An Impact Evaluation of Stadium Construction on Local Economies: Agglomeration and Neighborhood Change [*]

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Abstract

This paper leverages extensive micro-level data from various sources to analyze the impact of National Football League stadium construction on housing prices, employment, and business dynamics—specifically visits, spending, and churn—using a stacked synthetic control approach. Among the three stadiums analyzed, I identify positive effects on home prices in Atlanta, GA, and Inglewood, CA. While overall employment remains unchanged across all cities, specific industries in Las Vegas, NV, and Inglewood, CA, do experience notable effects. The findings on business visits are mixed, and I find evidence of negative impacts on establishment spending in Las Vegas, NV. Additionally, while overall business closure rates near the stadiums show no real significant change, businesses located in neighborhoods that experienced rapid growth following the stadium announcement were more likely to close, mainly in Las Vegas, NV.

Keywords: House Prices, Jobs, Foot Traffic, Spending, Business Churn, Gentrification

JEL Codes: D01, O18, R21, R30, Z20

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1 Introduction

Urban economics has traditionally viewed cities primarily as centers for production rather than consumption (Duranton and Puga, 2004; Moretti, 2011; Combes and Gobillon, 2015). Glaeser et al. (2001) argues that consumption amenities are an important residential choice determinate and find that high amenity cities have grown faster than low amenity cities. A recent wave of research argues that the success of cities can hinge on cities' role as centers of consumption (Glaeser et al., 2001; Couture and Handbury, 2020; Baum-Snow and Hartley, 2020; Moretti, 2012; Almagro and Domínguez-Iino, 2024; Diamond, 2016; Miyauchi et al., 2021). Glaeser et al. (2001) argues that professional sports facilities represent a specific entertainment service that the local government can promote through specific policies to revitalize a specific urban area.

Since 2000, state and local governments in the United States and Canada have invested $19 billion in professional sports venues, viewing stadiums as drivers of economic development (Bradbury et al., 2024). A stadium itself is a non-tradable good. Couture and Handbury (2020) highlights the significant role that a high initial concentration of non-tradable services—such as restaurants and nightlife—plays in attracting young college graduates to urban areas. Their findings suggests that areas with a strong foundation of these amenities are becoming increasingly appealing to this demographic.

The US has experienced a boom in professional sports venue construction over the past 25 years. Fifty-seven new sporting venues were built between 2000 and 2020 and many more new facilities will likely be announced over the next 15 years (Keeler et al., 2021). During the late 1990s through the early 2000s, roughly 50 percent of the 122 teams in the four major professional leagues in the United States moved into a new or substantially renovated venue (Depken et al., 2007). Figure 1 shows that construction boomed in the late 1990s and the early 2000s. On average, teams have replaced their existing stadiums every 27 years, which suggests that another wave of stadium construction might be expected within the next decade as the facilities built in the 1990s and early 2000s are deemed obsolete by team owners (Bradbury et al., 2024).

A growing literature has emerged to estimate the effect of proximity to a sports facility on local home prices and city growth. Economic theory predicts that positive or negative attributes in one location, like access to downtown, traffic congestion or environmental amenities should be capitalized into housing values (Rosen, 1979). Estimating the extent to which new stadium construction becomes capitalized in nearby house prices and its impact on economic activity can provide insight into how individuals and firms value proximity to the facility and other local spillovers generated by the venue.

Agglomeration economies can arise from the ability of professional sports to attract large numbers of consumers at the same time to a particular location, creating an "arena district" where city residents congregate to consume complementary entertainment goods and services (Humphreys and Zhou, 2015).[1] A key feature of sports-led urban redevelopment projects is the related development that takes place around new urban sports facilities, and the way in which the facilities are integrated into the urban tapestry. The size of the agglomeration effects depends on the number of customers who attend games at the facility and consumer services in and around the new facility. Fan-driven consumer traffic makes it profitable for related businesses to co-locate near sports facilities. Property owners within a certain range of the new professional sports facility experience an increase in property value due to the increase of service supply in the area.

However, by the start of the 21st century, economists generally agreed that stadiums were poor public investments (Bradbury et al., 2024). The prevailing interpretation of these studies is that sports merely redistribute economic activity within regions. Within a similar notion to the standard monocentric circular city model presented in (Alonso, 1964; Muth, 1969; Mills, 1967; Duranton and Puga, 2014), house prices are a function of distance from the consumption center (arena district). Residents who consume services live within the bounded distance from the consumption center. Residents outside of this range do not travel to the consumption center. This concept defines an "impact zone" in which case the presence of the consumption center affects housing values. If the impact zone is sufficiently large and travel costs are sufficiently low, spending in locations further from the consumption center could be transferred to areas closer to the consumption center point. This could lead to no

[1]Inglewood's SoFi stadium is the main attraction of the newly developed "Hollywood Park Specific Plan" where the stadium is the centerpiece of a 298-acre mixed-use development featuring retail, commercial office space, a hotel, residential units, and outdoor park spaces.

positive net impact in the city.

This common view however, largely stems from empirical evidence based on data that lacks granularity. Existing research often fails to fully assess the impact of professional sports facilities because it measures economic development at broader aggregated geographic levels, such as counties or metropolitan statistical areas. While significant economic impacts from sports venues are not evident at the metropolitan area level, neighborhoods close to stadiums and arenas may experience positive spillover effects that are not visible in broader city or regional data which are difficult to detect with aggregate data. (Propheter, 2019; Stitzel and Rogers, 2019)

Even if localized impacts occur, the assumption that sports commerce positively influences surrounding businesses is also problematic. Stadiums can either foster or hinder various types of economic development, depending on the specific characteristics of the host community. They can negatively impact local businesses by driving up commercial rent prices and reducing sales for those that don't complement the new consumption center. Additionally, increased competition from new establishments can further challenge existing businesses (Bradbury et al., 2024). These potential unintended effects warrant further exploration in which I tackle in this paper.

Using a variety of rich establishment-level data sources, in this paper I estimate the impact of new stadium construction on employment, local foot traffic and consumer spending, local business churn, residential property values, and overall neighborhood change in Inglewood, CA, Las Vegas, NV, and Atlanta, GA. To empirically analyze the effect of stadium construction on single-family home values, I use quality adjusted repeat-sales home price index data provided by the Federal Housing Financing Agency (FHFA). I measure local monthly foot traffic patterns using data provided by Advan that is generated based on cellphone location from 1000 apps on 5 million devices throughout the US giving detail information on the number of customer visits at each establishment.

I use these data in conjunction with a spending behavior dataset provided by SafeGraph. These data aggregate anonymized debit and credit card transaction data to individual places in the U.S. at a monthly time interval. To analyze employment and local business dynamics, I use an establishment-level, time series database provided by YourEconomy that tracks all establishments and their jobs. Last, I use American Community Survey 5-year estimates of demographic data to study neighborhood change. To the best of my knowledge this is the only paper which analyzes all the outcomes of interest mentioned and of which all use micro-level data to study the impact on a specific city.

In this paper I also take a different methodological approach from the prior literature and implement the recently developed stacked synthetic control method. This allows for estimation when there are more than one treated unit in order to reduce interpolation bias relative to the approach of constructing a synthetic control for an aggregate of all treated units (Wiltshire, 2021b; Abadie and L'Hour, 2021). While prior studies rely mainly on hedonic spatial difference-in-differences models (Bradbury et al., 2024), the synthetic control method controls for pre-treatment trends by constructing a counterfactual which traditional difference-in-differences models ignore and in turn could potentially overstate or understate the impact of a stadium.

Synthetic control methods have become widely applied in empirical research in economics and other disciplines and have been called arguably the most important innovation in the policy evaluation literature in the last 15 years (Athey and Imbens, 2017). The synthetic control method is based on the idea that a combination of unaffected units often provides a more appropriate comparison than any single unaffected unit alone. The synthetic control methodology formalizes the selection of the comparison units using a data driven procedure. In this paper I estimate Census tract-specific treatment effects with a synthetic control estimator, then stack and take the average of these estimates.

