchased land. He emphasized the NFL's stringent relocation policy, highlighting the significant practical and financial obstacles any relocation would face.[12] In addition, the parcel itself was too small for an entire stadium complex, and considering Kroenke's background as a real estate businessman, land acquisitions are not uncommon for him. Thus, it can be plausibly assumed that the purchase of land should not have triggered any anticipatory market reaction in St. Louis. Further, in December 2014, the Rams announced their decision not to exercise their right to relocate, confirming the intention to stay in St. Louis for the forthcoming season.[13]

(ii) On January 5, 2015, Rams owner Kroenke revealed intentions to construct an 80,000-seat stadium in Inglewood, projected for completion in 2018.[14] In regard of his ownership status, the Rams were obviously seen as a hot candidate to play in the new stadium. However, it should also be mentioned that two other NFL franchises, the Chargers and Raiders, who were in a similar situation and equally expressed dissatisfaction about their host facilities, positioned themselves for a move to Los Angeles. Moreover, as mentioned

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

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

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

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

[12]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)).

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

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

earlier, the practice of leveraging relocation threats to elicit larger public contributions for a new stadium or for considerable renovations of the current home ground, is a common practice in the American franchise system.[15]
Effectively, a mere four days later, the tacit threat of relocation seems to have proven fruitful as Missouri Governor Jay Nixon promptly established a stadium task-force, mandated to develop a concept for a new billion-dollar stadium, located a bit closer to the waterfront and equipped with a series of sophisticated features which would have made it one of the most modern stadiums in the NFL.[16] The plans were ultimately unveiled to the NFL during a conference on the future of the St. Louis franchise in October 2015, which was described by city officials as highly productive and insightful and led to the approval of the new stadium plans by various city committees in early December. Subsequently, these approved plans were submitted to the NFL in late December 2015. Despite these efforts, on January 4, 2016, the Rams submitted their relocation application to the NFL, coinciding with applications from the Chargers and Raiders. Alongside their application, the Rams' owners issued a statement declaring the city's proposed new stadium plans unacceptable. Only a few days later on January 9, the NFL also rejected the new stadium plans and labeled them as 'unsatisfactory'. Eventually, on January 12, the NFL approved the relocation of the Rams and Chargers who were supposed to share the new stadium in Inglewood upon completion.
Following the relocation, several public officials expressed disappointment and outrage at the NFL's decision and accused the league of dishonesty, claiming that it had promised St. Louis a good chance of keeping the franchise. Consequently, the City of St. Louis, St. Louis County, and the Regional Convention and Sports Complex authority filed a $1bn compensation lawsuit against the NFL. Finally, the case was settled at the end of 2021, with total damage payments of $820 million agreed upon.

Against this backdrop, we postulate that the likelihood of the Rams either staying or departing from St. Louis was equally plausible, in view of the ongoing negotiations involving the NFL, Rams, and the City of St. Louis, the concurrent developments across the three cities, the emergence of the billion-dollar stadium proposal, and the common practice of franchises exerting pressure on local governments for higher benefits or concessions. Moreover, there existed the credible possibility that the Chargers or Raiders could instantly replace the Rams in St. Louis should they win the 'race' for the LA market.[17] Hence, we contend that leveraging the relocation as a natural experiment within our identification strategy is justified.

[15]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 (C.f. Bradbury et al. (2023)).

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

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

4 Methodology

4.1 Hedonic Price Model

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

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

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

Notwithstanding, while the theoretical framework of hedonic regressions is clear-cut, several empirical issues arise in practice, as Tu (2005) constates. In short, Rosen's and subsequent theoretical works on hedonic models provide relatively little guidance on the choice of variables and functional form of the model. Ultimately, model specification remains at the researcher's discretion and should be guided by both theoretical principles and context-specific considerations.
In terms of functional form, hedonic models typically adopt one of three specifications: a) a simple linear model; b) a semi-log model; or c) a log-log specification. There is no evident theoretical justification for the superiority of either model and all three bring about advantages and caveats respectively (C.f. Feng and Humphreys (2018)). Hence, we follow the vast majority of the literature and specify a semi-log model which has two major advantages. First, the range of housing prices is often very large and possibly heavily influenced by outliers. In this regard, log-transforming the dependent variable helps to dampen the weight of prices at the lower and upper ends of the distribution, resulting in a less skewed and more normal looking distribution.[18] Second, 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 properties of different price categories, whereas the linear model is more strict and assumes a constant effect.[19]

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

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

In terms of variable selection, the analyst is facing a tradeoff between including as many control variables as possible to prevent omitted variable bias (OVB), and avoiding the inclusion of highly correlated covariates often stemming from structural dependencies among above all neighborhood characteristics, to prevent multicollinearity.[20] We discuss both of these concerns in the Online Appendix and argue that our model is correctly specified.

Another common concern that arises with hedonic modeling is endogeneity (C.f. Bayoh et al. (2004)). Specifically, one might suspect that the relocation of the Rams is ultimately provoked by abruptly or incrementally deteriorating economic conditions in the downtown area where the stadium is located, which would be likely to also induce a price depreciation of residential properties. In this case, one would mistakenly attribute the observable decline in property values to the relocation, whereas the causal chain is actually reversed. Responding to this concern, while the fact that St. Louis incorporates several facets of a quintessential Rust Belt City having been on a long term economic and demographic decline for about 70 years (Metzger et al. (2018)) has certainly contributed to the Rams general willingness to relocate to a larger market, it is essential to note that this continuous decline is primarily observable in the very long run and the economic situation over the sample period was relatively stable and characterized by an absence of any other major economic shock.[21] Additionally, it is shown in the Online Appendix that the inclusion or removal of potentially endogenous regressors does not alter the results, which leads us to argue that endogeneity should be less of a concern.

Further, as outlined in the prior section, we posit that the Rams' departure can be exploited as a natural experiment, since until the eventual date of approval by the NFL, the relocation of the Rams was as equally likely as their remainder in St. Louis. Consequently, the relocation-induced exogenous variation of housing prices invites to embed the hedonic pricing model within a quasi-experimental difference-in-differences framework. Thereby, we adopt the methodology proposed by Ahlfeldt and Kavetsos (2012) and pool housing price data into space-time cells. This approach enables us to divide the sample into a pre- and post-treatment period and compare the relative price evolution within a treatment area, defined based on prior literature findings as a three-mile radius ring around the stadium, with a control area consisting of properties located farther away. An inherent appeal of the difference-in-differences method is that it cancels out unobserved group fixed effects as well as time trends. Though, for the sake of causal inference, it is required to strongly assume that the treatment and control group embody reasonable counterparts, meaning that, in the absence of treatment, they would have followed the same trend. Typically, this assumption is considered plausible if the groups follow fairly identical pre-trends.
In this context, simply visualizing the pre-trends of both groups can already reveal obvious violations of the common trend assumption. Figure 1 plots these trends and shows that both groups followed a fairly similar trajectory until the occurrence of the treatment in January 2016,[22] and there are no obvious violations, i.e. reversed trends, of the common trend assumption. In addition, one can clearly see that the relocation has induced a considerable exogenous shock within the impact area, but also that average (log-) transaction prices quickly recovered a year later but flattened out over the following years.[23] In contrast, one can see a relatively constant increase of the average (log-) housing price within the control area throughout

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

[21]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.

[22]All observed transactions in 2016 occurred after the relocation submission, likely due to recording policies.

[23]The quick recovery may possibly be linked to positive sentiments surrounding the announcement of mixed-use development projects in late 2016 and mid-2017, including especially 'Ballpark Village II' and 'The Foundry'. As elaborated on in the Appendix, if capitalization effects were at play, the true impact of the Rams' departure might have been even more detrimental.

the sample period. Nonetheless, one may want to note that the pre-trends are not perfectly parallel, with housing prices appearing to increase slightly more in the impact area relative to the control area in 2013, although this difference in magnitude is relatively small.

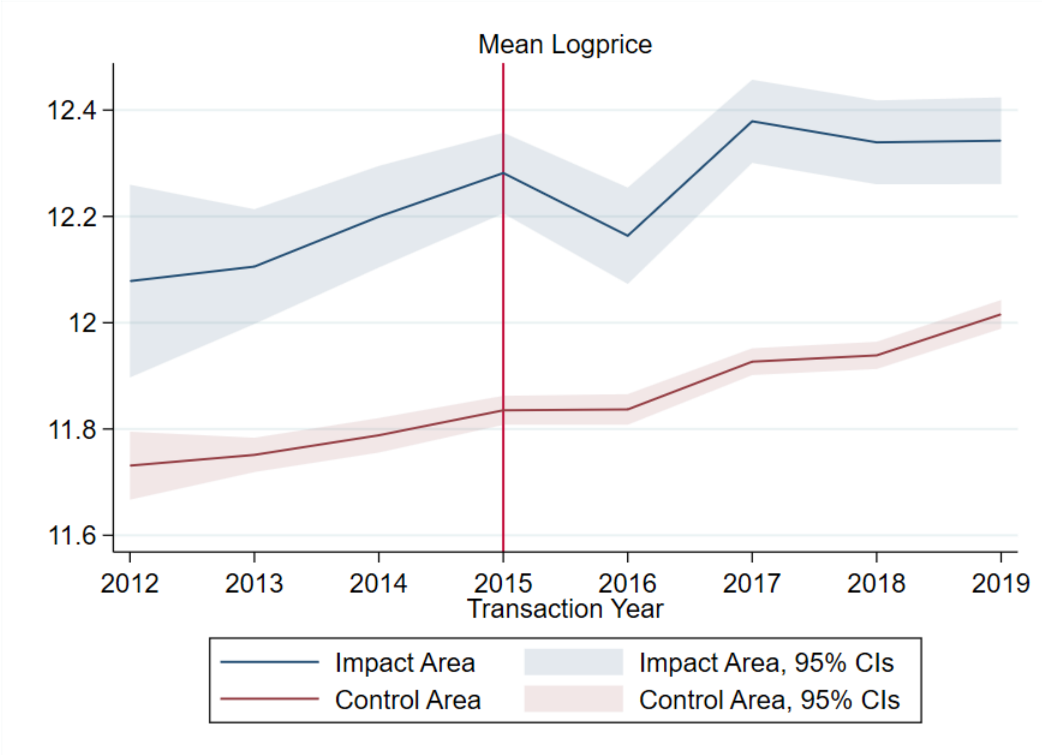


Figure 1: Parallel Trend Plot

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

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

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

whereby the natural logarithm of the price p of property i sold at time t is regressed on the difference-in-differences specification in the first line, and a number of covariates and fixed effects in the second line. Concretely, $x_{j,i,t}$ is a vector including time-invariant structural housing attributes, as well as time-varying

neighborhood characteristics, market features, and urban characteristics associated with property i's location at the point of transaction t. The β_j coefficients approximately reflect the percentage effect of a one unit change in x_j.[24] 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,[25] to account for base differences in neighborhood values.[26] Lastly, $\epsilon_{i,t}$ is the error term.
With respect to the difference-in-differences estimates, Post_t is a dummy taking the value one when a property was sold in the post-relocation period,[27] 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-differences estimator. It can be interpreted as the difference between changes in average (log-) transaction prices within the impact area before and after the relocation, relative to those changes in the control area:

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

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

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

The main coefficients of interest are the δ_r's, which denote the difference-in-differences estimates for properties located within ring r. The model is estimated twice. $N = a$ corresponds to the specification with one-mile distance rings, while $N = b$ indicates the specification with half-mile distance rings. For the one-mile specification, the control area corresponds to the outermost 7-8 mile ring. As it is widely argued that sports-related amenity benefits are highly concentrated within the immediate vicinity of a facility, for specification b, we follow Neto and Whetstone (2022) and only include half-mile distance rings within a 5-mile radius. This implies that the control area is composed of all houses located farther away.

4.2 General Equilibrium Effects

More recent literature warrants caution regarding the conventional hedonic DiD estimator, as it may be biased in the presence of unaccounted general equilibrium effects. In particular, Banzhaf (2021) reveals that exogenous amenity shocks may induce general equilibrium effects, conflating the interpretation of Rosen's first stage equation as marginal willingness to pay with endogenous changes in the hedonic price schedule. Intuitively, an exogenous amenity shock may trigger endogenous mechanisms, altering the shadow prices of

[24] 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)).

[25] As demonstrated in the Online Appendix, using neighborhood-level fixed effects yields identical results.

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

[27] Upon including year fixed effects, we may have also omitted the Post dummy due to collinearity. However, for 'aesthetic' reasons, we decided to keep it, also because we estimate model 1 below without fixed effects. In models 2-4, Stata automatically omits the last year dummy.

composite amenities and housing characteristics and implying a shift of the hedonic price function. Such a shift violates SUTVA, as non-treated housing units are also affected by it. As a rule of thumb, the longer the treatment period and the larger the number of the treated units, the more likely it is that the implicit assumption of a constant hedonic price gradient is questionable.

In this context, the inclusion of time-varying coefficients accounts for changes in the valuation of housing and locational characteristics, allowing for a more accurate assessment of (non-marginal) welfare changes. Ultimately, Banzhaf (2021) shows that one can identify the DiD coefficient as the desired change along the ex-post hedonic price function as a lower bound on Hicksian Equivalent Surplus.

Against this backdrop, I follow the application of Ding et al. (2023) and allow for time-varying coefficients by additionally interacting each covariate with the Post dummy:

$$
\begin{aligned}
\ln p_{i,t} =& \beta_0 + \delta_1 * \text{Post}_t + \delta_2 * \text{Impact}_i + \delta_3 * \text{Post}_t \times \text{Impact}_i \\
&+ \sum_{j=1}^{m} (\beta_j + \rho_j * \text{Post}_t) x_{j,i,t} + \sum_t \kappa_t y_t + \sum_l \theta_l m_l + \sum_q \psi_q c_q + \epsilon_{i,t}
\end{aligned}
\tag{4}
$$

4.3 Model Specification

Table 1 provides a comprehensive account of the variables used in our main analysis. While we primarily control for typical housing attributes and neighborhood characteristics requiring little methodological explanation, there are some covariates we would like to briefly comment on. For instance, given St. Louis' stark housing market segregation along racial lines, as further elaborated on in the Online Appendix, and the significant degree of urban blight in certain areas, we consider it essential to control for the share of the Black population and the share of vacant housing per neighborhood. Similarly, we control for local crime rates, both because St. Louis consistently ranks high in terms of violent and property crimes among major US cities and because the negative association between crime and professional sports has been well-documented in diverse contexts and from several perspectives (e.g. Kalist and Lee (2016), Marie (2016), Mares and Blackburn (2019)).

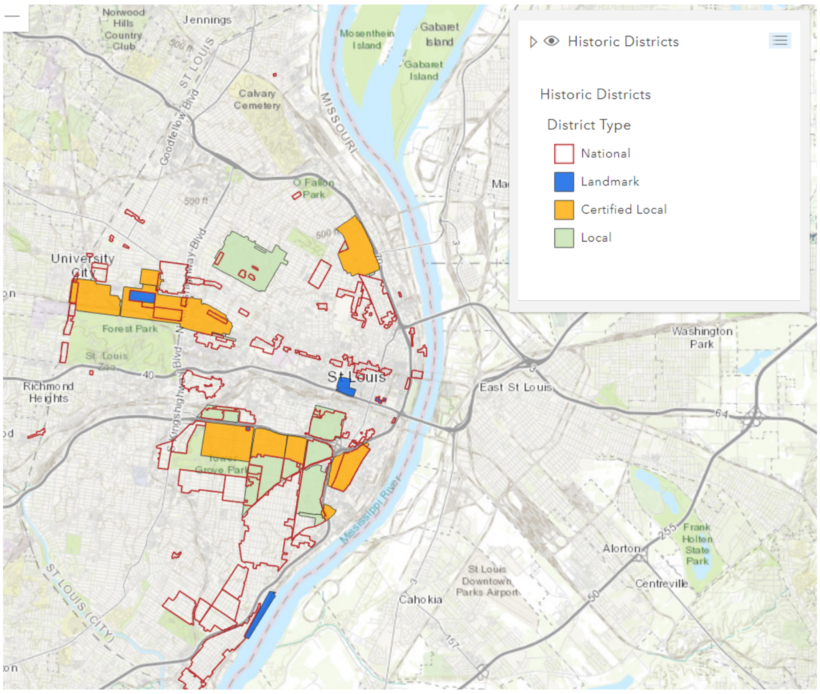
Moreover, our unique geospatial data set allows us to account for St. Louis' distinct geographical location and rich historic background, which are still evident in today's housing market. St. Louis served as a designated *'gateway to the west'* during the 19th-century westward expansion of the US. Consequently, much of the housing stock is relatively old, and a significant portion of the city has been historically designated as either local, certified local, or national historic districts, as portrayed in Figure 2. We regard controlling for historical designation important, as there is a general consensus in the literature that it appreciates property values (Mason (2005)).[28]

Likewise, we also include dummies for properties within Preservation Review Areas and those under the Housing Conservation Program, as they may serve as proxies for unobserved qualitative building standards that participating houses must meet. Additionally, we capture for potential negative spillover effects from industrial and commercial land use by including a dummy for single-family homes located within Enterprise Zones.

Further, St. Louis exhibits a distinct geography. Situated at the confluence of the two largest rivers in the

[28]We further argue in a digression in the Online Appendix, that these dummies may also serve as important proxies for unobserved external building features characteristic of a certain building period. Hence, they may be regarded as an approximate remedy to the Age-Period-Cohort Problem (APC) (Yiu and Cheung (2022)) that arises 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.

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



Source: www.stlouis-mo.gov

US, the Mississippi and the Missouri, and lacking surrounding mountains for shielding, the city is exposed to severe weather conditions, including heavy flooding.[29] Therefore, we include dummies for the 100-year and 500-year floodplains.[30]

Ultimately, as our last urban control, we account for the WTP for proximity to urban parks by regressing on a property's distance to the closest (major) urban park or green space. Similar to sports facilities, urban parks constitute local public goods in the Tieboutian sense, and their use is primarily defined by accessibility in terms of residential proximity. Hence, we claim that citizens may be willing to pay a premium for residing close to parks.[31] Notwithstanding, the inclusion of the covariate may be controversial if one believes that the valuation of residential proximity to sports facilities and urban spaces manifests a complementary or substitutional relationship.[32]

What is more, we place emphasis on the relevance of additionally including controls for local market and population characteristics in our case. Due to the integration of the stadium within downtown St. Louis, it is crucial to capture potential spillovers generated by the downtown area. In this light, we isolate the proximity effect of residing close to the stadium in two ways: First, we incorporate market controls, considering the number of three types of commercial establishments: 1) Accommodation and Food Services, 2) Retail Trade Establishments, and 3) Finance and Insurance Companies. Particularly the latter type serves as a

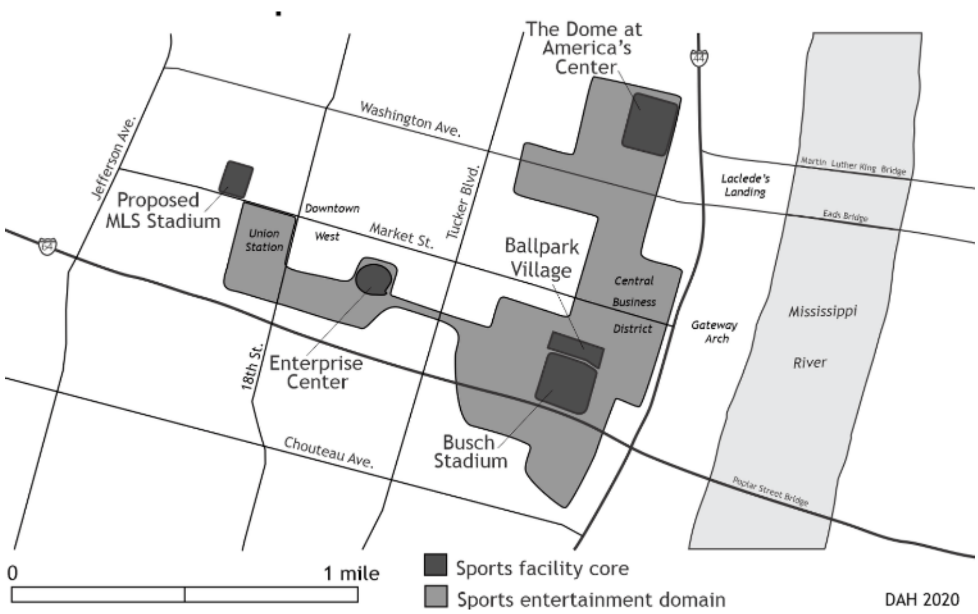
[29] C.f. Newamerica.com

[30] The prior relates to land exhibiting a one percent chance of being equaled or exceeded each year, whereas the latter is statistically flooded once in 500 years. Figure 10 in the Appendix depicts these floodplains in St. Louis.