Using the stacked synthetic control approach, I find positive effects on the FHFA HPI in, Atlanta, Georgia and Inglewood California. I find null effects in Las Vegas, Nevada. I find the largest effects in Inglewood, California which I suggest results because it uniquely was accompanied by ancillary construction: industrial, residential, business and other activities. I find no impact on overall employment in any city, however I do find significant employment effects for Las Vegas in service sector industries that complement with the stadium construction. I find moderate evidence of increased establishment visits in all three cities while I find moderate positive effects on overall consumer spending in Inglewood, CA.

To estimate the impact of stadium construction on local businesses and overall neighborhood change, I test the theoretical predictions of Glaeser et al. (2023) who present a model in which gentrification can reduce overall social welfare through an endogenous change in amenities. As higher-paid residents enter, stores enter that specialize in services that cater to them replace idiosyncratic stores that generate more consumer surplus. The key distinction is that a reduction in the number idiosyncratic stores is like a drop in the number of product varieties which can lower utility, while an increase in the number of generic service stores provide the same goods but at a lower time cost (Dixit and Stiglitz, 1977). The model shows how welfare-reducing gentrification could happen, but does not imply that welfare is actually being reduced.

Within a similar notion, Handbury (2021) also finds that stores in wealthier cities offer products representing a greater share of the high-income consumption bundle than the low-income consumption bundle and that they also charge relatively less for the high-income consumption bundle than the low-income bundle, conditional on availability. The author notes that once you account for income-specific tastes, markets that are relatively expensive for poor households can be instead relatively cheap for the wealthy households.

To explore closure rates across all three cities, I use a regression analysis based on a local businesses distance to the stadium and their degree of neighborhood change. I also categorize establishments based on whether they are considered a generic brand or a locally traded ("Mom and Pop") brand.[2] For these two groups I further subset based on whether the establishment is in an industry that could potentially benefit being located near a new facility. Overall, the results indicate negligible change in the probability of closing for local businesses based on their proximity to the stadium. This may be due to the fact that commercial leases tend to be long term and typically range from about five to ten years or even longer in some cases. However, I do find evidence that areas in Las Vegas which experienced significant neighborhood change, businesses were more likely to close.

In this paper I also find that there is substantial within-city differences in house price appreciation and demographic change in response to a stadium induced housing demand shock.

[2]The local brand category consists of establishment locations that are defined by YourEconomy as independent (place that does not report to a headquarters and does not have branch locations) or individual (a professional individual, often working within a practice with other individuals). Generic category consists of establishment locations that are classified as either being the Head Quarters, a Subsidiary or a Branch.

While most of the urban literature has focused on trying to explain cross-city differences in house price appreciation, the appreciation for a city as a whole is just a composite of the house price movements within all the neighborhoods of the city. Therefore, understanding the movements in house prices across neighborhoods within a city is essential for understanding house price movements for the entire city. Baum-Snow and Han (2024) also finds significant within-city variation in housing supply elasticities. Such precise measurement enables policymakers to identify neighborhoods with more inelastic supply, helping them to forecast where investments in neighborhood amenities are likely to have larger impacts on prices and rents.

To analyze the within-city differences, I examine the theoretical predictions of a model presented in Guerrieri et al. (2013) which links house price movements across neighborhoods within a city and the gentrification of those neighborhoods in response to a city wide housing demand shock. The model reveals a systematic pattern in variation with respect to within-city house price movements. Initially low price neighborhoods appreciate more than initially high price neighborhoods during a city wide housing demand shock. This is due to the positive externality of richer individuals preferring to live next to richer neighbors. This results in the in-migration of the richer residents who will bid up prices potentially causing the incumbent poorer residents to migrate out, they refer to as "endogenous gentrification".

In this paper I find supporting evidence of this being the case in Inglewood, CA and Atlanta, GA. As noted in Balboni et al. (2021), when policymakers invest in urban infrastructure—such as train lines, parks, and schools—they enhance specific places rather than directly benefiting particular individuals. This presents a significant challenge: if people are mobile within cities, improvements in one neighborhood may attract wealthier residents, driving up local prices and displacing lower-income residents. This process, known as infrastructure-induced gentrification (IIG), has sparked considerable debate regarding the appropriate design and impact of urban investments.

This paper contributes to a recent and growing literature relating to agglomeration effects through consumption and endogenous amenities (Couture and Handbury, 2020; Baum-Snow and Hartley, 2020; Moretti, 2012; Almagro and Domínguez-Iino, 2024; Diamond, 2016; Miyauchi et al., 2021). Urban economics has traditionally viewed cities as having advantages in production and disadvantages in consumption (Glaeser et al., 2001). My results in this paper also contribute to the literature studying the impact of sports venues on property values and local economic activity, which overall, contains mixed results. Although many studies contain evidence that sports facilities generate positive local amenities which are positively capitalized into house prices, others contain evidence supporting the generation of local dis-amenities (Bradbury et al., 2024). My findings also contribute to the understanding of stadium construction effects by providing empirical evidence from rich micro-level data, offering a more detailed perspective than the current literature, which has largely been shaped by studies relying on aggregated data that lack granularity.

Gould Ellen (2024) argues that while many economists have produced excellent, even groundbreaking, work on neighborhood trajectories and their significance in shaping life outcomes, numerous urban scholars tend to focus on cities or metropolitan areas as their unit of analysis. The study asserts that this approach often overlooks the variations within cities and pays little attention to the dynamics occurring within individual neighborhoods. In this paper I explore this black box highlighting the within-city heterogeneity in response to housing demand shocks.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the impact of stadium construction on property values and economic activity and briefly reviews the synthetic control methodology. Section 3 presents the data and the timeline for each stadium construction. In section 4, the empirical framework is explained. In section 5 the empirical results are discussed for each city. Section 6 provides additional findings regarding heterogeneity, local business dynamics and neighborhood change. Section 7 concludes the paper.

2 Literature Review

The economic development rationale for funding stadiums gained prominence in the 1980s as government officials saw them as magnets for new commercial activity in cities. Beyond promoting a city's "big-league" status, stadium-related spending was expected to benefit the wider region through economic multipliers—where each dollar spent generates additional economic activity as it circulates within the community—thereby boosting employment, income, property values, and tax revenues. Proponents often argue that stadiums are worthy public investments because they generate positive development externalities not fully captured by franchise owners (Bradbury et al., 2024).

During this era, economists began studying the economic impact of stadiums. They compared historical outcomes from metropolitan areas with and without teams and venues to assess the effect of hosting professional sports on various economic indicators, such as employment, income, and spending. This approach allowed for the identification of potential economic benefits from stadiums, both directly through fiscal stimulus and indirectly by attracting new businesses and residents due to an enhanced reputation as a big-league city. However, these studies consistently found little to no tangible economic benefits for communities hosting professional sports teams. By the start of the 21st century, economists largely agreed that stadiums were poor public investments (Bradbury et al., 2024).

However, this consensus largely stems from empirical evidence based on data that lacks granularity. Existing research often fails to fully assess the impact of professional sports facilities because it measures economic development at broader aggregated geographic levels, such as counties or metropolitan statistical areas. While significant economic impacts from sports venues are not evident at the metropolitan area level, neighborhoods close to stadiums and arenas may experience positive spillover effects that are not visible in broader city or regional data (Propheter, 2019; Abbiasov and Sedov, 2023).

While large metropolitan-wide economic effects from sports venues do not appear to exist, areas close to stadiums and arenas may experience spillover benefits that are not visible in aggregate city or regional data. The prevailing interpretation of these studies is that sports simply redistribute economic activity within regions. This suggests that the spillover effects from professional sports stadiums and arenas are localized, making them difficult to detect with aggregate data. Despite a noticeable shift towards research designs that provide richer descriptions of local business environments, only a few studies so far have utilized establishment-level data (Bradbury et al., 2024).

Abbiasov and Sedov (2023) analyze daily mobile foot traffic data from major league sports facilities and the surrounding commercial establishments in the U.S. to quantify the size and spatial distribution of foot traffic spillovers to local businesses. Using fixed effects and instrumental variable estimation strategies, they demonstrate that these spillover benefits vary across different sports and business sectors. Their findings reveal that 100 visits to a baseball stadium lead to approximately 29 additional visits to nearby food and accommodation businesses and about 6 visits to local retail establishments. While estimates for football stadiums are comparable, basketball and hockey arenas do not seem to generate significant spillovers for surrounding businesses.

The authors note that football stadiums also appear to influence foot traffic to local recreation facilities and other services, with spillovers extending to neighborhoods as far as 2.5 km away from the venues. The localized nature of these effects may explain the challenges earlier research has faced in detecting spillovers using aggregate data. The authors utilize data on the number of games, average event attendance, and assumptions about typical consumer spending at local businesses to estimate the additional consumer spending resulting from foot traffic externalities. Their results indicate that the median sports facility generates around \$11.3 million in additional spending for local food, accommodation, and retail businesses.

Stitzel and Rogers (2019) utilize annual establishment-level sales data from the National Establishment Time-Series (NETS) to assess the impact of the relocation of the NBA's Seattle franchise to Oklahoma City on local businesses. Their findings confirm the role of the consumption substitution effect: while food establishments located 1 to 2 miles from the arena experienced an increase in sales, there was a corresponding decline in entertainment sales within the same distance. Overall, the combined impact on sales across all related industries was found to be insignificant.

A growing literature has emerged to estimate how proximity to a sports facility impacts local home prices. Assessing the extent to which the opening of a new sports facility gets capitalized in nearby house prices can provide insight into how local residents value proximity to the facility and other local spillovers generated by the facility. Overall, the literature contains mixed results. Although many studies contain evidence that sports facilities generate positive local amenities, which are positively capitalized into house prices, others contain evidence supporting the generation of local dis-amenities which are negatively capitalized into house prices.

The vast majority of studies in the literature use a similar econometric approach to recover causal estimates in the form of hedonic spatial difference-in-differences models (Bradbury et al., 2022). Hedonic pricing is most often seen in the housing market as opposed to other markets, since real estate prices are determined by the characteristics of the property itself as well as the neighborhood or environment within which it exists (Rosen, 1979). Hedonic pricing captures consumers willingness to pay for what they perceive are environmental differences that add or detract from the intrinsic value of an asset or property. A commonly used difference-in-differences model in the literature and the one used in Keeler et al. (2021) takes the form

$$Log(Price)_{it} = \beta_0+\beta_1 Post+\beta_2 Treated+\beta_3(Post\times Treated)+\beta_4 H_{it}+\beta_5\omega_{it}+\theta_j+\eta_t+\epsilon_{ijt}, \quad (1)$$

where $Log(Price)_{it}$ is the natural log of house price i in time t. The vector H_{it} contains observable dwelling attributes (bedrooms, square feed, age, age squared), ω_{it} reflects other locational characteristics such as distances to fixed amenities such as highways and rail stations. The parameters θ_j is an indicator variables for school attendance zones which are used to control for heterogeneity in local school quality. Also included is an indicator for when the house was sold, η_t, to address any unobserved temporal heterogeneity. Last, ϵ_{ijt} is an error term that is assumed to be well behaved.

The authors use this approach to estimate the impact of the opening of the Staples Center for the Los Angeles Lakers National Basketball Association (NBA) team on log home prices in downtown Los Angeles, which was announced in 1997 and opened in 1999. Using housing price data from DataQuick the authors find that houses within close proximity to the Staples Center experienced between eleven and six percent price increases within one to two miles of the venue, respectively. The increased sale prices are consistent with positive spillovers that derive from the arena. The authors also find positive effects associated with the announcement of the new NBA arena.

Tu (2005) is one of the first empirical studies to assess the impact of a new sports facility on home prices. The study examines how proximity to the new FedEx Field in Landover, Maryland, impacted home prices within 2.5 miles of the facility. Using a hedonic spatial difference-in-differences approach, he estimates the log home price change controlling for housing characteristics such as lot size, the number of bedrooms and the number of bathroom. His hedonic model controls for distance to the stadium and demographic characteristics at the Census tract level. Using home transaction data from the Maryland Department of Planning he finds that properties near FedEx Field sold at a discount relative to comparable units in the city outside of the 3 mile radius. However, difference-in difference analyses that compare the impact of the stadium before and after its opening reveal that the price discount had existed before the stadium was built. In fact, the home price differential between the treatment and control group was narrowed after the announcement of the site selection, and reduced even further after the opening of the stadium.

Feng and Humphreys (2012) take a similar difference-in-differences approach and estimate the effect of stadium proximity on residential property values in US cities using a hedonic housing price model with spatial autocorrelation to control for spatial heterogeneity across cities. Spatial autocorrelation can be positive where homes with similar value tend to cluster in space, and can be negative in locations that tend to be surrounded by neighbors with very dissimilar home values. Estimates based on all 1990 and 2000 Census block groups within five miles of every NBA, National Hockey League (NHL), National Football League, and Major League Baseball (MLB) facility in the US suggest that the median house value is higher in block groups that are in close proximity to facilities, suggesting that positive externalities from professional sports facilities may be capitalized into residential real estate prices.

The authors acknowledge a potential limitation of their study and which should be a concern of any similar study in this literature. The observed effect of proximity of a sports stadium on residential housing prices could work through the effect of these facilities on business location, and the effect of business location on residential properties. If many bars and restaurants open close to sports facilities, this will increase the demand for land in these areas and drive up existing property values. If this is true, then the distance variable will be endogenous and the results in the paper may be biased and inconsistent.

As noted earlier, not all research identifies positive impacts on property values. Several studies find evidence consistent with the generation of local dis-amenities. Humphreys and Nowak (2017) use repeat sales data to analyze NBA teams that left Seattle, Washington, and Charlotte, North Carolina, and found that both team departures generated increases in residential home prices near the arenas where the teams had played, suggesting that the teams generated local disamenities in these markets. They reported increases of about 7 percent in Seattle, WA and 10 percent in Charlotte, NC within one to two miles of the facilities based hedonic spatial difference-in-differences models.

Joshi et al. (2020) use a similar hedonic pricing method along with repeat sales regressions to estimate the impact of the promotion of the Seattle Sounders to MLS in 2009. They estimate that property values depreciated after the Seattle Sounders Football Club was promoted from the Minor League Baseball Association to the MLS in 2009. The distance-decaying depreciation in condominium values occurs within a mile of the facility.

Kavetsos (2012) estimates the impact of London's successful 2012 summer Olympics bid on property prices. He estimates a hedonic difference-in-differences model for the Greater London area controlling for housing characteristics, distance to the nearest metro station and crime levels at the borough level. Applying a difference-in-differences estimator, he finds that properties in the host boroughs are sold between 2.1 and 3.3 percent higher compared to non-hosts boroughs, depending on the definition of the impact area. A similar investigation based on radius rings suggests that properties up to three miles away from the main Olympic stadium sell for 5 percent higher. The impact on host boroughs leads to an estimated overall property price increase of £1.4 billion.

Feng and Humphreys (2018) use a hedonic difference-in-differences model to examine the impact proximity of residential homes near two new privately financed stadiums in Columbus, Ohio, which host MLS and NHL teams, on property values. They control for housing characteristics, school quality, environmental quality local crime. The authors control for spatial autocorrelation to address spatial heterogeneity across cities. Using Ohio home transaction data, they find increased housing values of 1.75 percent for each ten percent decrease in distance from the arenas.