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

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

Figure 3: St. Louis - Sports Entertainment District



Source: Hurt (2021)

proxy for distance to the downtown area, specifically the central business district (CBD), where the majority of finance and insurance companies are typically located. Second, we control for population density per neighborhood following standard urban economic theory (C.f. Alonso (1964), Muth (1985), Fujita (1989)). The covariate not only serves as a proxy for proximity to the CBD but also allows to account for spatial heterogeneity resulting from zoning ordinances, natural barriers, or imperfections in the local housing market (C.f. Buck et al. (1991)).

However, the integration of the Edward Jones Dome into a designated sports-and entertainment district, which also includes the *Enterprise Center* (a multipurpose-arena home to the St. Louis Blues, NHL) and *Busch Stadium* (an open-air baseball stadium hosting the St. Louis Cardinals, MLB), presents an additional empirical challenge for isolating the proximity effect. The three major league stadiums are situated just a few hundred meters away from each other, as displayed in Figure 3. We therefore equally control for proximity to the other two stadiums as the relocation of the Rams might have elicited a decrease in WTP for proximity to the other two stadiums, potentially due to foregone spatial synergies leveraged by the presence of three major league teams, rather than two.[33]

4.4 Confounding Events and Development Projects

To uphold our identification strategy, we must rule out that the observed effects are driven by confounding development projects or sports-related events occurring concurrently with the treatment. In this context, we identify two potentially confounding events: First, the surprising Stanley Cup win of the Blues during the 2018/2019 season may have evoked significant spatial externalities, such as civic pride or social cohesion among supporters.[34] Alternatively, in the negative sense, it could have led to increased congestion resulting from fan gatherings, for instance. Second, in 2014, 'Ballpark Village I', an entertainment and

[33] On the cost side, we control for two highly collinear variables. Though, we demonstrate in the Online Appendix that these variables have no virtual impact on the DiD estimate, which is why we include them in our baseline.

[34] 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.

business district, opened adjacent to the Busch Stadium, offering ample space for offices, retail stores, restaurants, as well as the Cardinals Hall of Fame and Museum (Click (2014)). It might be that the additional consumption benefits are somewhat capitalized into local property values.[35]

Against this backdrop, we test for the robustness of our findings by replicating our analysis on a shortened pre- and post-treatment period from 2014 to mid-2018 excluding potentially spurious transactions from the sample. For brevity, the adjusted regression outputs are presented in the Appendix.[36] In short, the findings align with the general conclusions and imply that neither the Blues' heroic triumph nor the new Ballpark entertainment district lead to considerable estimation bias.

Furthermore, in the Appendix, we conduct a placebo analysis on Nashville, Tennessee, to rule out the existence of a secular trend in the urban price gradient of larger American cities regarding the preference for residing within downtown versus within the inner-city. We consider Nashville the best available proxy as it is a mid-sized city somewhat similar in size and popularity to St. Louis, which also hosts an NFL franchise in a stadium close to downtown but did not experience any major economic shock around the departure of the Rams. Importantly, we were able to collect the detailed micro-data on housing characteristics needed for hedonic analysis, which was unfortunately not feasible for other candidate cities.
Replicating our hedonic analysis, we find evidence of an opposing trend in Nashville, where single-family homes within a three-mile radius of Nissan Stadium appreciated in value over the sample period. This suggests that the findings for St. Louis are not influenced by a general trend and are likely specific to the local context.

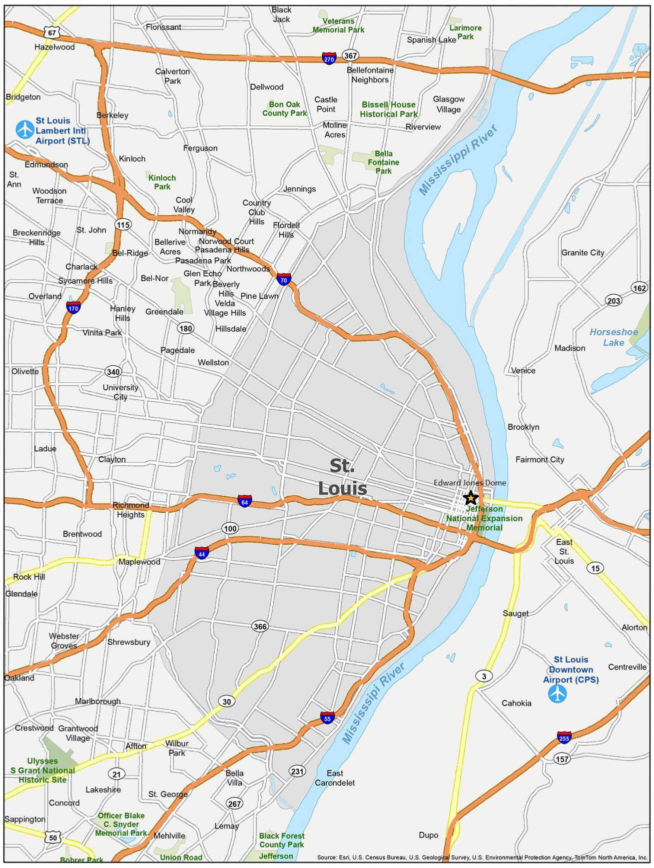
[35]This is particularly crucial in view of reported displacement effects following the inauguration of the first phase, expressed in multiple closures of downtown restaurants and bars, highlighting the popularity of Ballpark village and its substitutional effect on the local economy (Hurt (2021)). The follow-up project, 'Ballpark Village II', and the mixed-use development project, 'The Foundry', might have a similar impact upon their completion, although both projects were inaugurated after our sample period. Nevertheless, as mentioned above, if the announcements and start of construction have already induced capitalization effects, our estimates may be upward-biased, i.e. too small.

[36]Simultaneously shortening the pre- and post-sample periods is additionally desirable to rule out a confounding effect of local urban development projects, such as the renovation of Union Station in 2014 or the makeover of the iconic Gateway Arch Museum, re-inaugurated in July 2018. In particular, in recent years, St. Louis underwent a phase of significant redevelopment projects; however, most of these projects were initiated across the entire city after 2018 and continuing into subsequent years.

Table 1: Variable Definitions

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

Figure 4: St. Louis - City Map



Source: gisgeography.com

5 Data

5.1 Sample Selection & Distance Calculation

St. Louis City's Planning & Urban Design Agency manages a publicly accessible data-portal called *Geo St. Louis*, which provides geospatial parcel data on the City of St. Louis, including a comprehensive record of parcel sales from 1977 to 2019. Each transaction comes with a report exhibiting factual information on the precise location, characteristics, i.e. building attributes, legal history, and transaction history of any parcel. With the help of web-scraping techniques in Python, we first scraped all recorded transactions occurring between January 1, 2012, and December 31, 2019 ($n = 43,818$). This data was then merged with information on a parcels' location and, when available, information on building attributes. The sample period was intentionally selected to encompass a balanced pre- and post-treatment phase, approximately four years each, surrounding the relocation application and ratification on January 4, 2016, and January 12, 2016, respectively. This duration is considered adequately long for discerning capitalization effects, relocation-induced population dynamics, and changes in neighborhood features at both large and minor scales. Simultaneously, the sample period is sufficiently short to mitigate potential bias from nearby urban development projects.[37]

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

Furthermore, as the parcel data is restricted to St. Louis, the sample area is conceptually predetermined by the city fringe, which was established in 1876 and has remained unchanged ever since (C.f. Metzger et al. (2018)). This consistency is advantageous, as it allows for comparison of the treatment effect across properties situated within a fairly homogeneous context of long-term economic and urban policies. However, as shown in Figure 4, the Edward Jones Dome is situated at the eastern edge of the city near the Mississippi River, which serves as a natural state line between St. Louis, Missouri, and East St. Louis, Illinois. Therefore, one natural data limitation is that our three-mile treatment area intersects the city border and overlaps into East St. Louis, as shown in Figure 6, whereas we are only able to analyze properties which were transacted within St. Louis.
In this context, we rely on address information from the parcel records to determine each property's coordinates via Google's geocoding API. Next, we computed the geodesic distance of each property from the Edward Jones Dome using Geopy's freely available API in Python. In the process, 34 single-family homes were discarded from the sample, as their address information appeared outdated.

5.2 Data Cleansing & Selection of Covariates

Housing Types & Structural Housing Attributes

As we are only interested in residential housing sales, we first filtered the transaction records and assigned each transaction to one of three categories, primarily based on information on the assessor use and building type: 1) Residential, 2) Mixed-Residential, i.e. apartments above stores or restaurants, or 3) Commercial/Industrial/Other parcels. The vast majority of transactions are residential sales, which make up 93.14% ($n = 40,842$) of the data, followed by commercial, industrial, or miscellaneous parcels totaling about 6,2 % ($n = 2697$), and lastly mixed-residential parcel sales only accounting for 0.71% ($n = 313$) of the data. Ultimately, we only kept residential parcel sales.

The retrieved building information reflects a snapshot in time of primarily time-invariant structural housing attributes, namely, the parcel size, floor size, exterior facade (e.g. brick, stone, or frame wall), number of stories, number of carports, number of garages, building year, and information on whether houses have attics. Unfortunately, information on whether buildings have central air conditioning or heating systems, as well as the number of full and half bathrooms, could not be used due to insufficient variation in outcomes and categorically incomplete data. Moreover, it must be remarked that a substantial number of building records exhibits zero- or missing values across the selected structural housing attributes. Faced with the trade-off of either reducing the number of independent variables to increase the sample size and include as many observations as possible, or discarding observations with missing or zero values and controlling for as many housing attributes as possible to increase the precision of the estimates and to prevent OVB (C.f. Agha and Coates (2015)), we opted for the latter approach. This decision aligns with the widely reported observation that structural housing attributes alone account for the vast majority of variation in housing prices. Additionally, our final sample size, as shown below, remains adequately high.[38]
Besides, we conducted additional data cleansing to address the issue of a small number of parcels that are shared by multiple buildings registered under the same address. Distinguishing the specific value of each individual property in these cases was challenging, so we only included sales of unique parcels in our sample. In addition, we removed a few observations of properties that were sold before they were constructed.

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

Furthermore, in line with most prior studies, we restrict our analysis to single-family residential homes only. Given that 78.35% ($n = 31,972$) of all residential sales within the sample period are single-family homes, this selection provides an ample sample size for our hedonic regressions. Table 2 contains summary information on the consecutive distance rings and shows that, with exception of the immediate one-mile area surrounding the stadium, all rings are reasonably populated.[39]

In this context, it is also noteworthy that due data limitations, there are few alternatives to selecting single-family homes. Some hedonic papers choose to analyze apartment buildings or condominiums instead. In general, there is again no clear theoretical guideline dictating the superiority of either choice over the other. While, on the one hand, one might assume homogeneous treatment effects across all building types, on the other hand, spatial heterogeneity resulting from zoning ordinances, among other factors, might lead to detecting heterogeneous effects conditional on building types. In this respect, due to the integration of the Edward Jones Dome into downtown, it would have been desirable to also examine the price evolution of apartment complexes or condominiums. Unfortunately, the retrieved data only contains information on transactions of entire parcels, meaning that we lack information on the sale of individual apartments and only observe occasional sales of whole apartment complexes. Apart from the fact that the sample size would be insufficient, we also lack substantial information on building characteristics of multi-family residential buildings and hence would not be able to include them within our hedonic models.

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

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

[39]For the sake of clarity, we refer to the one-mile rings as *Impact*-rings, and to the half-mile rings as *Target*-rings.

Target3_5	653	0.0514	0.22	0.00	1.00
Target4	676	0.0532	0.22	0.00	1.00
Target4_5	623	0.0491	0.22	0.00	1.00
Target5	670	0.0528	0.22	0.00	1.00

Notwithstanding, in comparison to previous papers, one eminent asset of the data is that each parcel transaction is neatly classified by sales type, enabling us to seamlessly exclude non-arms length transactions from the data. In short, we only retain 'Valid' sales, as they form the majority of single-family home sales over the sample period ($n = 13,872$; 43.39%) and are expected to be the least biased and most 'pure' market transactions. Other sale types, classified, for example, as 'Gift', 'Not Open', or 'Related Party', were evidently discarded as the sales price is likely to be non-representative of the true market value of the corresponding properties. Foreclosures and investor sales were likewise dropped for similar reasons.

Further, consistent with prior literature, we limit our analysis to transactions over $30,000. This cutoff value is conservative and well-below half the median value of the valid single-family home transactions in the sample, which is $145,000. Lower-priced properties were excluded as they are more likely to have unobserved qualitative deficiencies or significant mortgage debt, which could introduce bias. However, as the St. Louis housing market is deeply segregated and some areas experience severe distress and urban blight (Tighe and Ganning (2015)), the exclusion of property transactions below the cutoff value of $30,000 could lead to bias, particularly if it evokes a structural change in the spatial composition of either the specified treatment or control area. To address this, we replicate our models on a sample without a lower price bound and find that the results remain unaffected.[40] This robustness check is presented in the Online Appendix.

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

Table 3: Summary Statistics (N=12695)

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

[40] We likewise observe the same results when using a 'ghetto sample' (Jud (1980)) instead.

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
Urban Characteristics				
DistancePark	0.82	0.39	0.02	4.08
Local	0.07	0.26	0.00	1.00
National	0.20	0.40	0.00	1.00
CertifiedLocal	0.08	0.28	0.00	1.00
Conservation	1.00	0.06	0.00	1.00
Preservation	0.95	0.22	0.00	1.00
Enterprise	0.14	0.35	0.00	1.00
Flood100	0.01	0.09	0.00	1.00
Flood500	0.01	0.10	0.00	1.00
DistanceBusch	4.90	1.46	0.54	8.50
DistanceEC	4.63	1.45	0.64	8.21

Neighborhood and Market Characteristics

We retrieve neighborhood data from two primary sources. First, we obtain socio-demographic information from the 2010 and 2020 US Census, available on the neighborhood level.[41] 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.[42] Aiming to better depict variation in local neighborhood characteristics, we construct annual weighted averages, assuming a fairly linear trend in the evolution of socio-demographic compositions of neighborhoods.

Further, we determine population density by matching the annual population numbers from the Census Data with information on the size of each neighborhood retrieved from Wikipedia. We adjust the scale so that a one-unit increase represents the percentage effect of a 100-person population increase, enhancing the readability of the coefficient. Similarly, we apply a similar transformation to the crime coefficient so that it reflects the approximate percentage effect of an increase in ten total crimes per 1000 residents. The underlying crime statistics are obtained from the St. Louis Metropolitan Police Department.

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

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

Lastly, data on the number of retail trade establishments, accommodation and food services, as well as finance and insurance companies is obtained from the US Census Bureau's annual County Business Patterns (CBP) survey and available on the zip-code level. To enhance interpretability, we rescale the numbers such that each coefficient respectively corresponds to the approximate percentage effect of ten additional establishments.

Urban Characteristics

Data on historical designation, housing preservation and conservation, enterprise zones, and floodplains is directly obtained from the parcel records retrieved from Geo St. Louis.

Regarding the proximity to parks covariate, the City of St. Louis reports a total of 108 parks within the city boundaries. Using qualitative criteria, in particular in terms of size, location, and popularity, we have identified the 17 most relevant urban parks in St. Louis.[43] This selection is based on the somewhat strong assumption that only parks exceeding a certain size generate substantial and discernible amenity benefits, and that the impact of parks is approximately homogeneous, regardless of differences in attributes.

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

6 Empirical Results

6.1 Results of the Base Model

Table 4 presents four different specifications of our base model. Column (1) shows the results when only controlling for structural housing attributes and proximity to the other two stadiums. The adjusted R^2 increases from 0.5224 in Model 1 to 0.7401 in Model 2 with the addition of fixed effects. Columns (3) and (4) add neighborhood and market characteristics, as well as urban controls, respectively. This slightly increases the goodness of fit, with the largest adjusted R^2 value of 0.7571 observed in Model 4. Additionally, our analysis reveals consistent qualitative findings across the four specifications. There are no noteworthy differences in terms of direction, magnitude, and statistical significance across the models. Similarly, most covariates are highly significant, have the expected sign, and the coefficients appear plausible. These results suggest that the inclusion of additional covariates enhances the precision of the estimates and aids in isolating the treatment effect, which is why we consider Model 4 as our preferred model.

Ultimately, the difference-in-differences estimate reflecting the treatment effect of the Rams' departure is negative and reveals that the relocation has led to a relative decrease in single-family home values in vicinity to the stadium. The point estimate suggests that post-relocation, single-family homes located within three-miles to the Edward Jones Dome sold for a substantial discount of 7.52% relative to properties with similar characteristics transacted within the control area. These findings support our hypothesis that the Rams generated substantial amenity benefits prior to their departure. Likewise, it is important to recall that in our setting, the treatment effect is equivalent to the pure team effect due to the continuous use of the stadium for non-sports related events. In this vein, our results are striking, as they suggest that a major league franchise can effectively generate large positive externalities, contrasting with previous studies that found negative outcomes in different settings. We discuss these contrasting findings in the concluding discussion.

Table 4: 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				

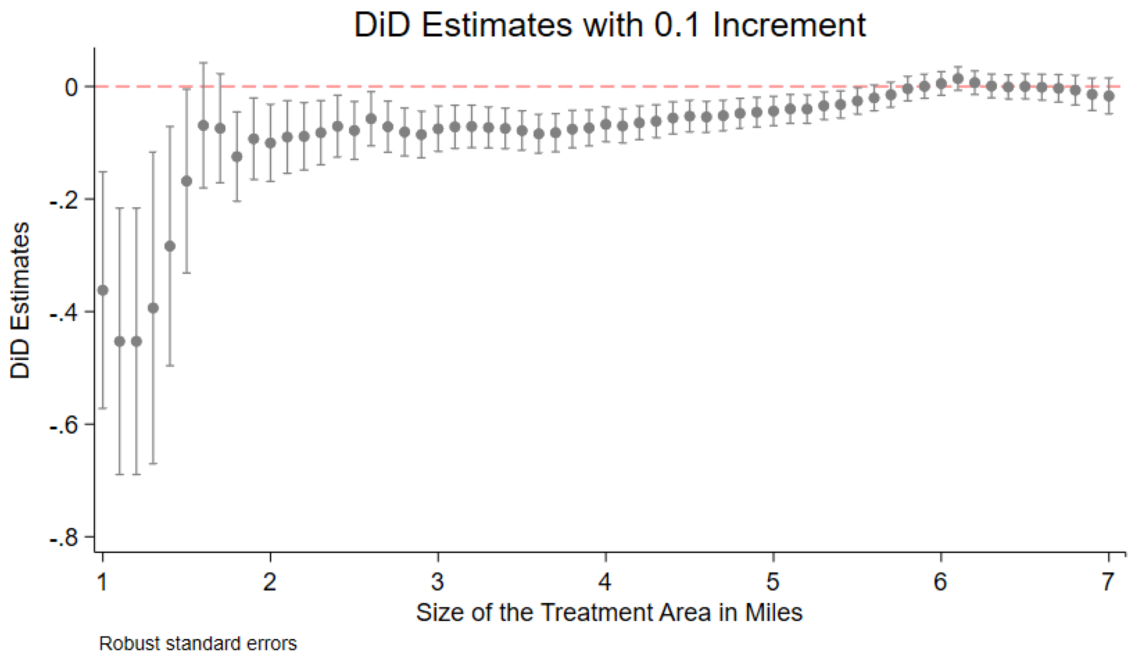
DistancePark				-0.2002***
				(0.015)
Local				0.1180***
				(0.037)
National				0.0848***
				(0.017)
CertifiedLocal				0.2478***
				(0.034)
Conservation				0.1945*
				(0.101)
Preservation				0.1091***
				(0.026)
Enterprise				-0.0018
				(0.014)
Flood100				-0.0636**
				(0.031)
Flood500				0.0013
				(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

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Further, correctly identifying the treatment effect requires accurately determining the extent of the impact area, as both too narrow or too wide a treatment area could introduce bias (Butts (2023)). Therefore, we replicate our analysis for varying treatment area sizes, starting from one mile and increasing in 0.1-mile increments up to seven miles. Figure 5 plots the corresponding DiD-coefficients and shows that the results are consistent across different treatment area selections.[44] Additionally, the relative continuity of the curve suggests that a three-mile treatment area is appropriate and the shape hints at a non-linear treatment effect curve.

[44]Clustering the error terms yields roughly the same plots. Similarly, we do not lose any significance in our base model when cluster-correcting the error terms on various geographical scale levels as shown in Table 26 in the Online Appendix.

Figure 5: Variation in Treatment Effects by Area Size



6.2 Results of the Distance Ring Models

One-Mile Distance Rings

Table 5 summarizes the results of estimating Equation 3 with one-mile distance rings across various error specifications. Regarding the DiD coefficients, the estimates indicate significant price depreciation rates for distances up to three or four miles, depending on the model specification. Importantly, our ring analysis reveals a non-linear distance-decaying structure, implying that the spatial externalities generated by the franchise are heterogeneously dispersed across space, most pronounced in the immediate vicinity of the stadium, and fading away with distance. In terms of magnitude, we find a substantial relative price depreciation ranging from 38% in the first ring to 5% in the four-mile ring.

In terms of significance, the coefficients of the first two rings are statistically significant at the highest level across all specifications, but we discern some loss of significance of the third ring and a total loss of significance of the fourth ring when clustering the error term. Overall, the results are nevertheless fairly consistent and support our selection of a three-mile treatment area.

Table 5: 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

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

Impact8 serves as the reference ring.

The full regression output can be found in the Online Appendix.

Half-Mile Distance Rings

The base coefficients of the one-mile ring model suggests that the general spillover effects of the city core seem to extend up to five miles. Therefore, we intensify our ring analysis and focus on a five-mile radius around the stadium, with all property transactions outside this area forming the control group. This adjustment is also made as amenity benefits are typically highly localized, and the eight-mile ring may not provide an ideal control area. Additionally, since the one-mile rings are relatively wide, the target area is further divided into half-mile distance rings to more precisely map out the heterogeneity of the treatment effect across space. The estimation results are displayed in Table 6.

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

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) Neighborhood
Post	0.313***	0.313***	0.313***	0.313***	0.313***
	(0.024)	(0.021)	(0.036)	(0.037)	(0.036)
Target0_5	0.462***	0.462	0.462**	0.462***	0.462***
	(0.155)	(0.369)	(0.204)	(0.146)	(0.164)
Target1	1.099***	1.099***	1.099***	1.099***	1.099***
	(0.190)	(0.247)	(0.234)	(0.179)	(0.363)
Target1_5	0.380***	0.380***	0.380*	0.380**	0.380**
	(0.119)	(0.106)	(0.221)	(0.156)	(0.190)
Target2_0	0.416***	0.416***	0.416**	0.416***	0.416***
	(0.099)	(0.081)	(0.205)	(0.134)	(0.152)
Target2_5	0.351***	0.351***	0.351**	0.351***	0.351**
	(0.083)	(0.069)	(0.173)	(0.109)	(0.138)
Target3	0.396***	0.396***	0.396**	0.396***	0.396***
	(0.072)	(0.060)	(0.170)	(0.126)	(0.131)
Target3_5	0.289***	0.289***	0.289**	0.289***	0.289***
	(0.062)	(0.052)	(0.126)	(0.081)	(0.099)
Target4	0.221***	0.221***	0.221*	0.221***	0.221**
	(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	-0.026	-0.026	-0.026	-0.026	-0.026
	(0.030)	(0.026)	(0.080)	(0.085)	(0.085)
Target0_5xPost	-0.365***	-0.365*	-0.365***	-0.365***	-0.365***
	(0.112)	(0.212)	(0.036)	(0.033)	(0.031)
Target1xPost	-0.138**	-0.138	-0.138***	-0.138**	-0.138**
	(0.069)	(0.289)	(0.045)	(0.061)	(0.063)
Target1_5xPost	-0.116	-0.116	-0.116***	-0.116*	-0.116**
	(0.093)	(0.094)	(0.036)	(0.068)	(0.056)
Target2_0xPost	-0.104***	-0.104***	-0.104**	-0.104***	-0.104***
	(0.038)	(0.037)	(0.043)	(0.031)	(0.029)
Target2_5xPost	-0.057	-0.057*	-0.057	-0.057*	-0.057

	(0.038)	(0.035)	(0.042)	(0.030)	(0.042)
Target3xPost	-0.074**	-0.074***	-0.074*	-0.074*	-0.074*
	(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	-0.028	-0.028	-0.028	-0.028	-0.028
	(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)	(0.036)
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	0.7582	0.7582	0.7582	0.7582	0.7582
Observations	12695	12695	12695	12695	12695

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

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

The full regression results can be found in the Online Appendix.

Looking at the DiD estimates, we observe significant negative effects up to three and a half miles from the facility. However, when cluster-correcting the error terms, we only observe partly significant or non-significant estimates in the third mile ring. Hence, the estimates from the half-mile model may rather support a more conservative treatment area of two miles.
One illustrative aspect of the half-mile model is its ability to neatly map out the distance-decaying effect of the treatment effect across space. Nonetheless, the large coefficients for the first two rings should be regarded with caution due to the limited number of transactions occurring in the immediate vicinity of the stadium, as suggested by Table 2.[45] To rule out the possibility that the main effects are driven by these few potentially non-representative transactions, we estimate 'donut models' and find only marginally smaller estimates compared to before.[46]

6.3 Results of the General Equilibrium Model

Table 7 presents the main coefficients from estimating the base model with time-varying covariates allowing for general equilibrium effects, as outlined in Section 4.2. Overall, the results are consistent with the baseline specification. However, the model becomes much noisier when controls for neighborhood and urban characteristics are added. This warrants caution in drawing strong conclusions and suggests the relevance of general equilibrium considerations in hedonic DiD models. At the same time, it is likely that the model is overfitted, with the loss of significance attributed to collinearity among the neighborhood and

[45] Though, Humphreys and Propheter (2024) find similar magnitude effects in San Francisco.

[46] The regression tables are shown in the Online Appendix. We additionally pooled the first two-mile rings together following Neto and Whetstone (2022). The estimate of the pooled two-mile ring is highly significant and suggests a mitigated depreciation rate of 11.1%.

urban covariates.[47]

Table 7: Estimates of the Base Model Considering Equilibrium Effects

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Impact	0.3514***	0.2015***	0.1074**	0.1037**
	(0.036)	(0.040)	(0.044)	(0.046)
Post	0.6105**	0.6516***	0.0366	-0.2696
	(0.260)	(0.189)	(0.233)	(0.277)
ImpactxPost	-0.1185***	-0.0971***	-0.0742*	-0.0014
	(0.046)	(0.033)	(0.042)	(0.046)
Census Tract FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes
Housing Features	Yes	Yes	Yes	Yes
Nhood Features	No	No	Yes	Yes
Urban Features	No	No	No	Yes
Adjusted R^2	0.5233	0.7409	0.7520	0.7596
Observations	12695	12695	12695	12695

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6.4 Estimating the Implicit Amenity Value of the Rams

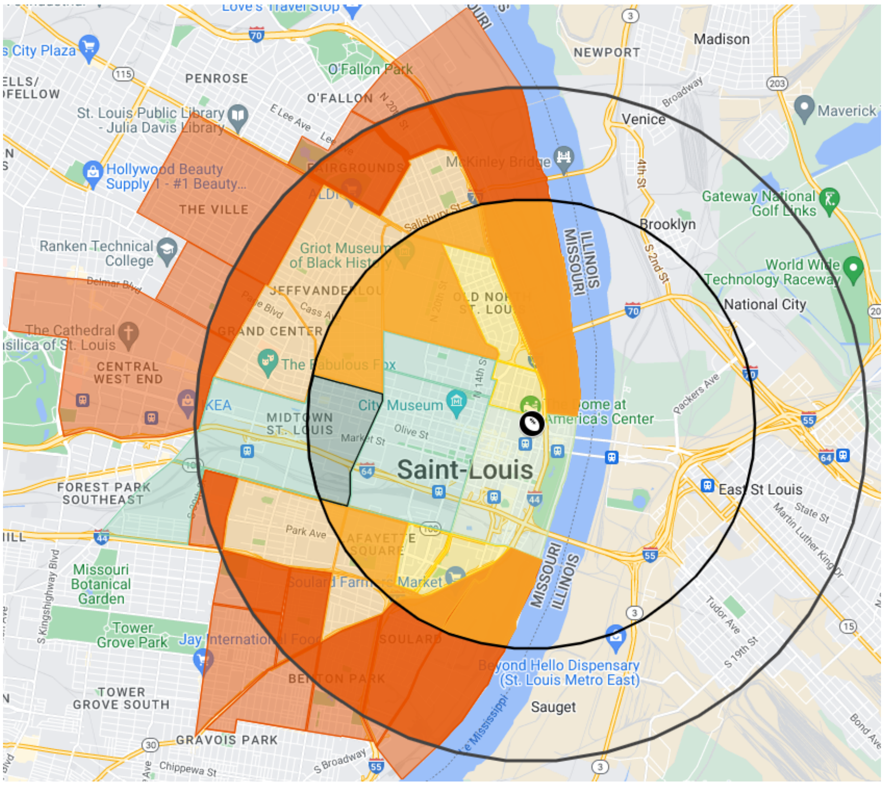
Our analysis provides preliminary evidence that a major league franchise may create considerable implicit amenity value, as indicated by a relative price discount of 7.52% in the St. Louis residential housing market following the relocation of the Rams franchise in 2016. However, this estimate alone cannot assess the severity of the team's departure or lead to informed policy conclusions regarding the practice of stadium subsidization. To address this, we perform a 'back-of-the-envelope' calculation to approximate the implicit loss in amenity value by aggregating the relative price depreciation of the residential housing stock in 2015, the year prior to the relocation. Ultimately, we compare this benchmark to the public spending on the Edward Jones Dome.

First, we approximate the number of total housing units per neighborhood in 2015 using the average of the 2010 and 2020 Census data. Second, we make the light assumption that the market is functioning efficiently and that the observed transaction prices are representative of the distribution of housing values of the latent housing stock. The observed sample median price of properties transacted in the impact area in 2015 was $229,500, which is naturally elevated due to the sample selection and data cleansing procedures. Therefore, we use the median sales price of all residential buildings, which was $170,750. This value also includes foreclosures, investor sales, and sales after rehab, which typically sell at a discount relative to valid sales. We believe this value to be a more accurate proxy for the median value of a residential property in the impact area of St. Louis in 2015.

[47] By arbitrarily dropping combinations of two urban covariates, we could deliberately reproduce the baseline results in model 4.

Our ring models reveal significant price discounts expanding about two to three miles from the stadium. However, neighborhood boundaries are shaped in somewhat arbitrary patterns across space. In this respect, Figure 6 shows that while some neighborhoods (in orange) are fully enclosed, others (in red) intersect the three-mile impact area, delineated by the outer thick ring. For these intersecting areas, we assume an approximately homogeneous dispersion of housing units across space. With the help of Google My Maps, we compute the share of each neighborhood falling into the impact area, allowing us to estimate the total number of housing units ($n_3 = 35,551$) within a three-mile radius of the Edward Jones Dome. The derived three-mile implicit amenity value can be considered an upper bound estimate, as the cluster-corrected half-mile ring model provides only mitigated support for effects reaching as far as three miles from the facility. To also provide a more conservative estimate, we likewise estimate the indirect costs of the departure based on a two-mile impact area ($n_2 = 18,109$), following the same steps as for the three-mile area.[48]

Figure 6: St. Louis - Impact Area



Created with Google's *My Maps* tool and *KML Circle Generator*.

Color Legend: a) Red: Neighborhoods intersecting the three-mile impact area; b) Orange: Neighborhoods intersecting the two-mile impact area c) Green: Downtown, Downtown West, Midtown and Carr Square; d) Yellow: Neighborhoods fully enclosed.

In this context, it is essential to note that the number of housing units considerably differs from the number of residential properties, due to some properties being shared by multiple units. Similarly, the median price per housing unit is typically not equivalent to the median price per property. As we only have information on the number of housing units, while our price information is based on sales of entire properties, we need to approximate the per-unit price of properties by building type. Specifically, we make the strong assumption that, on average, the per-unit value of a shared residential building roughly corresponds to the total sales price divided by the number of units. Additionally, we proxy the share of each residential building type

[48] The median price of the two-mile impact area in 2015, at $215,000, is higher as expected given the proximity to downtown.

within the impact area based on their transactional share over the entire sample period. Thereby, it is implicitly assumed that the observed transaction shares per building type reasonably reflect their share in the latent residential housing stock. In this context, we focus on five building types which together account for 94.73% of all transactions: single-family units, duplexes, triplexes, quadplexes, and multi-family buildings.

Unfortunately, we cannot apply this approach to six neighborhoods within the three-mile impact area due to either no or only a few residential housing transactions occurring over the sample period. Specifically, this means we lack sufficient information to make assumptions about the composition of the building stock within these neighborhoods. Two neighborhoods - Kosciusko and Botanical Heights - are simply excluded from the analysis. Kosciusko is primarily an industrial neighborhood with only 5 housing units recorded in 2020 according to the Census, while Botanical Heights has only 1.4% of its area falling within the three-mile area. Nevertheless, the remaining four neighborhoods - Downtown, Downtown West, Midtown, and Carr Square - account for a considerable share of about one third ($n = 10,535$) of all housing units within the impact area in 2015. One evident reason for the low number of observations within these neighborhoods has to do with the fact that Geo St. Louis records only parcel sales, which means, as elaborated earlier, that we do not observe sales of individual apartments and condominiums, but only sales of entire apartment complexes. Figure 6 illustrates that these neighborhoods, distinguished in green, are largely part of St. Louis' CBD and entertainment district, which is why it seems plausible to assume that the predominant building type in theses areas is apartment buildings. Moreover, the city's core is primarily characterized by commercial and industrial land use, as displayed in Figure 11, consistent with previous reports by Hurt (2021) and Mares and Blackburn (2019). Although the number of parcel sales is low, our data tells a similar story: out of 128 recorded parcel sales, 90.63% constitute commercial or industrial sales, with only five transactions involving multi-family residential buildings across the four concerned neighborhoods.

Against this background, it appears highly likely that the building stock within the four neighborhoods does not follow the same pattern as in the remaining neighborhoods.[49] Therefore, we approximate the building composition based on information on the housing stock within Downtown Nashville, assuming that the downtown areas of both cities are roughly comparable in size and composition. According to a report by Dickson (2020), there were 9,511 residential housing units in Downtown, Nashville, out of which 69% were rental apartment units, 28% condominiums, and only 3% were family homes with up to four units. We consider these numbers to be plausible proxies for St. Louis as well. Notwithstanding, one prevailing and unsolvable issue is that we do not have any information on the median sales price of residential buildings within the concerned neighborhoods. Therefore, we must make the strong assumption that their median sales price is roughly similar to the median price of the observed neighborhoods within the impact area.[50]

Ultimately, we determine the number of housing units per building type located within the impact area, both for the observed and latent neighborhoods. The total number is obtained by simply summing the two estimates together. Eventually, the total implicit loss in amenity value can be approximated as follows:

$$C_i = \sum_j h_{j,\,i,\,t=2015} * w_j * \bar{p}_{i,\,t=2015} \times \delta_i \tag{5}$$

where $h_{j,i}$ denotes the number of total housing units per building type $j \in [1, 5]$ and impact area $i \in [1 = 3\text{-mile}, 2 = 2\text{-mile}]$. $\bar{p}$ reflects the 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,

[49] In fact, for the three-mile area, our upper bound estimate would be approximately $85 million higher if we used the observed neighborhood shares.

[50] In view of their location, we use the median price of the two-mile impact area for the latent neighborhoods.

whereby $w_j = \{1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{16}\}$. For example, a duplex is weighted by the factor $\frac{1}{2}$ as it consists of two building units. As for multi-family buildings, we chose a weight of 16 which corresponds to the average number of apartments in multi-family buildings sold over the sample period. Lastly, δ_i stands for the estimated depreciation rates of 7.52% $(i = 1)$ and 10.04% $(i = 2)$.

Based on our three-mile specification, we obtain an upper inflation-adjusted estimate of $275,370,439 and a lower estimate of $155,538,191 for the two-mile specification.[51] The results underscore the substantial loss in implicit amenity value resulting from the departure of the Rams. Nevertheless, the indirect economic benefits brought by the Rams to St. Louis fall considerably short of the $258 million in governmental bonds paid in 1995 for the stadium construction (Click (2016)), which is equivalent to $531,691,614 in 2024 dollars.[52] Similarly, in late December 2015, the city board unveiled last-minute plans for a new stadium in hopes of preventing the Rams' relocation to Los Angeles or attracting another franchise to St. Louis. The total costs of the proposed stadium were projected to be up to $985 million, with plans including a public contribution of $405 million (Hunn (2015)). Our approximation suggests that such a public commitment would likely not have resulted in net positive benefits.[53]

[51] The inflation-adjusted prices were computed in July of 2024 with the US Inflation Calculator.