There are also studies that examine the impact of announcements on residential property values. Depken et al. (2007) combine hedonic pricing models, event study methodology, and difference-in-differences estimators to test of the impact of a series of announcements regarding a new publicly-subsidized stadium in nearby Arlington, Texas. In aggregate (both announcements combined as one treatment), average property values declined approximately 1.5 percent relative to the surrounding area before stadium construction commenced. Analyzing announcement effects on residential property values provides insights into the impact of information in housing markets, since at the time of the announcement of a proposed new sports facility no construction activity for the new stadium has commenced and none of its corresponding sporting events exist.

Neto and Whetstone (2022) estimate a hedonic model to study the effects on residential property values due to the relocation of the NFL's Raiders to Las Vegas, Nevada. Their results show that residential properties after the announcement and the opening of the stadium experienced an increase of 6 percent and 3 percent to 4.5 percent respectively for both the within 2.5 miles and 2.5 to 5 miles treatment groups.

Bradbury et al. (2022, 2024) conduct comprehensive reviews of the literature analyzing the impact of stadium construction on property values and local economies. Readers who are interested in a more detailed description of previous studies can refer to these articles.

2.1 The Synthetic Control Approach

Synthetic control methods were originally proposed in Abadie and Gardeazabal (2003) and Abadie et al. (2010) with the aim to estimate the effects of aggregate interventions, that is, interventions that are implemented at an aggregate level affecting a small number of treated units (such as a cities, regions, or countries), on some aggregate outcome of interest. More recently, synthetic control methods have been applied to settings with a large treated number of units (Abadie and L'Hour, 2021).

In comparative case studies, the researcher is typically interested in the before and after effect of an intervention on a particular outcome of interest. However, there is typically some degree of ambiguity about how comparison units are chosen. Researchers often select comparison groups on the basis of subjective, ad-hoc measures of similarity between treated and untreated units. Data-driven procedures reduce discretion in the choice of the comparison control units. Similar to matching estimators, the synthetic control method forces researchers to demonstrate the affinities between the treated and untreated units using observed quantifiable characteristics (Abadie et al., 2010).[3] The central idea behind the synthetic control approach is that a combination of units often provides a better comparison for the unit exposed to the intervention than any single unit alone.

3 Data and Descriptive Statistics

3.1 FHFA Home Price Index

To empirically analyze the effect of stadium construction on single-family home values, I use data from the Federal Housing Financing Agency which report home price indices (HPI) at the Census tract level. The FHFA HPI is a broad measure of the movement of single-family house prices. The HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales on the same properties within Census tracts which adjusts for the quality over time (Calhoun, 1996).[4] This information is obtained from repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac.

FHFA HPIs are based on data for a sample of houses with conforming mortgages, that is, mortgages below certain cut-off house values and loan-to-value ratios and that, in addition to sales prices, observations obtained from homes that were refinanced are used in constructing the index. Jumbo loans-mortgages that exceeds the limits set by the FHFA-are not eligible to be purchased, guaranteed, or securitized by Fannie Mae or Freddie Mac. If the market value of homes grow to exceed the conforming limit they are not excluded from the sample since the conforming limit is based on the mortgage balance of the home and not its market

[3]Synthetic Control also safeguards against specification searches. Synthetic controls do not require access to post-treatment outcomes in the design phase of the study when synthetic control weights are calculated. The SC weights can be calculated and pre-registered before the post-treatment outcomes are realized, or before the actual intervention takes place, providing a safeguard against specification searches and p-hacking.

[4]The index employs a weighting procedure that allows for greater sampling variability in the price appreciation for houses that experience a longer time between transactions. As noted in Calhoun (1996), given two identical properties, differential rates of appreciation, change in the neighborhood socio-demographics and other idiosyncratic deviations from market-level mean appreciation are more liable to arise the longer the time between transactions. This motivates using a generalized least squares weighting procedure in which the variance in house price appreciation is quadratic in the time between consecutive transactions for a given property.

value. Loan limit increases reflect the year-over-year percentage change in the FHFA HPI for the United States and are based on the third quarter.[5]

The FHFA HPI serves as a timely, accurate indicator of house price trends at various geographic levels. The key advantage of the FHFA HPIs is that they are available at the Census tract level for most of the United States over a long sample period. House price index data are missing for tracts where there are insufficient repeat sales within a tract to get an accurate estimate of house price trends for that tract. As a result some tracts for each city are missing from my analysis during the 2010-2022 period. For the stacked synthetic control estimates I use each Census tract as one treated unit. I use Geographic Information Systems (GIS) software to create distance rings for census tracts that fall within zero to one miles, one to two miles, two to three miles, three to four miles and four to five miles of each stadium to construct my treatment groups and census tracts that are seven to ten miles away from each stadium as my comparison group.

Table 1 through Table 4 report summary statistics for each city. Each table report statistics for the treatment zone (0 to 5 miles) using the average of the available years before construction began and after construction began for each city. Also I report corresponding statistics for the control groups (7-10 miles)

3.2 American Community Survey

I use these data in conjunction with demographic data from IPUMS National Historical Geographic Information System which provides summary statistics and GIS files for U.S. censuses and other nationwide surveys at the Census tract level (Manson et al., 2021). I use decennial Census data and American Community Survey 5-year estimates for the years 2008-2012 and 2015-2019 for the city of Atlanta, GA. I use ACS waves 2011-2015 and 2018-2022 for the city of Inglewood, CA. I use 2012-2016 and 2018-2022 waves for Las Vegas, NV

[5]Freddie Mac and Fannie Mae are government sponsored enterprises chartered by Congress to provide a secondary market in conventional mortgages and increase lending for home ownership. These data include mortgage records for single-family, single-unit, detached properties, excluding condominiums, cooperatives, and planned urban developments. Mortgage transactions on properties financed by government insured loans, and properties financed by mortgages exceeding the conforming loan limits by Freddie Mac or Fannie Mae are excluded. As of 2024, the conforming limit in expensive coastal markets is a loan value of $1,0149,825 and the maximum LTV is 97%. The conforming limit is $766,550 in the least expensive housing markets.

(Ruggles et al., 2022).[6]

3.3 Your-Economy Establishment Level Time-Series

Created exclusively by the Business Dynamics Research Consortium, the Your Economy Time Series (YTS) is an annual establishment-level time series database that tracks all types of establishments—including for-profit, non-profit, and government entities—along with their jobs. YTS focuses on establishments that are "in business," meaning they are actively engaged in commercial activities. The database includes annual establishment data from 1998 through the end of the most recent calendar year, with a comprehensive update conducted mid-year. YTS provides detailed information such as establishment names, street addresses, longitudes, latitudes, and employee counts. Their annual snapshots enable tracking of business entries and exits over the years.

On average, every company in the U.S. is contacted at least once a year to update records on start-ups, closures, and active establishments. YTS maintains transparency; when employment numbers cannot be confirmed through telephone interviews, a model is used to estimate the employment size, which typically accounts for about 1.5% of the total YTS data. Any questionable data is thoroughly examined using internal establishment databases and external sources, and corrections are made as needed. In rare instances where this validation process cannot verify the data to an acceptable standard, the individual establishment record is deactivated for further review.[7]

An establishment is classified as new if its name and address do not appear in the database and there is no evidence of relocation or a name change. An establishment is considered closed if its tenant or owner is no longer operating at that address and has not moved elsewhere. An establishment is marked as moved if it is not new, remains active, and its location code (such as county, CBSA, zip code, or census tract) has changed from one period to the next.

YTS defines jobs as all individuals currently employed at an establishment, including

[6]Note that Las Vegas has a two year gap between each 5-year wave while the other two cites have a 3 year gap.