[52] Even the most optimistic estimate of $365,250,584, assuming a four-mile capitalization effect, could not provide sufficient rationale for the public provision of the stadium.

[53] The total public burden may have even been substantially larger. Reuters (Respaut (2016)) reports that the bond debt and maintenance costs of the Edward Jones Dome amounted to $720 million accumulated over a 30-year time span. However, it must be noted that this sum was significantly offset by the direct tax revenue streams generated by the matches of the Rams. Eventually, at the time of relocation, the outstanding debt payment was $144 million ($188,435,903 in 2024 dollars). Lastly, in 2021, St. Louis and the Rams agreed on $820 million in damage payments (Raskin (2022)), which implicitly reveals an imperfect proxy for the foregone expected revenue stream that the Rams would have generated had they stayed another ten years and fulfilled their original contract.

7 Conclusion

7.1 Concluding Discussion

This paper exploits the exogenous price shock induced by the relocation of the NFL's Rams franchise from St. Louis to Los Angeles in 2016. It provides evidence that the team generated considerable amenity benefits in the market, as hedonic regressions reveal that the team's departure induced a relative price depreciation of single-family homes within a three-mile impact area by 7.52%. Subsequently, hedonic distance ring analyses show that the treatment effect expands heterogeneously across space and decays in a non-linear pattern up to two to three miles from the former host stadium. The most optimistic scenario even provides some evidence for effects reaching as far as four miles from the facility. Ultimately, we approximate the cumulative loss in implicit amenity value to lie between $155-275 million, for a two- and three-mile treatment radius, respectively. Lastly, we conduct several robustness checks in the Appendix, demonstrating that the results are robust against alternative model specifications and data cleansing procedures. Additionally, we rule out potential anticipation effects, confounding events, or secular trends in the urban price gradient. However, allowing for general equilibrium effects somewhat mitigates the strong findings.
Taken together, our analysis suggests that a major league franchise bears the potential to create substantially large positive externalities. However, in terms of magnitude, the cumulative intangible amenity value only covers a moderate fraction of stadium costs and may, therefore, provide at best only a partial justification for subsidies for sports facilities. Further, it seems likely that St. Louis is an outstanding example towards the upper end of the spectrum, and the results need to be evaluated in the context of local idiosyncrasies. In this regard, we contend that St. Louis' relatively unique urban composition, as well as its political and historical trajectory, may help explain why our analysis reveals substantially positive team effects, whereas prior research has found net negative externalities in other settings.

In this context, in terms of direction and magnitude, our results are generally consistent with prior research, primarily finding net positive externalities associated with the announcement or inauguration of a new stadium. Relative to prior hedonic studies, our estimated price discount of 7.52% is fairly moderate and reflects an approximate average of the effect of team arrivals and or new stadium constructions. Similarly, our estimated implicit amenity value is comparable in magnitude to prior estimates of the aggregate intangible value generated by major league teams. For example, it is comparable to the estimated median increase in occupied property value within three-miles of a facility of $279 million (in 2024 dollars) by Feng and Humphreys (2012), and likewise similar to Agha and Coates (2015), who estimated the aggregate gain of minor league baseball teams on mid-sized cities to range between $160-485 million (in 2024 dollars). Nonetheless, the impact of the Rams' relocation is unsurprisingly much smaller than the estimated £1.4 billion cumulative price increase observed in London's housing market following the official winning bid for the Olympic Games, as reported by Kavetsos (2012). It is likewise much smaller than the estimated £1.9 billion housing appreciation associated with the construction of the New Wembley Stadium in London (Ahlfeldt and Kavetsos (2014)). More importantly for our case though, Carlino and Coulson (2004) estimated the present value of the implied amenity benefits of an NFL franchise to be about $293 million (in 2024 dollars) in St. Louis. Our approximation provides a more conservative estimate of the effects.

While our finding of net amenity benefits in St. Louis aligns with the results of Humphreys and Propheter (2024) for San Francisco, it disaligns with the finding of null effects in San Diego and further contrasts with the findings of Humphreys and Nowak (2017) and Joshi et al. (2020), who demonstrated that basketball and soccer franchises created disamenities in the housing markets of Charlotte and Seattle, 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. We identify four potential explanations for the contrasting findings.

Firstly, there are important distinctions between the NFL and other major leagues, such as the NBA. A typical NFL season consists of only about eight home games, whereas an average NBA season includes more than 40 home games. NBA games primarily attract local residents who arrive shortly before the game begins, while NFL games draw many fans from farther away, often staying for the entire weekend. This results in game-related traffic being spread out over several days (C.f. Abbiasov and Sedov (2023)). Therefore, it could be argued that congestion is a larger issue surrounding NBA games, which might partly explain the inverse sign of the observed effects. Additionally, football is the most important sport in the US in terms of both revenue and popularity. Hosting an NFL franchise likely conveys additional status value to a city.

Secondly, it may be that the facility's design and location play a non-negligible role in preventing congestion externalities in St. Louis. A typical argument brought forward among others by Nelson (2001) is that sports facilities create larger benefits the more they are integrated into urban areas. Similarly, he argues that stadiums should not be surrounded by large parking lots as they would prevent the unfolding of positive spillovers. Mirroring this logic, we contend that the integration of the Edward Jones Dome into the CBD may have also contributed to mitigating congestion externalities affecting residential areas. Thereby, we implicitly follow the reasoning of Propheter (2021), who posits that a large parking lot around Dodgers Stadium potentially acts as a buffer to prevent nuisances such as noise and congestion. We argue that the primarily commercial and industrial land use around the Edward Jones Dome, as shown in Figure 11, may fulfill a similar function. Therefore, it may be that most of the residential living quarters within the impact area are located close enough to conveniently experience the amenity benefits of the facility, but far enough away to not be exposed to strong congestion effects ((C.f. Horn et al. (2015), Bradbury et al. (2023)).[54] This reasoning aligns with Ahlfeldt and Maennig (2009) & Ahlfeldt and Maennig (2010), who argue that the emanation of positive externalities largely depends on policymakers' ability to limit congestion effects, especially by selecting an adequate location neatly integrating the facility into its surrounding neighborhood.

Thirdly, the relatively large effects likely correlate with St. Louis' distressed economic and demographic situation, along with the pivotal role sports plays in driving urban revitalization within the city core. Over the last century, St. Louis has lost much of its old glamour, with the sports industry serving as a beacon of hope, making residents somewhat agnostic about the city's challenges. Moreover, having three major league teams in a city the size of St. Louis is somewhat uncommon, potentially fostering particularly strong feelings of community identity and civic pride. In this vein, the departure of the Rams evoked a highly emotional response from both fans and public officials, underscoring the deep-seated societal and political significance of the team for the city.[55]

Fourthly, closely related to the previous point, the Rams highlighted within their relocation application

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

[55] Since February 2020, the minor league XFL franchise BattleHawks has been playing their home games in the Rams' old stadium, consistently drawing high attendance figures across the league (Barrabi (2020)), further highlighting the enduring bond between football in particular, and sports in general, and the St. Louis community.

that St. Louis does not provide a sufficiently large market potential for a 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 found by Agha and Coates (2015), minor league sports teams can have a particularly strong impact in mid-sized cities like St. Louis, alluding to the notion of relative effects (Coates and Depken (2011)). 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. Similarly, larger cities typically exhibit more entertainment substitutes, which mitigates the relative importance of a sports team for residents.

Lastly, we need to report a few caveats of this paper. As elaborated earlier, one major data-related limitation is that we were only able to acquire information on parcel sales and hence focus on single-family home transactions. Although the selection of single-family homes is common in the hedonic literature, it would have been desirable to also assess the robustness of the results for alternative residential building types. In particular, transactions of apartments and condominiums could have shed additional light on the impact of the relocation, especially on properties within very close proximity to the stadium, as those building types are typically more prevalent in downtown areas. Consequently, the results may suffer to some degree from selection bias.

Moreover, another potential source of bias might stem from time-invariant non-observed housing or location characteristics that are somewhat correlated with the treatment. In this vein, it would have been desirable to additionally run repeated sales regressions to address this bias. However, our sample does not contain sufficient repeated sales to neatly identify the effect of the departure.

Finally, while our analysis enables a holistic assessment of the implicit amenity value of a sports franchise, providing valuable insights for policymakers deciding on stadium financing, due to identification challenges and data limitations, this paper cannot disentangle the specific mechanisms contributing to the aggregate effect observed.[56] We believe this to be a promising direction for future research.

7.2 Policy Implications

While the case of St. Louis suggests that major league franchises may generate substantial intangible amenity value, particularly in distressed and non-saturated markets, the magnitude of this effect supports only smaller, partial public subsidies and does not provide a compelling argument for the generous public subsidies seen over the past decades. Further, the results from this study are likely idiosyncratic, and the case of St. Louis may be somewhat exceptional. Given that prior research has found opposite effects in other contexts, more work is needed to carve out the urban and locational characteristics driving the effects of team departures.

Additionally, our analysis does not address whether public funds might generate greater benefits if invested in other sectors. For a city with persistent structural problems like St. Louis, it is plausible that investments in education or public safety might yield more substantial returns.

Moreover, stadium financing encompasses a non-negligible distributional dimension. While the effects of stadiums are typically highly localized, public subsidies for sports facilities often result in an increase in the property tax rate across the whole city. Also, these subsidies sometimes include state or federal funds, meaning that non-beneficiaries end up cross-subsidizing beneficiaries, such as home-owners in the impact area.

Finally, franchise owners particularly tend to benefit from public subsidization, which significantly boosted

[56] Concretely, we are unable to determine to what extent the relative price depreciation is attributable to (i) 'pure' decreases in living quality, (ii) reductions in civic pride and social morale, (iii) potential reductions in consumption opportunities owing to changes in the commercial landscape, such as bars and restaurants, or (iv) any other unidentified mechanisms following the departure.

team values in the past (Hanau (2016)). As franchise owners wield considerable bargaining power over their host city, primarily through the threat of relocation, it appears desirable to increase corporate accountability and simultaneously strengthen relocation regulations. Future public-private stadium projects may find promising opportunities in exploring new blended-financing mechanisms, such as the *sports communities model*,[57] which offer increased involvement from franchises, thereby increasing their 'skin in the game'.

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

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Appendix

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

Appendix A - Robustness Checks

Testing for the Parallel Trend Assumption

DiD with Leads and Lags

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

$$\begin{aligned} \ln p_{i,t} =& \beta_0 + \beta_1 * \mathsf{Impact}_i + \sum_{\tau=1}^{m} \delta_{-\tau} \mathsf{Impact}_{i,\,2016-\tau} + \sum_{\tau=0}^{q} \delta_{\tau} \mathsf{Impact}_{i,\,2016+\tau} \\ &+ \sum_{j=1}^{J} \beta_j x_{j,i,t} + \sum_t \kappa_t y_t + \sum_l \theta_l m_l + \sum_k \psi_k c_k + \epsilon_{i,t} \end{aligned} \tag{6}$$

whereby the model incorporates four leads (δ_{-1}, ... , δ_{-4}) capturing the pre-treatment-, i.e. anticipatory effects, and four lags (δ_0, ... , δ_3) capturing the post-treatment effects. The other model components remain as defined before.

Table 8 displays the estimates of the leads and lags, whereby Impact2015, the year prior to the relocation, serves as reference. In our preferred model with robust standard errors (column 1) and the model with standard errors clustered on the neighborhood level (column 5), none of the leads is statistically different from zero. However, in columns (2) - (4), the coefficient for 2013 is marginally significant, potentially reflecting the light kink observed in Figure 1. Finally, with respect to the lags, the results suggest that the treatment effect becomes larger over time. Figure 7 illustrates this evolution by plotting the model coefficients.

Table 8: Estimates of the Leads and Lags Model Across Different Error Specifications

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

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

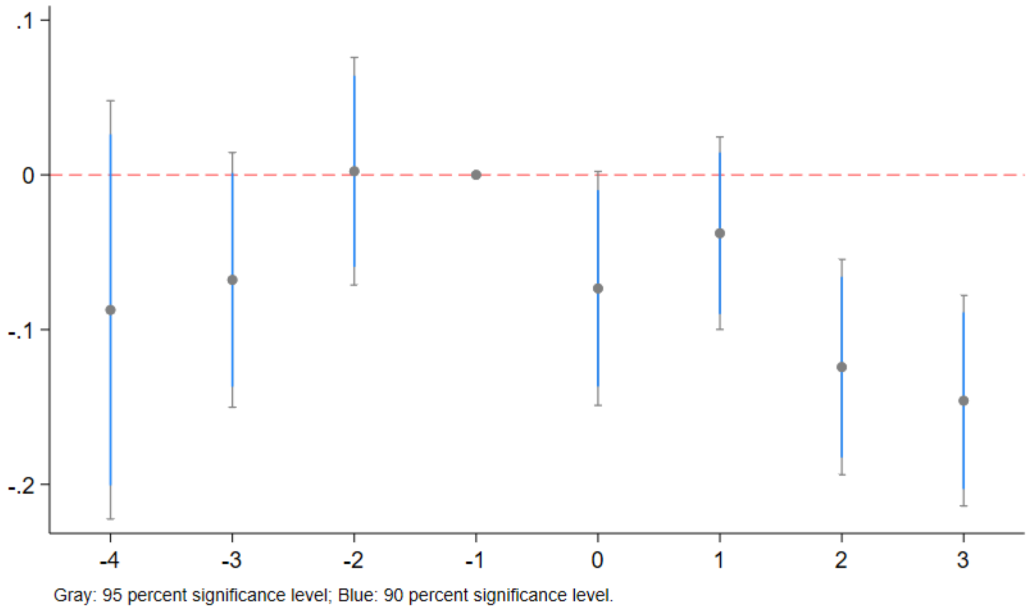
Reference is Impact2015.

The full regression output is available from the author.

In conclusion, the results provide reasonable support to believe that, in the absence of the treatment, the treatment and control group would have followed the same trend. However, given the marginally significant coefficient of Impact2013 for specific error specifications, we additionally test for the robustness of our results by replicating our hedonic analyses for adjusted sample periods, i.e. excluding 2012 and 2013 from the sample.[58] The results are presented below. Likewise, within the next subsection, we follow the recommendations from Roth et al. (2023) and employ novel diagnosis tools and conduct sensitivity analysis to further assess the robustness and credibility of the parallel trend assumption.

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

Figure 7: Coefplot - Leads and Lags



Pre-Trend Diagnosis and Sensitivity Analysis

First, Roth (2022) shows that conventional pre-trend tests in event-study designs may suffer from low power leading to an underdetection of pre-trends and consequently biased estimates. Hence, we employ the derived *pretrends* Stata package which provides tools for power calculations of pre-trend tests and allows to plot and assess possible violations of parallel trends for specified power levels. In this context, Figure 8 plots the linear trend for which we would have 80% power to detect it,[59] which has a slope of 0.0462.[60] Following the reasoning of Lovenheim and Willen (2018), we claim that an extrapolation of such a hypothesized pre-trend seems implausible for monotonicity reasons, because none of the post-treatment confidence intervals includes the red line.[61] If anything, as the trend goes in the opposite direction, we would underestimate the true relocation effect and in reality, the departure of the Rams would have even been more detrimental than our estimates already suggest.

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

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

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

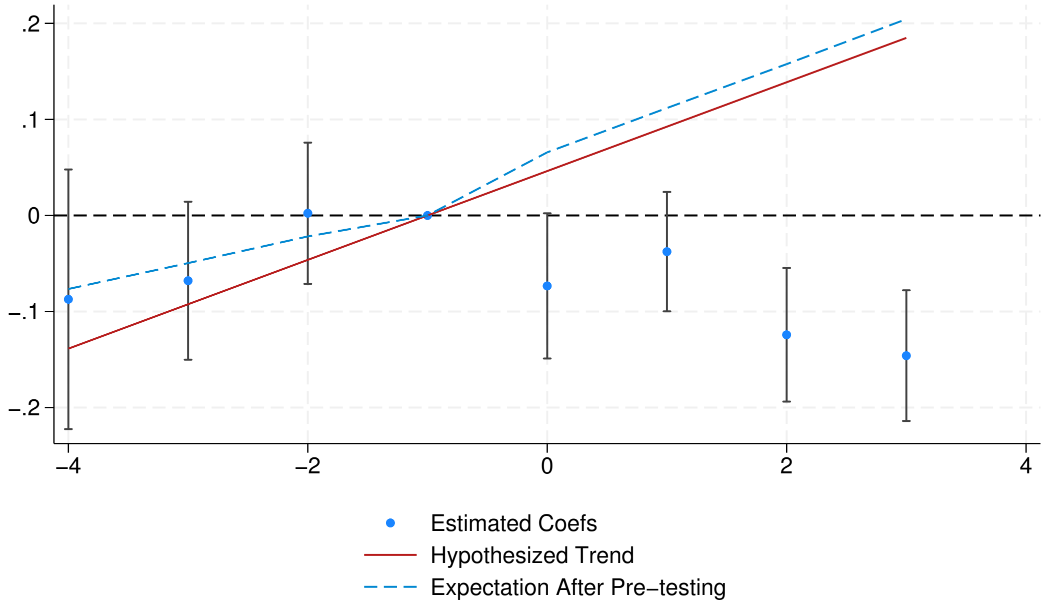


Figure 8: Linear Pre-Trend with 80% Power

Second, we can show that our significant result is robust even if the parallel trend assumption should not hold perfectly. Concretely, based on Rambachan and Roth (2023), the derived *honestdid* Stata package allows among other things to compute robust 95% confidence intervals for the average treatment effect imposing relative magnitude bounds on the post-treatment violation of parallel trends. Thereby, these bounds are determined in relation to the maximal pre-treatment deviation of parallel trends formalizing the intuition that the (observed) pre-treatment differences are informative about the (latent) counterfactual differences in trends. Accordingly, Figure 9 portrays such robust confidence intervals, whereby $\bar{M}$ indicates different degrees of restrictions imposed on the violation of parallel trends. We can see that the breakdown value is $\bar{M}^* = 0.25$, meaning that we would not overturn our significant result unless we believe that the violation of parallel trends is in fact more than a quarter as big as the maximal difference in pre-trends.