[7]Twice each year (June 30 and December 31), Data Axle(formerly Infogroup) delivers 437 data variables per record/establishment to the BDRC for all establishments in their database.

full-time, part-time, and temporary workers. This definition encompasses proprietorships and sole proprietorships (self-employed) without distinguishing between employee and non-employee status. Job expansion, as defined by YTS, refers to increases in the total number of jobs within an establishment. However, hiring to replace departed workers or transferring employees between departments does not qualify as job expansion. For this analysis I use data for the years 2010-2023.

3.4 Advan Monthly Foot Traffic

The Advan Monthly Patterns dataset provides visitor and demographic aggregations for points of interest (POIs) in the U.S. over a monthly period. This dataset is generated from cellphone location data collected from 1,000 apps across 5 million devices nationwide, with monthly updates from 2019 to the present. It includes aggregated raw counts of visits to POIs, detailing how often people visit, the duration of their stays, their origins, subsequent destinations, and more. The data is anonymized and aggregated to offer insights into visitor volume and overall behavioral patterns. A visit is counted only if the duration lasts at least four minutes. Due to the global reduction in foot traffic caused by the COVID-19 pandemic, I utilize data exclusively from 2023 to measure consumer foot traffic by establishment.

3.5 SafeGraph Consumer Spending

I use data on consumer spending behavior at specific points of interest (POIs) from SafeGraph. The Spend dataset aggregates anonymized debit and credit card transaction data for individual places in the U.S. on a monthly basis, dating back to January 2019. This dataset includes spending information for over 10 million customers at more than 1.1 million POIs across 5,454 brands. When aggregated to the parent brand level, SafeGraph's Spend data can be compared with financial indicators, such as quarterly revenue, to serve as a benchmark for validation.[8] SafeGraph also assesses geographic representativeness by comparing its state-by-state customer home location data to the true proportions reported by the 2019

[8]Based on one such analysis, SafeGraph data track with quarterly revenue from major brands like McDonald's, Chipotle, and Target, including cases where companies report online sales separately than overall revenue (e.g., Chipotle).

U.S. Census. SafeGraph's panel density closely mirrors actual population density, with an average percentage point difference of less than <1% and a maximum variation of +/-4% per state. For my analysis, I only use data from 2023 due to the impact of COVID-19 on local consumer spending.

3.6 Timeline and Background of Each Stadium Construction

In this paper I analyze the impact of the three most recent stadiums constructed in the United States as of 2024. Table 5 reports the cities of the seven new stadiums I examine in this study. Column 2 reports the announcement date of each stadium, Column 3 states when construction began in each city. Column 4 lists the opening date of each stadium.

Mercedes-Benz Stadium is a multi-purpose 71,000 stadium located in Atlanta, Georgia. Opened in August 2017 as a replacement for the Georgia Dome, it serves as the home stadium of the Atlanta Falcons of the NFL and Atlanta United FC of MLS. The Atlanta City Council officially approved the stadium on March 19, 2013. The stadium is owned by the state government of Georgia through the Georgia World Congress Center Authority, and operated by AMB Group, the parent organization of the Falcons and Atlanta United. Due to legal issues surrounding the issuing of bonds, the stadium did not break ground until May 19, 2014.

The NFL announced the Ram's relocation to the Los Angeles area in January 2016 and the stadium opened on September 8, 2020. The stadium is a privately funded new stadium with 70,000 seats. The stadium is the main attraction of the newly developed "Hollywood Park Specific Plan" which upon complete will encompass an 238-acre area that will include mixed-use development consisting of 2,500 new residential units, almost 900,000 square feet of retail space, 3000 hotel rooms, about four million square feet of office space, a 6,000-seat performance venue which is attached to the stadium, and four acres of civic space for community-serving uses (ALH Econ, 2019).

Allegiant Stadium is an 65,000 seat stadium located in Paradise, Nevada. It serves as the home stadium for the Las Vegas Raiders of the National Football League and the University of Nevada, Las Vegas Rebels college football team. NFL owners announced the team's transition from Oakland to Las Vegas on March 27, 2017. The construction of the

Allegiant Stadium took place from September 18, 2017 to July 31, 2020. The Las Vegas Raiders played their first game on September 21, 2020.

4 Synthetic Control Methodology

Following Abadie et al. (2010), suppose we have a panel of S Census tracts, indexed by s and observed for T periods. There is one treated tract ($s = 1$), while all other tracts are potential controls.

Let the outcome of interest absent treatment in tract s at time t be denoted $y_{st}(0)$, and let the outcome with treatment be denoted $y_{st}(1)$. The estimating equation is

$$\begin{aligned} y_{st}(0) &= \delta_t + \theta_t \mathbf{Z}_s + \lambda_t \mu_s + \epsilon_{st} \\ y_{st}(1) &= \alpha_{st} + y_{st}(0), \end{aligned} \tag{2}$$

where α_{st} is the treatment effect, $\mathbf{Z}_s$ is an r $\times$ 1 vector of observable predictors, and λ_t is a $1 \times m$ vector of common factors time-varying factors. The parameters to be estimated are α_{st}, the time-varying factor δ_t assumed to be common across Census tracts, the 1 $\times r$ vector of time-varying coefficients θ_t, and the unobservable $m\times$ 1 vector μ_s of factor loadings. The error terms ϵ_{st} are unobservable, mean zero, tract-by-time shocks.

Assume that treatment starts in year $T_0 + 1$ and that the treatment persists until time T, and assume that the treated tract is $s = 1$. From equation 2, the treatment effect is equal to

$$\alpha_{1t} = y_{1t}(1) - y_{1t}(0) \quad \text{for} \quad t \in \{T_0 + 1, ..., T\}. \tag{3}$$

However, the researcher does not observe the counterfactual $y_{st}(0)$ for treated Census tracts, or $y_{st}(1)$ for untreated Census tracts. In particular, the researcher only observes

$$y_{st} = d_{st} y_{st}(1) + (1 - d_{st}) y_{st}(0), \tag{4}$$

where d_{st} is an indicator equal to unity if the tract is treated and equal to zero otherwise. The synthetic cohort approach estimates $y_{1t}(0)$ as a weighted average of the $y_{st}(0), s \neq 1$, that is, a weighted average of the untreated outcomes in Census tracts other than $s = 1$. The weights, in turn, are chosen so as to result in a synthetic comparison group that looks like the treated Census tract in terms of the observables, which can be either $\mathbf{Z}_{st}$ or a proper subset $\mathbf{X}_{st}$.

Denote the set of $S-1$ weights $\mathbf{w} = (w_2 , \ldots ,w_S)$ in order to combine the untreated outcomes among control tracts and provide reasonable an approximation for the counterfactual.[9] Following Abadie et al. (2010), I choose the set of weights that solve

$$\mathbf{w}^*(V) = \arg\min_{w} (\mathbf{X}_1 - \sum_{s=2}^{S} w_s.\mathbf{X}_s)' \ \mathbf{V} \ (\mathbf{X}_1 - \sum_{s=2}^{S} w_s.\mathbf{X}_s), \tag{5}$$

where $\mathbf{X}_s$ is a (K $\times$ 1) vector consisting of some or all of the elements of ($\mathbf{Z}_s'$, y_{s1}, . . . , y_{sT_0}) and $\mathbf{V}$ is a positive definite and diagonal K $\times$ K matrix. In my application, the vector $\mathbf{X}_s$ is comprised of a set of variables $\mathbf{Z}_s$ related in the pre-intervention period. Through an iterative process, the matrix $\mathbf{V}$ places weights on the covariates that have the best predictive power of the outcome of interest. That matrix $\mathbf{V}$ is chosen as

$$\mathbf{V}^* = \arg\min_{V} \frac{1}{T_0} \sum_{t=1}^{T_0} (y_{0t} - \sum_{s=2}^{S} w_s^*(V).y_{st})^2. \tag{6}$$