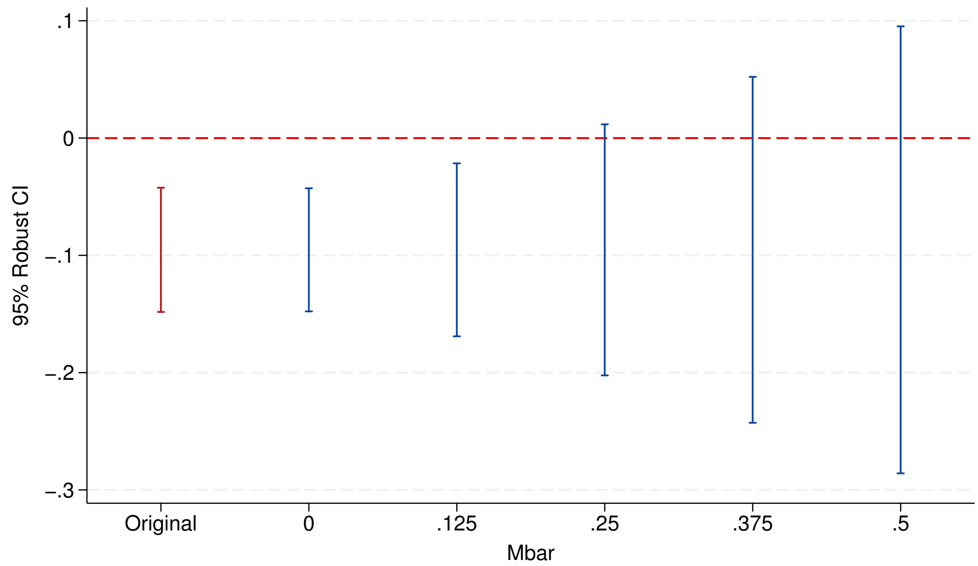


Figure 9: Robust Confidence Intervals for Different Relative Magnitude Restrictions

Anticipation Effects & Confounding Events - Adjusted Sample Periods

Within this section, we replicate our hedonic analyses by re-estimating Equations 2 & 3. Initially, we embed a third period within the model, to test for anticipation effects. Subsequently, we readjust the sample period to assess the robustness of our conclusions.

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

I **Pre-Treatment Period:**

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

II **Post-Treatment Period**:

- *18.07.2017*: Official launch of the first phase of The Foundry, a mixed-use $220 million development project in Midtown; elements: food hall, retail stores, offices (initial announcement in August 2016; start of construction: July 2018; inauguration in 2021).
- *04.07.2018*: Re-Opening of the Gateway Arch Museum following a makeover worth $380 million; Elements: new galleries, walking- and cycling paths, recreational outdoor space.
- *31.07.2018*: Opening of the Cortex MetroLink station.
- *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.
- *July 2019*: Announcement that Square will expand to St. Louis and create about 300 new jobs (completion in 2023).
- *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).
- *June 2020*: Inauguration of Ballpark Village II; Elements: residential tower, hotel, office building, health club, plaza ($300 million)(announcement: 25.10.2016; start of construction: 14.12.2017)
- *26.11.2020*: Start of construction of the new NGA headquarters in North St. Louis, $ 1.7 billion project (announcement of site location: 02.06.2016; scheduled inauguration: 2026)

Anticipation Effects I - Announcement of Stadium Construction in 2015

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

Table 9: Estimates Across Different Error Specifications - Anticipation Effects I

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) Neighborhood
Inter	0.0496	0.0496	0.0496	0.0496	0.0496
	(0.061)	(0.051)	(0.062)	(0.044)	(0.054)
Post	0.319***	0.319***	0.319***	0.319***	0.319***
	(0.022)	(0.021)	(0.032)	(0.033)	(0.032)
Impact	0.133***	0.133***	0.133*	0.133	0.133*
	(0.039)	(0.031)	(0.075)	(0.085)	(0.070)
ImpactxInter	0.0268	0.0268	0.0268	0.0268	0.0268
	(0.032)	(0.029)	(0.029)	(0.017)	(0.032)
ImpactxPost	-0.0637**	-0.0637***	-0.0637***	-0.0637**	-0.0637**
	(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

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

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 output is available from the author.

Table 9 presents the estimates of the main coefficients of interest. Inter denotes the dummy for the anticipation period. Accordingly, ImpactxInter is the interaction term for properties located in the impact area and sold within the anticipation period. As one can see, in neither column, the coefficient is significantly different from zero, whereas the coefficient of the post treatment effect remains relatively unaffected. Therefore, the model provides evidence that the announcement of the stadium construction has not provoked anticipatory market reactions in St. Louis' single-family housing market supporting our identification strategy.

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

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

Table 10: 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
Inter1	-0.140	-0.140	-0.140	-0.140	-0.140
	(0.126)	(0.111)	(0.113)	(0.114)	(0.106)
Post	0.315***	0.315***	0.315***	0.315***	0.315***
	(0.022)	(0.021)	(0.032)	(0.032)	(0.031)
Impact	0.0920**	0.0920**	0.0920	0.0920	0.0920
	(0.045)	(0.036)	(0.077)	(0.079)	(0.074)
ImpactxInter1	0.0732**	0.0732**	0.0732*	0.0732***	0.0732*
	(0.036)	(0.031)	(0.038)	(0.021)	(0.039)
ImpactxPost	-0.0236	-0.0236	-0.0236	-0.0236	-0.0236
	(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	0.7572	0.7572	0.7572	0.7572	0.7572
Observations	12695	12695	12695	12695	12695

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

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 output is available from the author.

Table 10 displays the estimation results. The coefficient for ImpactxInter2 is positive and significant across all error specifications, whereas we do not observe a significant coefficient for ImpactxPost anymore, when using 2012 and 2013 as reference years. These results, alongside the previous estimation, therefore suggest that there seems to be some significant change in (log-) average prices between the impact and control area occurring between 2013 and 2014, that is not associated with the treatment in 2016.

Regarding the potential confounding events identified within that time frame, doubts arise as to whether the opening of Ballpark Village I can fully explain the significant findings presented in Table 9. While the adjacent 'village' provides consumers with numerous new consumption benefits, it seems questionable whether the intangible benefits associated with the opening of the first phase are as substantial. Likewise, as argued in Section 3, the purchase of land in Inglewood should not have a discernible impact on the

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

Adjusted Sample Period - 2014 - 2018

Given the prior results, it appears essential to check for the robustness of the main conclusions by shortening the pre-treatment period so that it does not cover the significant price jump anymore. Likewise, several potentially confounding events occur during the post-treatment period after July 4th, 2018.[62] Consequently, we re-estimate our models on a minimal sample consisting only of transactions taking place between January 1st, 2014, and July 4th, 2018. Table 11 summarizes the results of the base model. Despite the significant sample reduction, the findings remain nearly identical to those of the full sample period.[63]

Table 11: Estimates Across Different Error Specifications - Base Model - 2014-2018

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

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The sample period is shortened to 01.01.2014 - 04.07.2018.
The full regression output is available from the author.

[62] Some of the identified events were already announced earlier; however, a clear disentanglement is unfortunately not feasible due to the proximity to the treatment date. If the future expected amenity value of these projects was already capitalized at the time of the announcements, our estimates may be upwardly biased, i.e. too small. In that case, the true effect of the Rams' departure might have been even more detrimental.

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

Placebo Analysis on Nashville

Due to the location of the stadium in downtown, one concern may be that the observed effects could be driven by a secular change in the urban price gradient of larger US cities occurring concurrently with the treatment. To address this, we replicate the hedonic regression analysis using a dataset on Nashville that includes detailed information on housing transactions and corresponding housing characteristics from 2013-2016. The data was retrieved from Kaggle and was cleansed using the same qualitative criteria as for St. Louis. The final sample consists of 17,793 single-family transactions.

Table 12: Estimates of the Base Model - Placebo Analysis

	Robust Se		Clustered Se	
	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 1	Model 2
Impact	-0.0153	-0.0182	-0.0153	-0.0182
	(0.013)	(0.016)	(0.075)	(0.019)
Post	0.1892***	0.3700***	0.1892***	0.3700***
	(0.007)	(0.007)	(0.013)	(0.014)
ImpactxPost	0.1151***	0.1085***	0.1151***	0.1085***
	(0.022)	(0.015)	(0.033)	(0.035)
Housing Controls	Yes	Yes	Yes	Yes
Neighborhood FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes
Adjusted R^2	0.6032	0.8310	0.6032	0.8310
Observations	17793	17793	17793	17793

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

The standard errors in columns (3) and (4) are neighborhood-clustered.

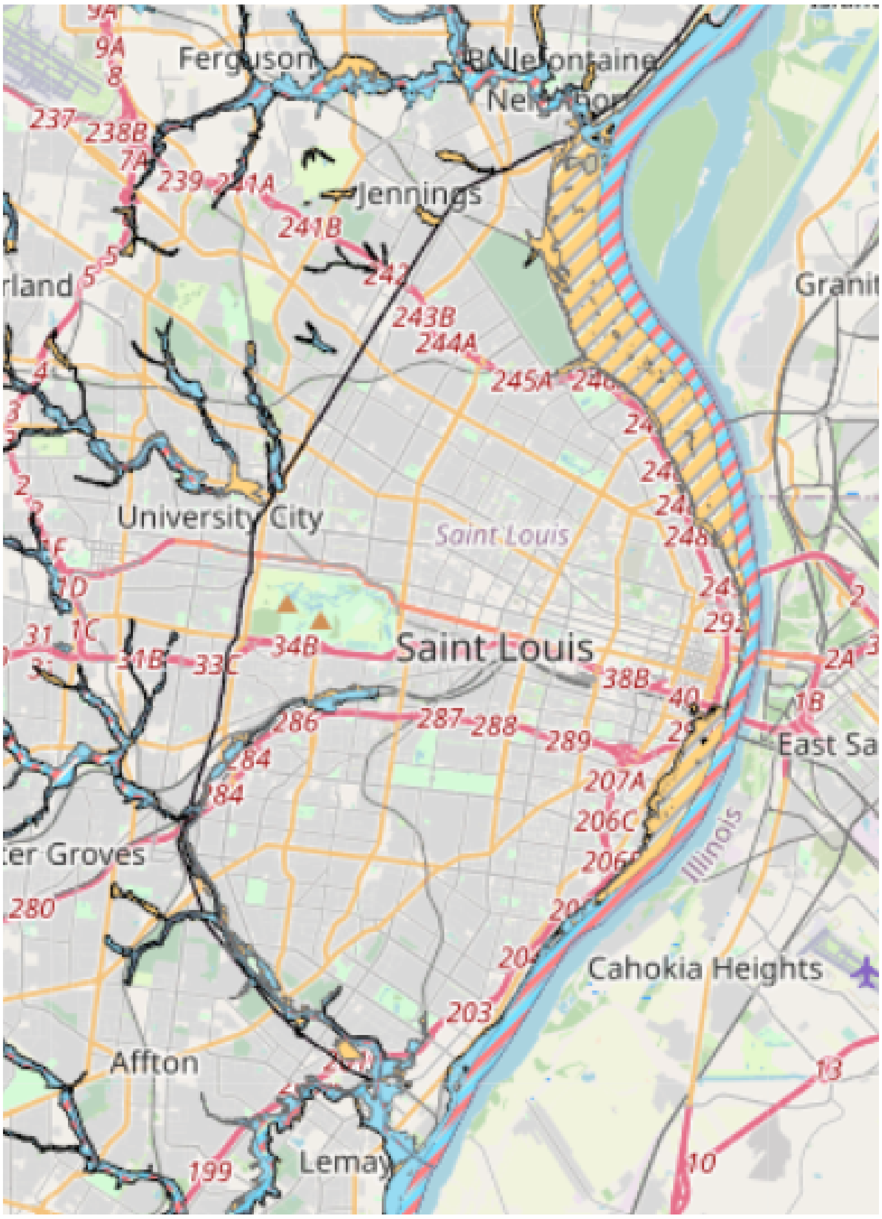
The full regression output can be found in the Online Appendix.

Table 12 suggests that single-family property values within a three-mile radius to Nashville's city center appreciated by about 10% during the time of the Ram's departure from St. Louis.[64] This contrary finding motivates us to infer that the observed market reaction in St. Louis is not driven by a secular trend but can be exclusively attributed to the relocation.

[64] The significant finding should not be overly emphasized, as Figure 12 clearly indicates a pre-trend.

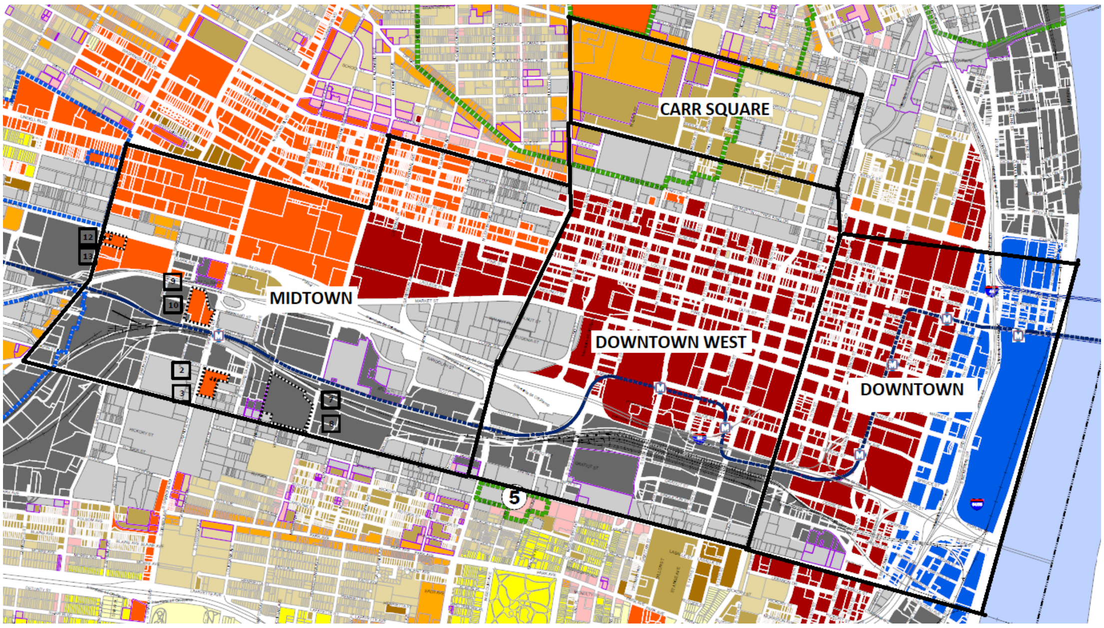
Appendix B - Supplementary Figures

Figure 10: St. Louis - Floodplains



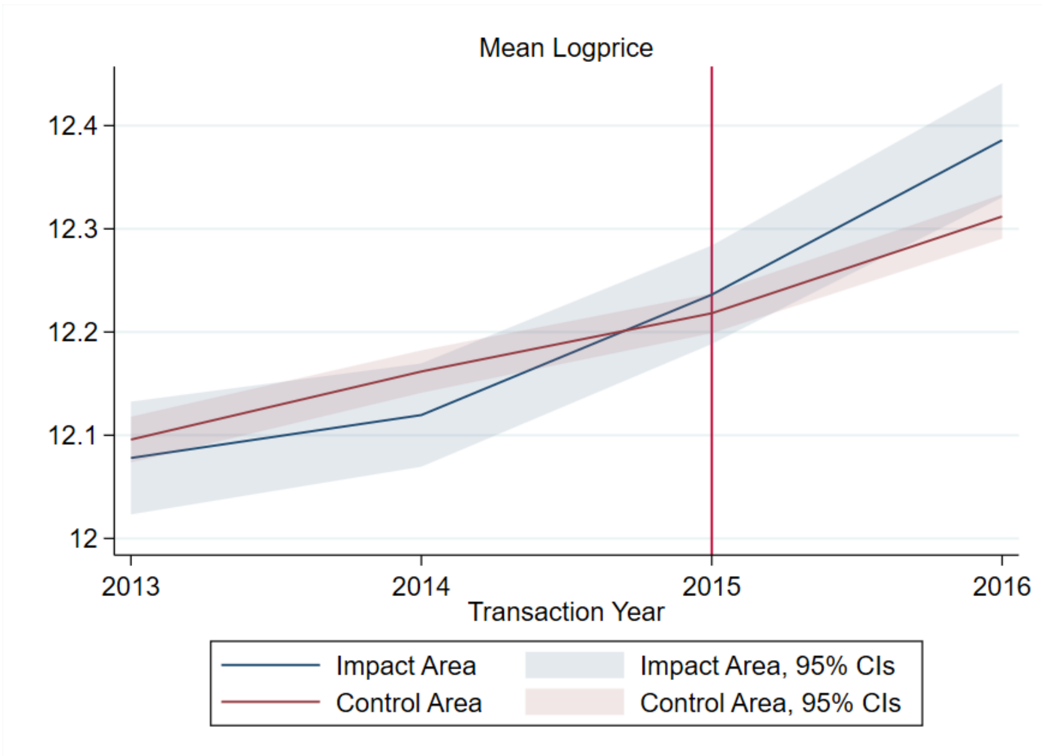
Source: FEMA Flood Zones Viewer
Color Legend: a) Blue: Flood100 Plain, b) Orange: Flood500 Plain

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



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

Figure 12: Pre-Trends Plot - Nashville



Online Appendix

Supplementary Robustness Checks

Is the Model Overspecified? - Examining Multicollinearity and Endogeneity

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

One potential criticism to our model may be that it includes a large number of covariates, potentially introducing multicollinearity and hampering the interpretation of the coefficients. Effectively, Table 13 shows that the variance inflation factors (VIFs) of several regressors in our base model exceed the typical threshold value of 10. Particularly, the controls for residential proximity to the other two major league stadiums have unsurprisingly exorbitantly high VIFs. Furthermore, some neighborhood and urban controls seem to be structurally related, as expected. Nevertheless, it is important to note that the main coefficient of interest, ImpactxPost, has a moderate VIF of only 2.69, and is only highly correlated with the Impact dummy, by construction of the interaction term (Allison (2012)).
Therefore, we contend that the multicollinearity within our model appears to be a relatively minor issue, as it only occurs among some of the independent variables, which does not impair their function as controls. Similarly, despite potentially inflated standard errors, most of the coefficients remain highly significant.

Nevertheless, we also follow the common practice of removing highly correlated covariates from our model to demonstrate the consistency of our results.[65] In this vein, Table 14 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) reveals that the exclusion of the controls for the other two stadiums has no visible effect on our findings. Similarly, in Column (3), we still draw the same overall conclusions when additionally removing the highly correlated neighborhood controls.[66] The slim model also emphasizes the irrelevance of potentially endogenous socio-demographic regressors, such as the crime covariate. We interpret this consistency as bolstering our identification strategy, suggesting that the relocation serves an exogenous shock unrelated to local changes in neighborhood features.

Table 14: Estimates - Removing Highly Correlated Covariates

	(1) Base Model	(2) No Distance Controls	(3) Slim Model
Target Variables			

[65] O'Brien (2007) cautions that doing so may shift the model and alter the underlying theory being tested. Thus, dropping individual regressors must be theoretically motivated. Given the contextual relevance of controlling for the presence of the other two stadiums in downtown, as well as St. Louis' idiosyncratic socio-demographic and urban environment, we assess the specification of our base model as justified.

[66] As shown in Table 13, within this reduced 'slim' model, no individual coefficient, except for the naturally inflated Post coefficient, exceeds the threshold of 10 anymore.