I additionally constrain the weights so that $\sum w_s = 1$ and $w_s \geq 0 \ \forall$ s $\in \{1 , . . . , \text{S} \}$. Once I have arrived at a set of weights, our estimator for α_{1t} is

$$\hat{\alpha}_{1t} = y_{1t} - \sum_{s=2}^{S} w_s^*(\mathbf{V^*}) y_{st} \tag{7}$$

for t $\in \{T_0 +1 , . . . , \text{T} \}$. In practice, I report the average difference between the treatment unit and the synthetic control during the period where the stadium was announced in each

[9]To reduce interpolation biases and risk of overfitting, Abadie et al. (2010) reccomends restricting the donor pool to units that are similar to the treated unit. In this analysis I restrict the donor pool to Census tracts that are 7 to 10 miles away from each stadium instead of using the entire county as potential weights. There are no ex-ante guarantees on the fit. If the fit is poor, they recommend against the use of synthetic controls. $\mathbf{V}$ is chosen such that the synthetic control $\mathbf{W}(\mathbf{V})$ minimizes the mean squared prediction error(MSPE) of the synthetic control with respect to the counterfactual of interest.

city (the treatment period)

$$\hat{\alpha}_1 = \frac{1}{T - T_0 + 1} \sum_{t=T_0+1}^{T_1} \hat{\alpha}_{1t}.\text{[10]} \tag{8}$$

To quantify the significance of my estimates, I implement the permutation method suggested by Abadie et al. (2010), comparing my synthetic control estimate to a distribution of placebo estimates. In particular, I implement the above synthetic control procedure for all Census tracts in the donor pool and repeat this exercise as if the treatment year occurred in each of my observed time periods. This allows me to assess whether the effect estimated by the synthetic control for the Census tracts in close proximity to the stadium construction is large relative to the effect estimated for Census tracts in the donor pool chosen at random. In my setting, I find synthetic controls for the treated tracts based on up to 5 years prior to treatment, or 8 months in the case for foot traffic and spending estimates for the year 2023. Define $\hat{\alpha}_{st}$ as the estimate for tract s with placebo treatment year t. I then conduct a two-tailed test of the null hypothesis of no effect in my treatment state by comparing the observed estimate for $s = 1$ and true treatment year, $t = T_0 + 1$, to the empirical distribution of placebo estimates. Specifically, my "p-value" is defined as

$$p = \frac{\sum_s \sum_t \mathbb{1}\{|\hat{\alpha}_{1t}| \leq |\hat{\alpha}_{st}|\}}{N_{st}}, \tag{9}$$

where N_{st} is the total number of placebo estimates. The statistic p measures the share of the placebo effects that are larger in absolute value than those in close proximity to the stadium construction site.

4.1 Stacked Synthetic Control Estimator

While many applications of the synthetic control framework have focused on cases where only one aggregate unit is exposed to the intervention of interest as described above, the method has found recent applications in contexts with disaggregated data, where datasets

[10] To avoid extrapolation, the weights are restricted to be nonnegative and to sum to one, so synthetic controls are weighted averages of the units in the donor pool. The requirement that weights should be nonnegative and no greater than one can be relaxed at the cost of allowing extrapolation.

contain multiple treated units. In settings with a large number of treated units, the interest may lie on the average effect of the treatment among the treated. In such settings, one could simply construct a synthetic control for an aggregate of all treated units. However, interpolation biases may be much smaller if the estimator of the aggregate outcome that would have been observed for the treated in the absence of the treatment is based on the aggregation of multiple synthetic controls, one for each treated unit (Abadie and L'Hour, 2021). In this paper I take the later approach.

Another important feature of the synthetic control method (SCM) is to implement the method only when the fit on pre-treatment outcomes has a low Root Mean Squared Prediction Error (RMSPE). Bias may be present in the synthetic control estimated marginal treatment effects (and thus the estimated average treatment effect estimates) because of discrepancies between the predictor variable values in each treated unit and its synthetic control donors. (Abadie and L'Hour, 2021; Ben-Michael et al., 2021) propose an augmented SCM as an extension of the SCM to settings where such pre-treatment fit is infeasible. This augmented SCM uses an outcome model to estimate the bias due to imperfect pretreatment fit and then de-biases the original SCM estimate.

To illustrate, let $\hat{\mu}_s(\mathrm{x})$ be a regression predictor of the outcome of Y_s of an untreated unit with covariate values $X_s = \mathrm{x}$. A biased-corrected version of the synthetic control estimator in Equation (7) takes the form

$$\alpha\hat{_{BC}} = (y_{1t} - \hat{\mu}_{st}(X_1)) - \sum_{s=2}^{S} w_s^*(\mathbf{V^*}).(y_{st} - \hat{\mu}_{st}(X_s)). \tag{10}$$

Equation (10) adjusts for mismatches between the characteristics of the treated units and the characteristics of each of the units that contribute to the synthetic control. A bias correction of this type was studied by Ben-Michael et al. (2021), who propose using ridge regression to estimate $\hat{\mu}_s(\mathrm{x})$. In this paper I use the "allsynth" Stata package provided by Wiltshire (2021a) to automate implementation of this procedure when pre-treatment fit is infeasible.

5 Main Results

5.1 Federal Housing Financing Agency: Home Price Index

As noted in Section 4, if the synthetic control is able to track the FHFA HPI for each city in the pretreatment period and reproduce the values of the key predictors, it lends credibility to my identification assumption that the synthetic control unit provides the counterfactual path of the HPI in the absence of each stadium construction. Kaul et al. (2022) show that if the outcomes for each pre-intervention period are used to estimate the weights, the iterative process mechanically sets the elements of $\mathbf{V}$ that correspond to $\mathbf{Z}_s$ to zero, and thus, additional covariates cease to inform the procedure. Based on this finding, for my analysis I only use lag home price indices as predictors to construct each synthetic control. As described in Section 4 of this paper, if the synthetic control is not able to track the HPI in the pretreatment period I implement the bias-correction procedure proposed by Abadie and L'Hour (2021) to address this issue.

For the placebo test, the treatment is iteratively reassigned to every Census tract in the donor pool, again using the synthetic control method to construct synthetic counterparts. This gives me a method to establish if the result obtained in each city is unusually large, by comparing that result with the placebo results for all the Census tracts in the donor pool. This form of permutation test allows for inference and the calculation of p-values: one tabulates the fraction of Census tracts with estimated effects larger than or as large as the one obtained for the treated unit (Abadie et al., 2015).[11] The number of values of $\hat{\alpha_{st}}$ rises with the number of Census tracts estimated as does the number of possible placebo average treatment effects. Consequently, with uniform probability I sample 100 placebo averages to construct each sample empirical permutation distribution of average treatment effects (Wiltshire, 2021a).

Figure 2 through Figure 4 show the estimated effect of stadium construction for Ingle-

[11] One potential complication with this procedure is that, even if a synthetic control is able to closely fit the trajectory of the outcome variable for the treated unit before the intervention, the same may not be true for all the units in the donor pool. For this reason a test statistic proposed by Abadie et al. (2010) is used that measures the ratio of the post-intervention fit relative to the pre-intervention fit.

wood, California, Las Vegas, NV and Atlanta GA respectively for Census tracts within each distance measure from the stadium site. As mentioned previously, Inglewood was uniquely accompanied by ancillary construction: industrial, residential, business and other activities. Therefore the positive results of the effect of the actual stadium on house prices in Inglewood should therefore be interpreted with caution due to these forces. If for example, many bars and restaurants open close to sports facilities, this will increase the demand for land in these areas and drive up existing property values. The estimation results are reported in column 1 of Table 6 through Table 8. I also find positive effects on home prices in Atlanta, GA and no effect in Las Vegas, NV, however I do not observe a sufficient amount of home transactions in Census tracts that are that are within one mile of the stadium for these two cities to construct HPI estimates.

Neto and Whetstone (2022) also estimate the impact of stadium construction in Las Vegas on residential property values. The authors use data from the Clark County Assessor's office which contains information on the characteristics of the residential properties as well as other transactions' information.[12] Their results show that residential properties after the announcement and the opening of the stadium experienced an increase of approximately 6 percent and 3 to 4.5 percent respectively for both the within 2.5 miles and 2.5 to 5 miles treatment groups.[13]

5.2 Employment

Government officials tend to view stadiums as magnets that could attract new commercial activity into cities and generate multipliers—where each dollar spent generates more than one dollar of economic activity as it is recirculated within the community—thereby growing employment, income, property values, and tax revenues (Bradbury et al., 2024). Using

[12]Residential properties in their sample are on average 15 years-old with three bedrooms and two bathrooms, with a real price of $307,455 and located 10.2 miles from the stadium. The authors focus only on single-family residential properties resulting in a sample size of 879,184 observations during their period of study. Their treatment groups comprise of homes within 2.5 miles and within 2.5 to 5 miles of the stadium in their main analysis.

[13]The authors estimate a hedonic model of log home prices controlling for housing characteristics, an interaction of an indicator for sales after an NHL arena opened in 2016 with the distance to the NHL arena. They also include residential property and time fixed effects. Because there may be property and location factors that are correlated with the treatment, they also focus on a repeated sales sample only considering properties that have been sold at least twice in their sample period.

establishment-level employment data form YourEconomy, in this paper I estimate the impact of stadium construction in each city on overall employment and employment in specific industries. I find no effect on overall employment in all three cities. Results are reported in column 2 and column 5 of Table 6 though Table 8 for each city respectively. Table 9 lists the specific 3-digit NAICS codes in which I define to complement stadium construction. For these industries, I find positive effects in Las Vegas, NV for all distance measures excluding the ‘two to three miles‘ estimates and positive effects in Inglewood, CA for establishments within one-two miles. I find no statistically significant effect in Atlanta, GA. Figure 5 through Figure 10 plot the employment estimates for each city respectively.

5.3 Foot Traffic and Consumer Spending

To my knowledge this is the first study that uses establishment-level credit/debit car transaction data to measure local consumer spending. Leveraging business spending and visit data from private vendors SafeGraph and Advan, I estimate the impact of each stadium on Sunday establishment visits and spending for the year 2023.[14] I use August as the treatment period, as this marks the start of preseason games and I in turn estimate monthly treatment effects. I also estimate the impact for the related industries specified in Table 9. Results of the overall effect are reported in column 3 and column 4 of Table 6 through Table 8 and industry specific results are reported in column 6 and column 7 of Table 6 though Table 8 for each city respectively for each city. Figure 11 through Figure 16 plot the visits estimates for each city respectively. For Inglewood, CA, I find positive effects on visits mainly for establishments within one to two miles of the stadium for both the ‘overall’ and ‘specific industry’ estimates. Results for Las Vegas and Atlanta show signs of both positive and negative effects within each city, suggesting that areas that saw increases in visits may have been transferred over from other areas.

Figure 17 through Figure 22 plot the consumer spending estimates for each city respectively. I find null spending effects in Inglewood, CA. While some months do appear to have one time spikes where spending increases, it appears to be an outlier of the spending trend

[14] I only observe Advan and SafeGraph data for the years 2019 to 2023 so I am unable to estimate yearly effects of stadium construction

during the football season suggesting that a specific event unrelated to the stadium may have caused this spike in spending. For Las Vegas spending significantly decreased at establishments within one miles for both overall and specific industry estimates. Null effects are found on spending in Atlanta.

Abbiasov and Sedov (2023) also use visits data for the year 2018, exploiting information on the number of games, average event attendance statistics, and an assumption regarding the spending of a typical consumer in local businesses when visiting a sports facility, the authors approximate the additional consumer spending due to foot traffic externalities. Their results indicate that the median sports facility generates roughly $11.3M of additional spending for the local food & accommodation and retail businesses. These finding don't appear to be in line with actual spending behaviors as apposed to predicted spending.

6 Additional Results: Demographic & Business Dynamics

6.1 Measuring Neighborhood Change

Glaeser et al. (2020) highlights the multitude of approaches to define and measure gentrification, mirroring the diverse array of research papers on the topic. Common metrics involve examining neighborhood demographics, including the percentage of college-educated residents, the proportion of individuals aged 25 to 34, racial composition, household income, and housing prices (Glaeser et al., 2018; Guerrieri et al., 2013). Alternatively, unconventional measures leverage big data sources such as Streetscore, a computer-generated metric gauging the perceived safety of a Google Streetview image, serving as a proxy for changes in the neighborhood's physical quality (Glaeser et al., 2018). Other studies incorporate Yelp reviews to pinpoint store closures, shifts from tradable goods to non-tradable ones, and alterations in price points (Glaeser et al., 2018).

As a preferred measure of gentrification I follow (Institute on Metropolitan Opportunity, 2019; LaPoint, 2023) and employ a two-stage, semi-parametric model that focuses on income-based population sorting to classify Census tracts into gentrifying and non-gentrifying categories. The model accounts for four distinct neighborhood migration patterns: “abandonment”, “gentrification”, “growth”, and “low-income concentration”. Stringency in each type definition is regulated by threshold parameters, including an “unclassified” category that encompasses neighborhoods undergoing negligible demographic shifts. The primary objective of this approach is to unveil patterns of neighborhood change and development at the census tract level. By facilitating the comparison of various types of neighborhood change, the model reveals the prevalence of each kind and allows for a examination of how different communities within major metropolitan areas are evolving. The model has been shown to be consistent with anecdotes and predictions of structural models in Urban Economics (LaPoint, 2023; Owens et al., 2020)

6.1.1 Step 1

The first step of the model initially categorizes neighborhoods into two distinct groups: “economically expanding” and “economically declining”. Economically expanding neighborhoods denote those that have undergone changes indicative of growth, gentrification, and economic strengthening. Conversely, economically declining neighborhoods are characterized by changes associated with impoverishment, disinvestment, and an exacerbation of poverty. Notably, not all neighborhoods undergo significant changes and are therefore left unclassified in this metric.

For example, to classify individual tracts in Atlanta, GA since the 2013 stadium announcement, I examine shifts in the population of low-income and non-low-income individuals between the American Community Survey 2008-2012 5-year wave and the 2015-2019 5-year wave which takes the following form

$$\Delta Y_i = Y_{i,2015-2019} - Y_{i,2008-2012} \tag{11}$$

where Y_i is a Census variable pertaining to tract i. Low-income individuals are defined as those falling below 200 percent of the federal poverty line, while non-low-income individuals constitute the remainder of the population.

I follow (Institute on Metropolitan Opportunity, 2019; LaPoint, 2023) and classify a tract as "economically expanding" when, between the two 5-year ACS waves, the *absolute* number of non-low-income individuals increases by over 10 percent, along with a decrease of more than 5 percentage points in the population share of low-income individuals. Conversely, a tract is labeled as "economically declining" if, during the same period, the *absolute* number of non-low-income individuals decreases by more than 10 percent, and the population share of low-income individuals increase of more than 5 percentage points. As discussed Institute on Metropolitan Opportunity (2019), the percentage cutoffs were established following an analysis of the distribution of shifts in the non-low-income population and low-income population share across all U.S. census tracts. These cutoffs guarantee that the observed changes are significant and genuine.

6.1.2 Step 2

The second step examines the changing low-income population share in an area, which functions as an indicator of the overall economic trajectory of that area. It assesses whether the general economic trajectory aligns with the demand indicated by the first condition. Following the initial classification of tracts as either economically expanding or declining, the model further categorizes these tracts into four groups based on changes in the low-income population within each tract.