Impact	0.145***	0.138***	0.161***
	(0.036)	(0.035)	(0.036)
Post	0.320***	0.323***	0.360***
	(0.022)	(0.022)	(0.018)
ImpactxPost	-0.0752***	-0.0752***	-0.0603***
	(0.021)	(0.021)	(0.021)
Housing Characteristics			
logFloorsize	0.451***	0.451***	0.451***
	(0.015)	(0.015)	(0.015)
logParcelsize	0.190***	0.191***	0.188***
	(0.009)	(0.009)	(0.009)
Age	-0.00364***	-0.00364***	-0.00363***
	(0.000)	(0.000)	(0.000)
Frame	-0.115***	-0.115***	-0.110***
	(0.008)	(0.008)	(0.008)
Stone	0.105*	0.106*	0.115**
	(0.055)	(0.055)	(0.054)
Stories	0.248***	0.247***	0.250***
	(0.010)	(0.010)	(0.010)
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

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13: 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	

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

Although we already control for a wide range of covariates, some covariates commonly used in previous hedonic studies were not included in our analysis, either by choice or due to data limitations.
There are two potentially relevant omitted covariates for which information was restricted or unavailable: the proximity of a property to transport infrastructure (such as the nearest bus/train station or the closest highway interchange) and quality of local schools. Both factors have been shown to significantly influence housing values.[67] While the latter omission is presumably less problematic, as the quality of local schools is likely to be mostly captured by our neighborhood controls,[68] the omission of transport amenities needs to be contemplated. Standard urban economic theory suggests a negative correlation between housing values and commuting times, resulting in spatial 'peaks' of the house price gradient near transport infrastructure. To the best of our knowledge, except for the new Cortex MetroLink station inaugurated in July 2018, we are unaware of any major changes in the local transportation infrastructure that may significantly affect our results. However, unfortunately, we are unable to control for the impact of changes in the valuation of proximity to transport infrastructure linked to changes in the consumption of transport infrastructure - such as reduced congestion during games - induced by the departure of the Rams.

In attempting to approximate residential proximity to major transport infrastructure, we additionally include the average commuting time to work as a control variable, retrieved at the zip-code level from the ACS. Similarly, to account for school quality, we add the share of the population with a high-school or academic degree, also available at the zip-code level. Additionally, we test the results by controlling for a set of supplementary local controls commonly used in previous studies, including the average household size, the share of owner-occupied housing, the share of Asian and Hispanic population, the unemployment rate, annual payrolls, various crime measures, and zoning designations.[69] Likewise, we examine the impact of being located within an Empowerment Zone.[70]

Table 15 displays the estimation results of this deliberately oversaturated model. Upon including the supplementary covariates, we draw the same conclusions as before, supporting the robustness of our findings. However, some variables, such as the share of the population holding an academic degree, introduce severe multicollinearity into the model, as expected due to structural dependencies among some independent variables. In this vein, the coefficient for the share of academics is only significant in columns (1) and (2), likely due to collinearity among the neighborhood controls. Additionally, we find that the coefficient for average commuting time is insignificant across all model specifications.[71]

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

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

[69] Table 37 provides summary statistics for these additional covariates.

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

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

Table 15: Estimates Across Different Error Specifications - Oversaturated Base Model

	Robust Se	Normal Se	Clustered Se		
	(1)	(2)	(3)	(4)	(5)
	Robust	OLS	Census Tract	Ward	Neighborhood
Target Variables					
Impact	0.1331***	0.1331***	0.1331	0.1331	0.1331*
	(0.038)	(0.029)	(0.085)	(0.093)	(0.078)
Post	0.2519***	0.2519***	0.2519**	0.2519**	0.2519**
	(0.061)	(0.053)	(0.098)	(0.121)	(0.116)
ImpactxPost	-0.0717***	-0.0717***	-0.0717**	-0.0717**	-0.0717**
	(0.022)	(0.020)	(0.031)	(0.028)	(0.032)
Housing Characteristics					
logFloorsize	0.4516***	0.4516***	0.4516***	0.4516***	0.4516***
	(0.015)	(0.012)	(0.027)	(0.035)	(0.032)
logParcelsize	0.1871***	0.1871***	0.1871***	0.1871***	0.1871***
	(0.009)	(0.009)	(0.020)	(0.014)	(0.020)
Age	-0.0036***	-0.0036***	-0.0036***	-0.0036***	-0.0036***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Frame	-0.1107***	-0.1107***	-0.1107***	-0.1107***	-0.1107***
	(0.008)	(0.008)	(0.014)	(0.013)	(0.013)
Stone	0.1073*	0.1073*	0.1073**	0.1073***	0.1073*
	(0.055)	(0.057)	(0.052)	(0.035)	(0.057)
Stories	0.2444***	0.2444***	0.2444***	0.2444***	0.2444***
	(0.010)	(0.009)	(0.019)	(0.025)	(0.019)
Garages	0.0888***	0.0888***	0.0888***	0.0888***	0.0888***
	(0.006)	(0.006)	(0.008)	(0.009)	(0.008)
Carports	0.0173***	0.0173***	0.0173***	0.0173**	0.0173***
	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)
Attic	0.1512***	0.1512***	0.1512***	0.1512***	0.1512***
	(0.006)	(0.007)	(0.009)	(0.008)	(0.010)
Demographic Characteristics					
PopDensity	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
PersonCrime	0.0004	0.0004	0.0004	0.0004	0.0004
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
PropertyCrime	-0.0012***	-0.0012***	-0.0012	-0.0012*	-0.0012*

	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Black	-0.3778***	-0.3778***	-0.3778**	-0.3778**	-0.3778**
	(0.085)	(0.076)	(0.171)	(0.154)	(0.163)
Asian	-0.7076**	-0.7076**	-0.7076	-0.7076	-0.7076
	(0.322)	(0.294)	(0.668)	(0.563)	(0.557)
Hispanic	-1.5223***	-1.5223***	-1.5223*	-1.5223**	-1.5223**
	(0.452)	(0.382)	(0.854)	(0.709)	(0.641)
Vacancy	-0.8617***	-0.8617***	-0.8617	-0.8617*	-0.8617*
	(0.259)	(0.208)	(0.552)	(0.477)	(0.433)
Youth	0.3232	0.3232	0.3232	0.3232	0.3232
	(0.279)	(0.241)	(0.616)	(0.444)	(0.586)
MedianIncome	-0.0015	-0.0015	-0.0015	-0.0015	-0.0015
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Academic	0.0024**	0.0024***	0.0024	0.0024	0.0024
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Commutes	-0.0049	-0.0049	-0.0049	-0.0049	-0.0049
	(0.005)	(0.004)	(0.006)	(0.006)	(0.006)
HHsize	-0.0505	-0.0505	-0.0505	-0.0505	-0.0505
	(0.071)	(0.062)	(0.126)	(0.136)	(0.133)
Ownership	0.0011	0.0011	0.0011	0.0011	0.0011
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Market Characteristics					
Payroll	-0.0000	-0.0000*	-0.0000	-0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.0035	-0.0035	-0.0035	-0.0035	-0.0035
	(0.003)	(0.002)	(0.004)	(0.005)	(0.004)
AccFood	0.0072	0.0072	0.0072	0.0072	0.0072
	(0.006)	(0.005)	(0.010)	(0.011)	(0.011)
Finance	0.0129***	0.0129***	0.0129*	0.0129*	0.0129**
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)
Retail	-0.0127***	-0.0127***	-0.0127**	-0.0127*	-0.0127**
	(0.004)	(0.004)	(0.006)	(0.007)	(0.006)
Urban Characteristics					
DistancePark	-0.1885***	-0.1885***	-0.1885***	-0.1885***	-0.1885***
	(0.015)	(0.015)	(0.050)	(0.057)	(0.049)
Local	0.1110***	0.1110***	0.1110*	0.1110**	0.1110**
	(0.037)	(0.028)	(0.061)	(0.042)	(0.052)

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

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

Spatial Inequality along Delmar Boulevard: Housing Segregation & Housing Submarkets

Describing housing segregation in St. Louis, the *BBC* has coined the term *'Delmar Divide'*, alluding to the fact that the population living north of Delmar Boulevard is 95% black, while 75% of those living south of the Boulevard are white (Cooperman (2014)), as displayed in Figure 13. This racial segregation is rooted in decades of malfunctioning housing policies and urban development programs that disproportionately benefited more affluent neighborhoods, resulting in other neighborhoods falling behind in terms of economic and social development (Cohen (1990), Judd (1997), Farley (2005)).

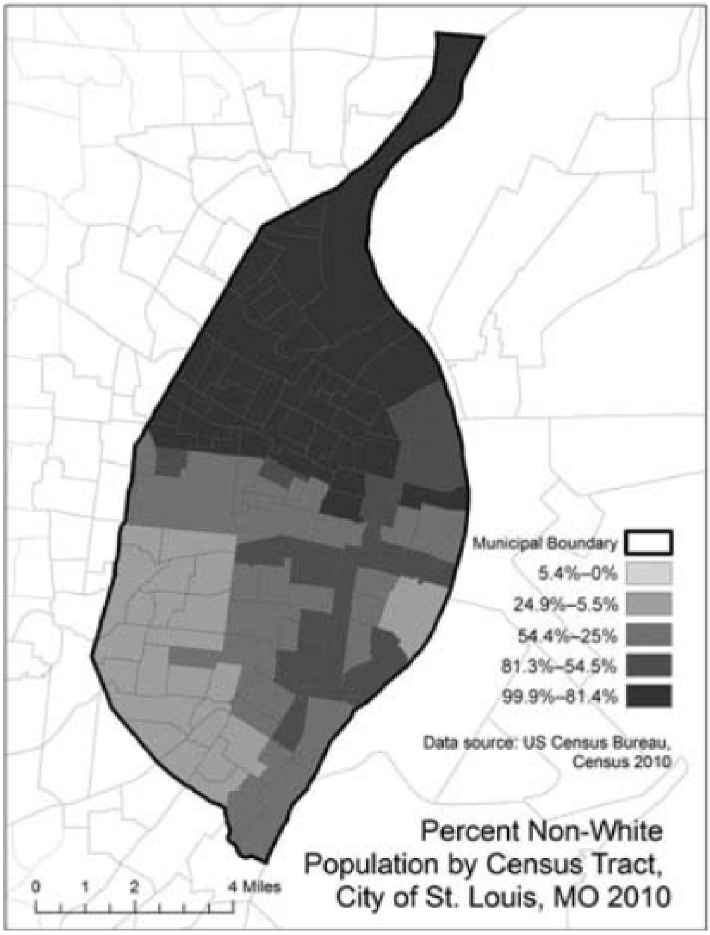


Figure 13: Racial Segregation in St. Louis
Source: Tighe and Ganning (2015), p.658

St. Louis, as depicted by Metzger et al. (2018), exemplifies an extreme case of urban decay, characterized by a 70-year trend of economic and population decline, mirroring the broader trajectory of Rust Belt cities since the latter half of the previous century. In 1950, St. Louis had a population of around 850,000, which has since plummeted by over half to approximately 350,000 in 2000. Suburban areas have seen an influx of affluent, predominantly white families, leaving the central city relatively impoverished and somewhat desolate. This trend of decline and growth is also evident in residential neighborhoods manifested as spatial inequality, which led Tighe and Ganning (2015) to designate St. Louis as a 'divergent city'.[72] According to the authors, St. Louis exhibits clear patterns of racial segregation, with the North being predominantly black, characterized by high crime and vacancy rates, while the South is mostly white, featuring vibrant

[72] While racial segregation patterns are evident citywide (as shown in Figure 13), downtown and adjacent neighborhoods exhibit relative diversity. This is good news as it suggests that any price reactions upon relocation are unlikely to be influenced by unobserved spatial clustering concentrated in the impact area.

commercial areas and stable real estate markets.

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

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

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

b) We add a simple dummy to the model for houses located north of Delmar Boulevard.[73]

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

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

Approach a) - Ghetto Sample

Table 16 presents the results. While generally consistent with our base model, the point estimate is smaller at 4.71%. Also, clustering the error term renders the coefficients largely insignificant. These findings suggest a stronger market reaction in predominantly black neighborhoods, with the observed effect mitigated by excluding them from the sample.

Table 16: 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)

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

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

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

Neighborhoods >50% black residents were excluded.

The full regression ouput is available from the author.

Approach b) - North-South Divide

Table 17 depicts the results. Including a dummy for houses located north of Delmar Boulevard does not notably affect the main results. As expected, the coefficient of the dummy variable is negative, however, it is insignificant across all specifications. These results do not necessarily invalidate the existence of the Delmar Divide, as we observe the expected sign, and the insignificance is likely due to artificially inflated errors.[74] Thus, we maintain that these findings suggest that our base model adequately accounts for price variation attributed to differences in neighborhoods along racial lines.

Table 17: Estimates Allowing for a North-South-Divide - Base Model

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

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

The full regression output is available from the author.

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

Approach c) - Omitting the Lower Price Bound - Selection Bias

The exclusion of non-arms length transactions, i.e. transactions priced below $30,000, may introduce selection bias if the population residing in these lower-priced properties exhibits a distinct valuation for proximity to sports amenities.[75] Hence, we re-estimate our models for a sample without lower price bound.[76]

Table 18 presents the results. The inclusion of transactions below $30,000 does not significantly bias the findings. However, the DiD coefficient is slightly larger at 9.26%. This increase could be attributed to larger and positive effects of sports amenities on houses in the lower tail of the conditional distribution, while the effects diminish and potentially become negative for houses in the upper tail. A similar pattern was observed by Neto and Whetstone (2022) following the announcement of the construction of a new stadium for the Raiders (NFL) in Las Vegas.

Table 18: Estimates Across Different Error Specifications - Base Model - No Price Bound

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

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

The full regression output is available from the author.

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

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

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

Proximity Model

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

$$\begin{aligned}\ln p_{i,t} =&\beta_0 + \delta_1 * \text{Post}_t + \delta_2 * \text{Distance}_i + \delta_3 * \text{Post}_t \times \text{Distance}_i + \\ &\sum_{j=1}^{m} \beta_j x_{j,i,t} + \sum_t \kappa_t y_t + \sum_l \theta_l m_l + \sum_q \psi_q c_q + \epsilon_{i,t}\end{aligned} \tag{7}$$

whereby Distance_i denotes the distance in miles of property i to the Edward Jones Dome, and $\text{Post}_t \times \text{Distance}_i$ captures the interaction between the Post dummy and Distance. The remaining model components are defined as before. Table 19 presents the estimation results. Our preferred model specification with robust standard errors is displayed in column (1). Additionally, selected model specifications are presented in columns (2) - (5). In columns (2) and (4), standard errors are clustered on the census tract levels. In columns (3) and (4), the distance controls for the other two stadiums in St. Louis, the Busch Stadium and the Enterprise Center, are excluded from the model. This exclusion is due to the proximity of the three stadiums, as shown in Figure 3, which naturally introduces high correlation among the distance variables. Finally, column (5) presents the estimates without any covariates.
We observe that the DiD estimate is highly significant across columns (1) to (4) and exhibits the expected positive sign. Regarding our preferred model, the estimate suggests that, following the relocation of the Rams, each additional mile away from the stadium increases the value of single-family homes by about 1.37% on average, relative to the pre-relocation period. Importantly, these results remain consistent in sign, magnitude, and significance, irrespective of the inclusion of the additional distance controls for the other two stadiums in downtown. Therefore, the observed results align with our main analysis, providing further support to infer that residing closer to the stadium becomes relatively less attractive after the team's departure.

Table 19: Estimates of the Proximity Model

	Distance Controls Included		Distance Controls Excluded		No Controls
	(1) Robust	(2) Clustered	(3) Robust	(4) Clustered	(5) Robust
Post	0.2314***	0.2314***	0.2290***	0.2290***	0.1375***
	(0.033)	(0.039)	(0.033)	(0.040)	(0.043)
Distance	0.4390**	0.4390	-0.0012	-0.0012	-0.0720***
	(0.206)	(0.356)	(0.014)	(0.045)	(0.006)
PostxDistance	0.0137***	0.0137**	0.0140***	0.0140**	-0.0006
	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)
DistanceBusch	-0.1941	-0.1941			
	(0.131)	(0.316)			
DistanceEC	-0.2458	-0.2458			
	(0.175)	(0.364)			

Controls	Yes	Yes	Yes	Yes	No
Census Tract FE	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	No
Month FE	Yes	Yes	Yes	Yes	No
Adjusted R^2	0.7569	0.7569	0.7568	0.7568	0.0450
Observations	12695	12695	12695	12695	12695

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

The full regression output is available from the author.

Notwithstanding, the results need to be interpreted with some caution. As Table 19 shows, the proximity model suffers from severe multicollinearity due to a near-perfect linear relationship between *Distance*, *DistanceBusch*, and *DistanceEC*, as shown in Table 21. Importantly though, the DiD coefficient only shows moderate correlations of around $r = 0.3$ with the distance covariates and remains relatively stable across the different specifications. In this regard, column (5) suggests that the high VIF naturally arises from the interaction of the variables and is therefore not a cause for concern (C.f. Allison (2012)).[77]

Table 20: 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			

Table 21: 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

[77] Other specifications, such as restricting 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); or including quadratic distance terms, following Tu (2005), led to multicollinearity of similar severity.

Estimation Results With Neighborhood Fixed Effects

We incorporate census tract fixed effects in our models since the inclusion of neighborhood fixed effects substantially inflates the standard errors of several of the neighborhood covariates. However, from a theoretical standpoint, it remains unclear at which scale level the fixed effects should be measured. While census tracts are often appealing as the smallest geographical scale level for which data is available, neighborhood boundaries typically evolve more naturally, making neighborhoods potentially more intuitive geographical clusters. In this context, Table 22 presents the estimates of the base model with neighborhood fixed effects.

Table 22: Estimates Across Different Error Specifications - Base Model - Neighborhood FE

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) Neighborhood
Impact	0.0370	0.0370	0.0370	0.0370	0.0370
	(0.041)	(0.030)	(0.075)	(0.100)	(0.085)
Post	0.231***	0.231***	0.231***	0.231***	0.231***
	(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)
Controls	Yes	Yes	Yes	Yes	Yes
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

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

The full regression output is available from the author.

In short, the overall conclusions remain unchanged. Nevertheless, there are two minor differences to note. Firstly, the use of neighborhood fixed effects yields a smaller point estimate of the treatment effect at 5.33%. Secondly, we observe a decrease in the significance of its coefficient when clustering the standard errors.[78]

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

Digression: The Age-Period-Cohort-Problem

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

Although Yiu and Cheung (2022) propose a solution to the APC problem by including external information on the quality and renovation status of a house, such as appraised-improvement values of housing structures, we are unable to replicate their approach due to the lack of reliable information on assessment values of individual properties in our sample. Moreover, as mentioned previously, we incorporate time-invariant structural housing characteristics as covariates within our models, providing a snapshot in time. We argue that this approach is rather unproblematic given our relatively recent sample period, as most structural characteristics typically do not vary over time (e.g., parcel size), and any variations (e.g., in the number of carports) are likely to result in marginal estimation bias.
Notwithstanding, given that the housing stock in St. Louis is relatively old and encompasses a wide range of building ages, it is possible that our error terms suffer from dwelling age-heteroskedasticity. This is because the likelihood of significant upgrades and renovations, and thus the size of the error term, is likely to increase with dwelling age (Goodman and Thibodeau (1995)).[79]
We adopt two approaches to address the APC problem and the potential non-linearity of age depreciation in our sample. First, we include control dummy variables indicating the listing of a property within the local, local certified, or national historic register. St. Louis exhibits a relatively large share of historic districts, as depicted in Figure 14, owing to its crucial role during the Westward Expansion of the United States in the 19th century. In total, the City of St. Louis designates 18 local historic districts and 10 certified local historic districts.[80] These districts require approval through political ordinance and are subject to strict regulations upon designation. For example, any changes made to the exterior or core structure of properties located in historical districts must be ratified by the Cultural Resources Office.[81]

Further, the criteria for eligibility for listing in the NRHP were initially established in the *National Historic Preservation Act of 1966* and synthesized by the City of St. Louis as: *'To qualify, a property must represent an important facet of U.S. history, architecture, archaeology, engineering, or culture; and retain integrity of location, design, setting, materials, workmanship, feeling, and association'*.[82]

In addition to designating historic neighborhoods, the City of St. Louis has made the preservation and conservation of historic buildings and landmarks a central target of its Strategic Land Use Plan.[83] Specifically,

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

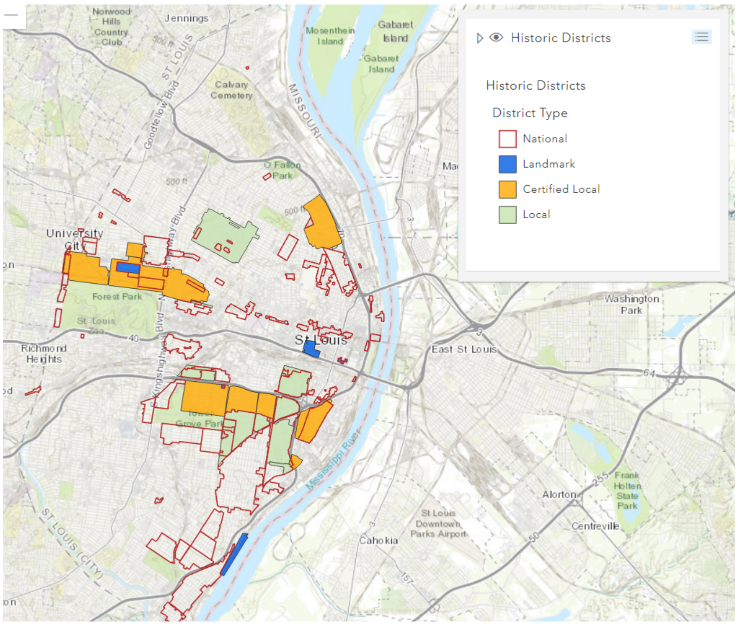
[80] The latter are eligible for inclusion within the National Register of Historic Places (NRHP).

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

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

[83] The plan, initially adopted in 2005 and subsequently amended, assigns specific land use designations to each

Figure 14: Map of the Local and National Historic Districts in St. Louis



Source: www.stlouis-mo.gov

St. Louis has established Preservation Review Areas, as depicted in Figure 15, where demolition applications require review due to the significance of these areas on their immediate and surrounding neighborhoods.[84] Additionally, the city has implemented a Housing Conservation Program to ensure that houses meet specific building standards and prevent obsolescence and blight.[85]
Against this backdrop, we postulate that the inclusion of dummy variables representing a property's affiliation with any historic district, a Preservation Review Area, or participation in the Housing Conservation Program can act as a proxy for unobserved building features. These features may include distinctive exterior architectural designs, unique structural elements characteristic of specific building periods, and potential variations in building quality. However, this approach may have limitations in capturing cohort effects associated with more modern building styles.

Our estimations consistently show that the coefficients for the urban control dummies are highly significant across all our models and have the expected signs. Specifically, for our base model presented in Table 4, we estimate that single-family homes located in local, national, or certified local historic districts sell for approximately 12.52%, 8.85%, and 28.15% higher, respectively. Similarly, participation in the Housing Conservation Program corresponds to an average price increase of approximately 21.53%, while homes located in preservation review areas sell for about 11.51% more on average.[86]
To contextualize these findings, we briefly review previous research on historical designation, conservation, and preservation. Mason (2005) provides a comprehensive survey revealing a general consensus about the explicit and tacit benefits of historical designation and preservation, despite some mixed evidence, as noted by Coulson and Leichenko (2001). While onerous rules and regulations may impose negative externalities, the positive externalities associated with historical designation seem to predominate. For instance, Clark and Herrin (1997) show that properties in Sacramento experienced an average appreciation rate of 17% fol-

block in the city, guiding residents and investors in maintenance, enhancement, and development efforts.

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

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

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

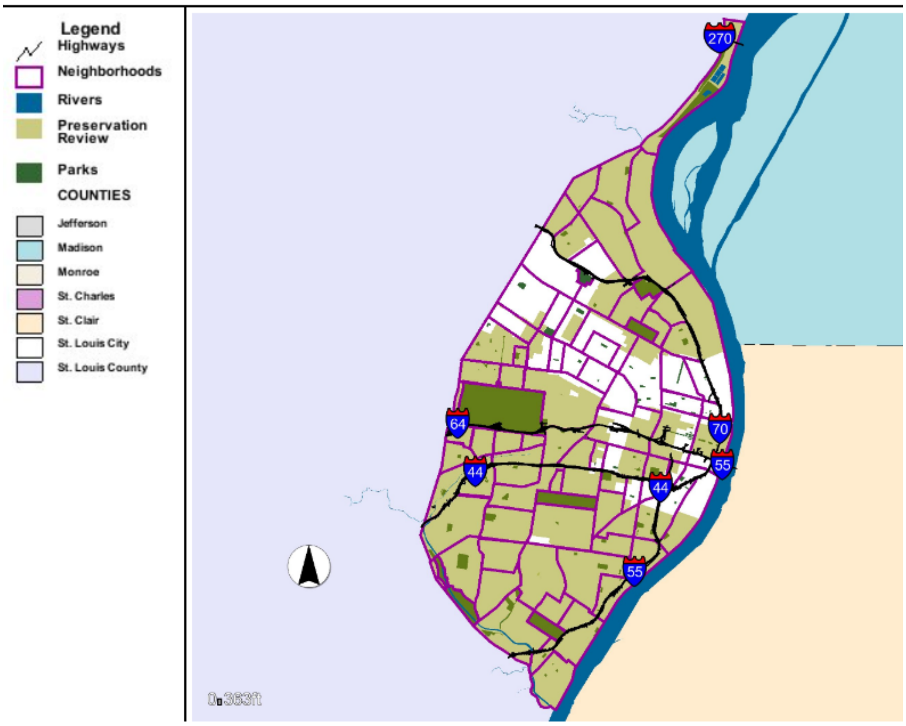


Figure 15: Map of the Preservation Review Areas in St. Louis
Source: Created via Geo St. Louis

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

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

Regarding our second approach, Goodman and Thibodeau (1995) propose addressing age-induced heteroskedasticity by including the square of age into the hedonic price function, allowing for non-linear

depreciation effects. Table 23 presents the results.
As can be seen, the main results of our base model are unaffected when allowing for non-linear age depreciation. The coefficient for age remains highly significant and negative, though, its absolute estimate is slightly larger: $\mid -0.0078 \mid > \mid -0.00364 \mid$. Regarding the coefficient for the square of age, the estimates are highly significant and positive, indicating that the effect of age on price may indeed be best described by a concave relationship. Although the point estimate is relatively low in magnitude, the adjusted model suggests that a 100-year old building sells on average for about 38% less than a new property, which equals a considerable difference in estimates of about 8 percentage points compared to the model omitting the square of age.[87] Notwithstanding, due to the concavity, the difference between the models is rather negligible for buildings at the lower and upper end of the age spectrum.[88]

In conclusion, while the results suggest that housing depreciation exhibits a concave relationship, allowing for this non-linearity does not affect the sign, significance, or magnitude of any coefficient other than age. Therefore, we contend that our conclusions are robust against age-induced heteroskedasticity and argue that our model specification, including dummies for historical designation, is justified.

Table 23: 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

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

The full regression output is available from the author.

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

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

Digression: Residential Proximity to Parks

The inclusion of a covariate capturing the distance to the closest urban park might lead to spurious estimates if the WTP for proximity to urban parks is an endogenous function of the WTP for proximity to sports facilities. Consequently, we re-estimate the base model without this regressor. The results are presented in column (2) of Table 24. Further, in column (4), we test for non-linearity by including a squared coefficient to the model, as prior research provides mixed evidence on how the effects of parks are spatially distributed (More et al. (1988)). Finally, in column (3), we examine the effect of residential proximity to parks using a 600-meter distance control ring.

Table 24: 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

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The full regression output is available from the author.

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

Furthermore, compared to the relatively consistent literature on sports amenities, prior evidence of the intangible benefits of natural urban amenities, such as parks and green spaces, is much more ambiguous. While the positive effects of parks on property prices are well-documented, questions remain about which

Table 25: List of the Selected Urban Parks and Green Spaces

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

types of green spaces matter most (Panduro and Veie (2013)), which inherent features induce the largest price effects (Morancho (2003)), and how the effects are spatially shaped. Although this paper cannot address all of these questions, the estimates shed some light on the magnitude and spatial distribution of the impact of parks. Specifically, column (1) suggests that each additional mile away from the closest urban park decreases the value of a single-family home by about 18.3% on average.[89] Further, column (4) reveals a positive and significant coefficient for the squared distance, indicating a non-linear effect that decreases in a concave fashion. This implies that the effect is most pronounced in direct proximity to parks and diminishes disproportionately with distance until it completely dissipates at a distance of 2.93 miles.[90] Concerning the distance ring specification in column (3), the point estimate suggests a price premium of approximately 12.75%,[91] for single-family homes located within 600 meters of any of the selected urban parks or green spaces, consistent with prior literature.

Lastly, there are some caveats to report. Firstly, our findings might be affected by selection bias as we only include the most important parks based on qualitative criteria. We implicitly assume that only parks of a certain size or reputation have a considerable impact on the housing market. Additionally, another reason for the inability to control for all 108 parks in St. Louis is that we lack data to map the parks within a geographical information system. However, smaller parks, such as playgrounds, may also have a particularly local effect. Secondly, we assume homogeneity in the effect of residential proximity to any of the selected parks, although in reality, considerable differences may exist based on the idiosyncratic features characterizing each park. Unfortunately, we lack sufficient information on such features for more sophisticated analyses. Finally, our findings may exhibit a small measurement error, primarily due to the approach of measuring the distance to the center of each park, as we lack data on entry points to parks.[92]

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

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

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

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

Variable Transformations

Figure 16: Log-Transformation of Price

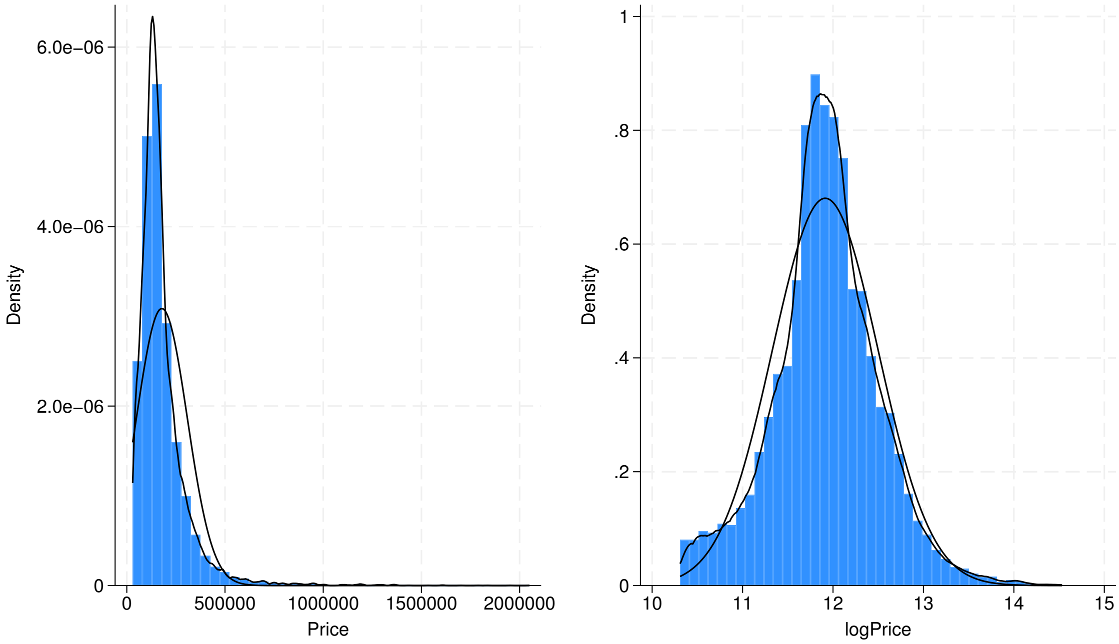


Figure 17: Log-transformation of Floorsize

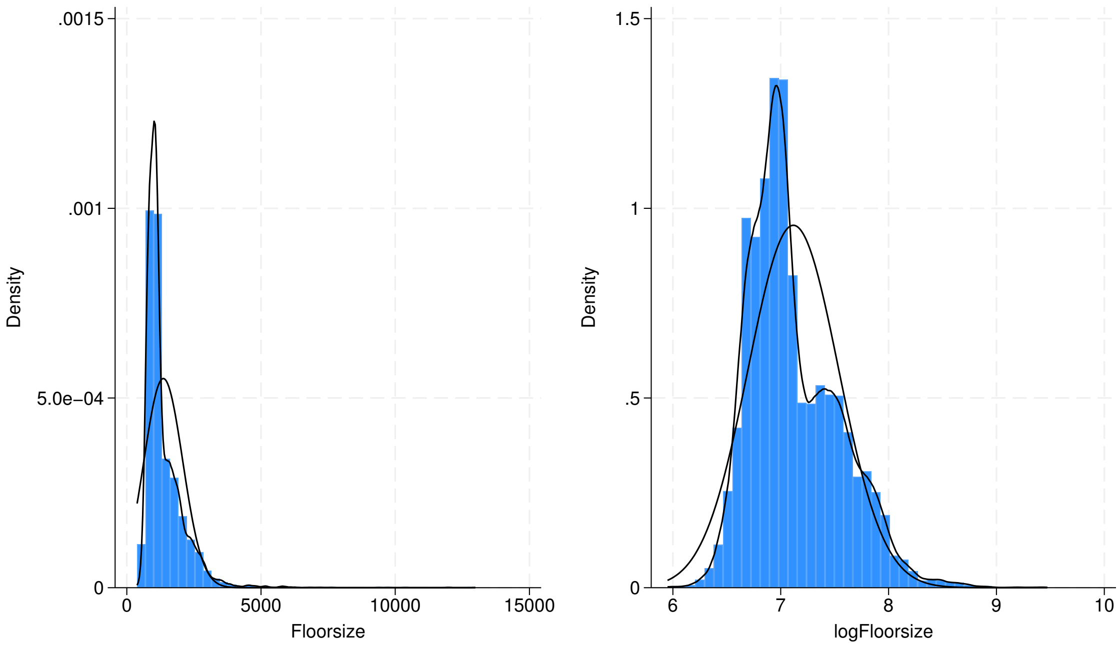
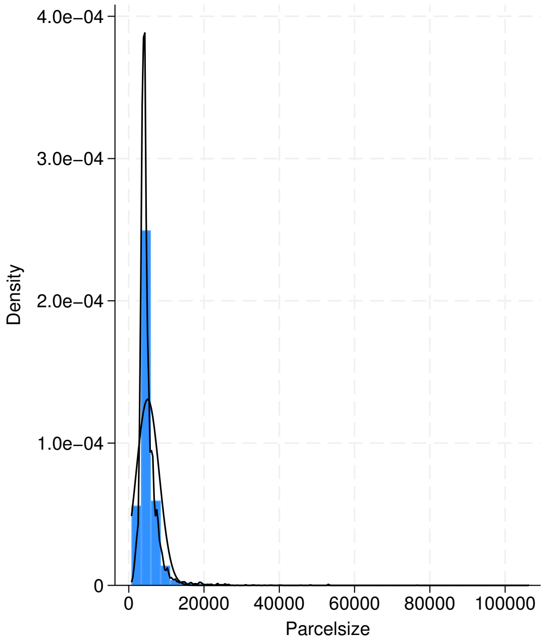
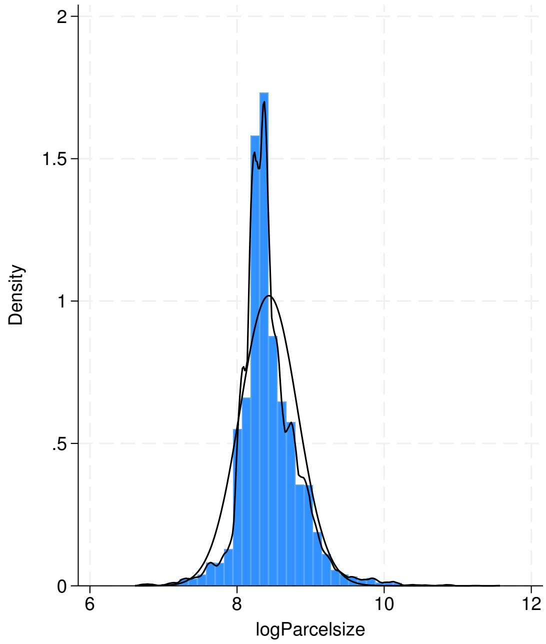


Figure 18: Log-Transformation of Parcelsize





Supplementary Regression Outputs

Main Body

Table 26: 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

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

Table 27: 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

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

Reference is the outermost distance ring Impact8.

Table 28: Estimates Across Different Error Specifications - Half-Mile Distance Rings

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) Neighborhood
Post	0.313***	0.313***	0.313***	0.313***	0.313***
	(0.024)	(0.021)	(0.036)	(0.037)	(0.036)
Target0_5	0.462***	0.462	0.462**	0.462***	0.462***
	(0.155)	(0.369)	(0.204)	(0.146)	(0.164)
Target1	1.099***	1.099***	1.099***	1.099***	1.099***
	(0.190)	(0.247)	(0.234)	(0.179)	(0.363)
Target1_5	0.380***	0.380***	0.380*	0.380**	0.380**
	(0.119)	(0.106)	(0.221)	(0.156)	(0.190)
Target2_0	0.416***	0.416***	0.416**	0.416***	0.416***
	(0.099)	(0.081)	(0.205)	(0.134)	(0.152)
Target2_5	0.351***	0.351***	0.351**	0.351***	0.351**
	(0.083)	(0.069)	(0.173)	(0.109)	(0.138)
Target3	0.396***	0.396***	0.396**	0.396***	0.396***
	(0.072)	(0.060)	(0.170)	(0.126)	(0.131)
Target3_5	0.289***	0.289***	0.289**	0.289***	0.289***
	(0.062)	(0.052)	(0.126)	(0.081)	(0.099)
Target4	0.221***	0.221***	0.221*	0.221***	0.221**
	(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	-0.026	-0.026	-0.026	-0.026	-0.026
	(0.030)	(0.026)	(0.080)	(0.085)	(0.085)
Target0_5xPost	-0.365***	-0.365*	-0.365***	-0.365***	-0.365***
	(0.112)	(0.212)	(0.036)	(0.033)	(0.031)
Target1xPost	-0.138**	-0.138	-0.138***	-0.138**	-0.138**
	(0.069)	(0.289)	(0.045)	(0.061)	(0.063)
Target1_5xPost	-0.116	-0.116	-0.116***	-0.116*	-0.116**

	(0.093)	(0.094)	(0.036)	(0.068)	(0.056)
Target2_0xPost	-0.104***	-0.104***	-0.104**	-0.104***	-0.104***
	(0.038)	(0.037)	(0.043)	(0.031)	(0.029)
Target2_5xPost	-0.057	-0.057*	-0.057	-0.057*	-0.057
	(0.038)	(0.035)	(0.042)	(0.030)	(0.042)
Target3xPost	-0.074**	-0.074***	-0.074*	-0.074*	-0.074*
	(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	-0.028	-0.028	-0.028	-0.028	-0.028
	(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)	(0.036)
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	-0.118***	-0.118***	-0.118***	-0.118***	-0.118***
	(0.008)	(0.008)	(0.014)	(0.012)	(0.012)
Stone	0.107*	0.107*	0.107**	0.107***	0.107**
	(0.056)	(0.057)	(0.048)	(0.034)	(0.053)
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***
	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)
Attic	0.149***	0.149***	0.149***	0.149***	0.149***
	(0.006)	(0.007)	(0.009)	(0.009)	(0.010)
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	-0.312***	-0.312***	-0.312*	-0.312*	-0.312*
	(0.089)	(0.076)	(0.176)	(0.172)	(0.176)

Vacancy	-1.191***	-1.191***	-1.191**	-1.191***	-1.191***
	(0.265)	(0.214)	(0.465)	(0.416)	(0.395)
Youth	0.363	0.363	0.363	0.363	0.363
	(0.261)	(0.227)	(0.551)	(0.502)	(0.619)
MedianIncome	0.003**	0.003***	0.003	0.003	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
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)
DistancePark	-0.197***	-0.197***	-0.197***	-0.197***	-0.197***
	(0.015)	(0.015)	(0.048)	(0.054)	(0.049)
Local	0.114***	0.114***	0.114*	0.114***	0.114**
	(0.038)	(0.028)	(0.057)	(0.040)	(0.050)
National	0.070***	0.070***	0.070	0.070	0.070*
	(0.017)	(0.014)	(0.044)	(0.044)	(0.041)
CertifiedLocal	0.239***	0.239***	0.239***	0.239***	0.239***
	(0.034)	(0.028)	(0.074)	(0.070)	(0.067)
Conservation	0.195*	0.195***	0.195	0.195	0.195
	(0.101)	(0.058)	(0.138)	(0.139)	(0.169)
Preservation	0.114***	0.114***	0.114**	0.114***	0.114***
	(0.026)	(0.022)	(0.049)	(0.030)	(0.042)
Enterprise	0.007	0.007	0.007	0.007	0.007
	(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	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.024)	(0.028)	(0.040)	(0.027)	(0.028)
DistanceBusch	-0.031	-0.031	-0.031	-0.031	-0.031
	(0.118)	(0.110)	(0.281)	(0.328)	(0.331)
DistanceEC	0.069	0.069	0.069	0.069	0.069
	(0.121)	(0.111)	(0.290)	(0.326)	(0.342)
Constant	6.212***	6.212***	6.212***	6.212***	6.212***
	(0.177)	(0.151)	(0.354)	(0.369)	(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	0.7582	0.7582	0.7582	0.7582	0.7582
Observations	12695	12695	12695	12695	12695

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Reference are properties located outside of a 5 mile radius ring around the stadium.

Table 29: Estimates Across Different Error Specifications - Donut Model - 0.5

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) Neighborhood
Impact	0.143***	0.143***	0.143*	0.143*	0.143*
	(0.036)	(0.028)	(0.080)	(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	-0.0732***	-0.0732***	-0.0732***	-0.0732***	-0.0732***
	(0.021)	(0.019)	(0.028)	(0.023)	(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	0.7570	0.7570	0.7570	0.7570	0.7570
Observations	12686	12686	12686	12686	12686

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Transactions within the first half-mile ring were discarded.

Table 30: Estimates Across Different Error Specifications - Donut Model - 1

	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)	(0.073)
Post	0.320***	0.320***	0.320***	0.320***	0.320***
	(0.022)	(0.021)	(0.032)	(0.033)	(0.032)
ImpactxPost	-0.0730***	-0.0730***	-0.0730**	-0.0730***	-0.0730***
	(0.021)	(0.019)	(0.028)	(0.023)	(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	0.7573	0.7573	0.7573	0.7573	0.7573

Observations	12682	12682	12682	12682	12682

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

Transactions within the first mile ring were discarded.

Table 31: Estimates Across Different Error Specifications - Donut Model - 1.5

	Robust Se	Normal Se	Clustered Se		
	(1) Robust	(2) OLS	(3) Census Tract	(4) Ward	(5) Neighborhood
Impact	0.147***	0.147***	0.147*	0.147*	0.147**
	(0.036)	(0.028)	(0.079)	(0.083)	(0.073)
Post	0.321***	0.321***	0.321***	0.321***	0.321***
	(0.022)	(0.021)	(0.033)	(0.033)	(0.032)
ImpactxPost	-0.0739***	-0.0739***	-0.0739**	-0.0739***	-0.0739***
	(0.021)	(0.019)	(0.029)	(0.023)	(0.027)
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	0.7575	0.7575	0.7575	0.7575	0.7575
Observations	12641	12641	12641	12641	12641

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

Transactions within one and a half miles were discarded.

Table 32: Estimates of the Base Model Considering Equilibrium Effects

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
Target Variables				
Impact	0.3514***	0.2015***	0.1074**	0.1037**
	(0.036)	(0.040)	(0.044)	(0.046)
Post	0.6105**	0.6516***	0.0366	-0.2696
	(0.260)	(0.189)	(0.233)	(0.277)
ImpactxPost	-0.1185***	-0.0971***	-0.0742*	-0.0014
	(0.046)	(0.033)	(0.042)	(0.046)
Housing Characteristics				
logFloorsize	0.5381***	0.5078***	0.4927***	0.4598***
	(0.031)	(0.025)	(0.024)	(0.024)
logParcelsize	0.1741***	0.1909***	0.1888***	0.1791***

	(0.021)	(0.015)	(0.015)	(0.014)
Age	-0.0040***	-0.0038***	-0.0039***	-0.0041***
	(0.000)	(0.000)	(0.000)	(0.000)
Frame	-0.2037***	-0.1589***	-0.1536***	-0.1385***
	(0.016)	(0.014)	(0.014)	(0.014)
Stone	-0.0439	0.1283	0.0812	0.1090
	(0.141)	(0.088)	(0.088)	(0.079)
Stories	0.3110***	0.2711***	0.2582***	0.2512***
	(0.022)	(0.017)	(0.017)	(0.017)
Garages	0.1507***	0.0860***	0.0803***	0.0803***
	(0.014)	(0.010)	(0.010)	(0.010)
Carports	0.0309**	0.0120	0.0141*	0.0137
	(0.012)	(0.009)	(0.008)	(0.008)
Attic	0.1838***	0.1800***	0.1743***	0.1674***
	(0.015)	(0.011)	(0.011)	(0.011)
Demographic Characteristics				
PopDensity			-0.0011	-0.0006
			(0.001)	(0.001)
Crime			-0.0156***	-0.0132***
			(0.005)	(0.005)
Black			-0.6119***	-0.2124**
			(0.088)	(0.100)
Vacancy			-1.0691***	-1.8677***
			(0.286)	(0.297)
Youth			0.1981	0.1675
			(0.314)	(0.290)
MedianIncome			-0.0022	-0.0004
			(0.001)	(0.002)
Market Characteristics				
AccFood			0.0058	0.0068
			(0.007)	(0.007)
Finance			0.0085**	0.0138***
			(0.004)	(0.004)
Retail			-0.0164***	-0.0163***
			(0.005)	(0.005)
Urban Characteristics				

DistancePark				-0.2129***
				(0.019)
Local				0.1831***
				(0.045)
National				0.0960***
				(0.022)
CertifiedLocal				0.3051***
				(0.040)
Conservation				0.1453
				(0.108)
Preservation				0.0346
				(0.035)
Enterprise				0.0195
				(0.021)
Flood100				-0.0867*
				(0.048)
Flood500				-0.0541
				(0.040)
DistanceBusch	0.8182***	0.6209***	0.2847**	-0.0033
	(0.058)	(0.112)	(0.115)	(0.121)
DistanceEC	-0.7569***	-0.5280***	-0.2737**	0.0316
	(0.057)	(0.114)	(0.118)	(0.123)
Post Interaction Terms				
logfloorsizexPost	-0.0139	-0.0441	-0.0430	-0.0154
	(0.039)	(0.030)	(0.029)	(0.030)
logparcelsizexPost	-0.0309	0.0129	0.0173	0.0192
	(0.026)	(0.018)	(0.018)	(0.018)
AgexPost	0.0009***	0.0007***	0.0004	0.0006**
	(0.000)	(0.000)	(0.000)	(0.000)
FramexPost	0.0486**	0.0483***	0.0402**	0.0379**
	(0.019)	(0.016)	(0.016)	(0.016)
StonexPost	0.3612**	-0.0354	0.0529	0.0251
	(0.163)	(0.113)	(0.115)	(0.110)
StoriesxPost	-0.0456	-0.0263	-0.0112	-0.0051
	(0.028)	(0.021)	(0.021)	(0.021)
Number_of_GaragesxPost	-0.0039	0.0138	0.0184	0.0146
	(0.017)	(0.012)	(0.012)	(0.012)

Number_of_CarportsxPost	0.0050	0.0073	0.0057	0.0064
	(0.016)	(0.011)	(0.011)	(0.011)
AtticxPost	-0.0124	-0.0322**	-0.0278**	-0.0249*
	(0.019)	(0.013)	(0.013)	(0.013)
Population_Density_NxPost			-0.0010	-0.0008
			(0.001)	(0.001)
TotalCrime_1000xPost			0.0084	0.0084
			(0.005)	(0.006)
Black_percentage_NxPost			-0.3471***	-0.3623***
			(0.088)	(0.093)
Vacant_Housing_percentage_NxPost			0.9593***	1.1696***
			(0.287)	(0.288)
Youth_NxPost			0.7462***	0.5448**
			(0.262)	(0.258)
Median_IncomexPost			0.0059***	0.0051***
			(0.001)	(0.002)
Establishments_AccxPost			-0.0000	0.0006
			(0.006)	(0.006)
Establishments_FinancexPost			-0.0161***	-0.0163***
			(0.005)	(0.005)
Establishments_RetailxPost			0.0061	0.0011
			(0.005)	(0.005)
Distance_ParkxPost				0.0257
				(0.018)
LocalxPost				-0.1151***
				(0.038)
NationalxPost				-0.0223
				(0.025)
Certified_LocalxPost				-0.1156***
				(0.035)
ConservationxPost				0.0616
				(0.143)
PreservationxPost				0.1268***
				(0.042)
Enterprise_allxPost				-0.0353*
				(0.021)
Flood1xPost				0.0429
				(0.061)

Flood2xPost				0.0907*
				(0.048)
Distance_BSxPost	0.0463	-0.0208	-0.0031	0.0141
	(0.072)	(0.048)	(0.074)	(0.081)
DistanceECxPost	-0.0655	-0.0013	-0.0062	-0.0364
	(0.070)	(0.048)	(0.074)	(0.081)
Constant	5.7757***	5.5426***	6.5668***	6.7152***
	(0.203)	(0.172)	(0.211)	(0.236)
Census Tract FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Month FE	No	Yes	Yes	Yes
Adjusted R^2	0.5233	0.7409	0.7520	0.7596
Observations	12695	12695	12695	12695

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix A

Table 33: 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

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

The sample period is shortened to 01.01.2014 - 04.07.2018.

Reference is the outermost distance ring Impact8.

The full regression output is available from the author.

Table 34: 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	0.205***	0.205***	0.205***	0.205***	0.205***
	(0.018)	(0.017)	(0.026)	(0.033)	(0.028)
Target0_5	0.797***	0.797**	0.797***	0.797***	0.797***
	(0.168)	(0.384)	(0.249)	(0.172)	(0.204)
Target1	1.483***	1.483***	1.483***	1.483***	1.483***
	(0.247)	(0.340)	(0.288)	(0.162)	(0.306)
Target1_5	0.585***	0.585***	0.585**	0.585***	0.585**
	(0.144)	(0.129)	(0.280)	(0.183)	(0.235)
Target2_0	0.558***	0.558***	0.558**	0.558***	0.558***
	(0.121)	(0.101)	(0.239)	(0.134)	(0.186)
Target2_5	0.544***	0.544***	0.544***	0.544***	0.544***
	(0.100)	(0.085)	(0.200)	(0.125)	(0.167)
Target3	0.509***	0.509***	0.509**	0.509***	0.509***
	(0.089)	(0.074)	(0.196)	(0.153)	(0.167)
Target3_5	0.360***	0.360***	0.360***	0.360***	0.360***
	(0.076)	(0.065)	(0.136)	(0.105)	(0.127)
Target4	0.309***	0.309***	0.309**	0.309***	0.309***
	(0.063)	(0.054)	(0.121)	(0.100)	(0.114)
Target4_5	0.106**	0.106**	0.106	0.106	0.106
	(0.049)	(0.042)	(0.100)	(0.080)	(0.096)
Target5	0.012	0.012	0.012	0.012	0.012
	(0.039)	(0.031)	(0.096)	(0.104)	(0.105)
Target0_5xPost	-0.498***	-0.498**	-0.498***	-0.498***	-0.498***
	(0.108)	(0.234)	(0.063)	(0.055)	(0.052)
Target1xPost	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Target1_5xPost	-0.141	-0.141	-0.141***	-0.141***	-0.141

	(0.121)	(0.134)	(0.044)	(0.026)	(0.100)
Target2_0xPost	-0.066	-0.066	-0.066	-0.066**	-0.066
	(0.046)	(0.046)	(0.048)	(0.027)	(0.049)
Target2_5xPost	-0.075*	-0.075*	-0.075*	-0.075***	-0.075**
	(0.042)	(0.042)	(0.043)	(0.013)	(0.031)
Target3xPost	-0.092**	-0.092***	-0.092*	-0.092**	-0.092*
	(0.039)	(0.033)	(0.055)	(0.043)	(0.049)
Target3_5xPost	-0.111***	-0.111***	-0.111***	-0.111**	-0.111**
	(0.038)	(0.031)	(0.037)	(0.049)	(0.055)
Target4xPost	-0.059*	-0.059**	-0.059	-0.059	-0.059
	(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)	(0.029)
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	0.7665	0.7665	0.7665	0.7665	0.7665
Observations	8030	8030	8030	8030	8030

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

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.

Table 35: Estimates of the Base Model - Placebo Analysis

	Robust Se		Clustered Se	
	(1) Model 1	(2) Model 2	(3) Model 1	(4) Model 2
Target Variables				
Impact	-0.0153	-0.0182	-0.0153	-0.0182
	(0.013)	(0.016)	(0.075)	(0.019)
Post	0.1892***	0.3700***	0.1892***	0.3700***
	(0.007)	(0.007)	(0.013)	(0.014)
ImpactxPost	0.1151***	0.1085***	0.1151***	0.1085***
	(0.022)	(0.015)	(0.033)	(0.035)
Housing Characteristics				
logFloorsize	0.6407***	0.4604***	0.6407***	0.4604***

	(0.016)	(0.011)	(0.039)	(0.014)
logParcelsize	-0.0137	0.2288***	-0.0137	0.2288***
	(0.016)	(0.014)	(0.060)	(0.020)
Bedrooms	-0.0416***	-0.0013	-0.0416***	-0.0013
	(0.006)	(0.004)	(0.009)	(0.004)
Full Bath	0.1130***	0.0468***	0.1130***	0.0468***
	(0.007)	(0.005)	(0.012)	(0.006)
Half Bath	0.0668***	0.0199***	0.0668***	0.0199***
	(0.008)	(0.005)	(0.016)	(0.007)
Age	-0.0047***	-0.0093***	-0.0047**	-0.0093***
	(0.001)	(0.001)	(0.002)	(0.001)
AgeSquared	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Brick	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
Brick/Frame	-0.0954***	-0.0142*	-0.0954***	-0.0142
	(0.010)	(0.007)	(0.026)	(0.009)
Conc Blk	-0.0449	-0.0234	-0.0449	-0.0234
	(0.071)	(0.044)	(0.079)	(0.042)
Frame	-0.0698***	-0.0473***	-0.0698**	-0.0473***
	(0.009)	(0.007)	(0.034)	(0.010)
Frame/Stone	-0.0135	-0.0144	-0.0135	-0.0144
	(0.041)	(0.030)	(0.044)	(0.028)
Log	0.1619	0.2003**	0.1619	0.2003***
	(0.148)	(0.083)	(0.135)	(0.064)
Metal	0.0957	0.0103	0.0957	0.0103
	(0.312)	(0.243)	(0.294)	(0.151)
Stone	-0.0109	-0.0012	-0.0109	-0.0012
	(0.034)	(0.022)	(0.047)	(0.024)
Stucco	0.0339	-0.0162	0.0339	-0.0162
	(0.046)	(0.029)	(0.059)	(0.028)
Grade A	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
Grade B	-0.2431***	-0.1455***	-0.2431***	-0.1455***
	(0.021)	(0.019)	(0.040)	(0.021)
Grade C	-0.6303***	-0.2331***	-0.6303***	-0.2331***
	(0.023)	(0.022)	(0.056)	(0.025)
Grade D	-0.9126***	-0.4076***	-0.9126***	-0.4076***
	(0.029)	(0.027)	(0.105)	(0.033)

Grade E	-1.2797***	-0.7777***	-1.2797***	-0.7777***
	(0.080)	(0.062)	(0.115)	(0.063)
Grade OFB	-0.2950***	-0.0464	-0.2950***	-0.0464
	(0.041)	(0.077)	(0.105)	(0.035)
Grade SSC	-0.7346***	-0.4034***	-0.7346***	-0.4034***
	(0.033)	(0.082)	(0.080)	(0.064)
Grade X	0.1524***	0.0984***	0.1524***	0.0984***
	(0.032)	(0.028)	(0.046)	(0.031)
Crawl	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)
Full Bsmt	-0.0315***	-0.0197***	-0.0315	-0.0197**
	(0.009)	(0.006)	(0.024)	(0.010)
Piers	0.0509	-0.0271	0.0509	-0.0271
	(0.118)	(0.067)	(0.112)	(0.051)
Pt Bsmt	0.0968***	0.0206***	0.0968***	0.0206***
	(0.011)	(0.007)	(0.025)	(0.007)
Slab	-0.1378***	-0.0226***	-0.1378***	-0.0226
	(0.011)	(0.008)	(0.028)	(0.014)
Constant	7.9110***	9.2553***	7.9110***	9.2553***
	(0.116)	(0.112)	(0.294)	(0.113)
Neighborhood FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes
Adjusted R^2	0.6032	0.8310	0.6032	0.8310
Observations	17793	17793	17793	17793

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

The standard errors in columns (3) and (4) are nieghborhood-clustered.

Supplementary Tables

Table 36: Supplementary Variable Definitions

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

Table 37: 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.

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