Again, using Atlanta, GA as an example, this secondary classification is contingent on variations in the low-income population from the 2008-2012 ACS to 2015-2019 ACS. A tract is labeled as a "growth" tract if it is economically expanding and experiences an increase in the low-income population. Conversely, if a tract is economically expanding but witnesses a reduction in the low-income population, it is classified as a "low-income displacement" tract. In the case of an economically declining tract with a growing low-income population, it falls under the category of a "low-income concentration" tract. Last, if a tract is economically declining and sees a decrease in the low-income population, it is designated as an "abandonment" tract. This schema is represented in Figure 23.

Similar to any analytical approach, this model comes with both strengths and weaknesses. Importantly, the categories presented here rely on observations at the tract level rather than on individual homeowners.The non-longitudinal tract level data lacks the ability to differentiate between individuals leaving a tract and those experiencing changes in their economic circumstances. Also, it is plausible for multiple concurrent neighborhood change processes to be occurring within a tract, either simultaneously or sequentially. The ultimate categorization of a tract hinges on which trend proves more prevalent. Despite these complexities, this measure establishes a framework for discussing and quantifying neighborhood change. Figure 24 through Figure 26 show maps of the degree of demographic change since the announcement of each stadium respectively. I use these estimates for the analysis of local business dynamics discussed in section 6.2.

6.2 Local Business Dynamics

Glaeser et al. (2023) present a model in which gentrification can reduce overall social welfare through an endogenous change in amenities. As higher-paid residents enter, stores enter that specialize in services which cater to them replace idiosyncratic stores that generate more consumer surplus. The key distinction is that a reduction in the number idiosyncratic stores is like a drop in the number of product varieties which can lower utility, while an increase in the number of generic service stores provide the same goods but at a lower time cost (Dixit and Stiglitz, 1977). The model shows how welfare-reducing gentrification could happen, but does not imply that welfare is actually being reduced.

Handbury (2021) finds that stores favor high-income consumers more in wealthy locations than in poor ones through both their pricing and product offerings. The analysis also finds that the same patterns are observed across stores in different neighborhoods of the same city and once you account for income-specific tastes, markets that are relatively expensive for poor households can be instead relatively cheap for the wealthy.

Following Glaeser et al. (2023) I now turn to the regression analysis of closure rates across all three cities. My basic regression aggregates the total number of establishments within a Census tract and treats each Census tract as a unit of observation. The model predicts whether a business that was open at the time the stadium was announced, closes in the subsequent eight years (seven in Las Vegas). My key independent variables are distance measured dummy variables based on how far from the stadium businesses are in a given tract. More formally, my main probit specification for Atlanta, GA takes the following form

$$Pr((Closed)_{iz}^{2013-2020}) = \beta_0 + \beta_1 DistanceToStadium_{iz} + \delta \mathbf{X}_{iz} + \epsilon_{iz} \quad (12)$$

where i indexes tracts, z indexes zip-code and $\mathbf{X}$ denotes the vector of controls. I use ACS 5-year estimates to control for initial Census tract level demographic characteristics the year before the stadiums were announced. In the case for Atlanta, GA, I use 2008-2012 estimates. Specifically I control for; population density, population share between the ages of 25 to 34, black population share, the share of people with at least a bachelors degree, household income and rental prices. In addition, I control for the neighborhood change classification measure discussed in the previous section. Last, I control for both zip-code and tract fixed effects. All standard errors are clustered at the tract level.

Table 10 through Table 12 report regression estimates for each city respectively. To exploit the heterogeneity, for each city I specify five different regression models. Column 1 of each corresponding table reports estimates for the sample of all businesses. Column 2 report results for establishments that are classified by YourEconomy as being locally traded ("mom and pop") and are in the related industries reported in Table 9 while Column 3 reports estimates for the locally traded and unrelated industries. Column 4 and column 5 follow the previous two columns but for businesses that are classified as generic [15]

Similar to the findings in Glaeser et al. (2023), overall, I find negligible change in the probability of closing for local businesses based on their proximity to the stadium. This may be due to the fact that commercial leases tend to be long term and typically range from about five to ten years or even longer in some cases. However, I do find evidence that areas in Las Vegas which experienced significant neighborhood change, businesses were more likely to close.

Figure 27 highlights the breakdown of location choices of new establishments within 3 miles of each new stadium since its announcement through the end of 2023 broken down by that Census tract's neighborhood change classification. Not surprisingly, tracts that are classified as expanding (growth or low income displacement) see a higher average in the

[15] The locally traded category consists of establishment locations that are defined by YourEconomy as independent (place that does not report to a headquarters and does not have branch locations) or individual (a professional individual, often working within a practice with other individuals). Generic category consists of establishment locations that are classified as either being the Head Quarters, a Subsidiary or a Branch.

number of new businesses. However it worth noting that the majority of tracts in each city tend to be classified as low income concentration.

6.3 Within-City Heterogeneity

While most of the urban literature has focused on trying to explain cross-city differences in house price appreciation and the trajectories of demographic change, there are also substantial within-city differences in these measures. The house price appreciation for a city as a whole is just a composite of the house price movements within all the neighborhoods of the city. Therefore, understanding the movements in house prices across neighborhoods within a city is essential for understanding house price movements for the entire city (Guerrieri et al., 2013).

Guerrieri et al. (2013) present a model which links house price movements across neighborhoods within a city and the gentrification of those neighborhoods in response to a city wide housing demand shock. A key ingredient of the model is a positive neighborhood externality: individuals like to live next to richer neighbors. The in-migration of the richer residents into these border neighborhoods will bid up prices in those neighborhoods causing the original poorer residents to migrate out. They refer to this as "endogenous gentrification". Moreover, they show that there is a systematic pattern in this variation. In particular, they document several hypotheses with respect to within-city house price movements, two of which I explore in the context of stadium construction.

6.3.1 Guerrieri et al. (2013) Hypothesis 1: Initially low price neighborhoods within a city appreciate more than high price neighborhoods during city-wide housing booms

Figure 28 shows a sharp negative relationship between housing prices in the year before the stadium announcement for a Census tract and the subsequent percentage change in that tract for Inglewood in Panel A and Atlanta in Panel C. The vertical axes for each panel plots the average of the post period estimated ATTs for each Census tract within 3 miles of respective stadium. Excluding Las Vegas, on average, tracts with lower initial housing prices appreciated several times the rate as tracts with higher initial housing prices during the post period consistent with the hypothesis.

6.3.2 Guerrieri et al. (2013) Hypothesis 2: The variance in appreciation rates is also higher for initially low price neighborhoods during city-wide housing booms

Figure 28 shows that the variance is greater for tracts that had initially low median home prices. One potential mechanism the authors highlight that can explain this pattern is due to the positive neighborhood externality of richer individuals preferring to live next to richer neighbors.

6.3.3 Rental Costs

In Figure 29 I use rent data to analyze hypothesis 1 and 2. However the vertical axes simply plots the average of the post period growth in the raw data since I do not have yearly rent data to estimate treatment effects. I find evidence that this pattern hold for Las Vegas but not for the other two cities. The city of Inglewood implemented a rent control ordinance in 2019. The ordinance limits rent increases up to 5 percent each year on properties built after 1995 (excluding single-family homes and condos). However this ordinance did not apply to apartment units that are vacant. This means that the landlord can set initial rent at a price of their choosing and then the 5 percent limit per year sets in. The ordinance also requires a "just cause" for eviction of tenants. This was put in place in order to prevent landlords from evicting tenants in order to raise the asking rent price on vacant units. Landlords can evict tenants for causes such as non-payment, criminal activity and drug use.[16]

[16] The State of California implemented the "Tenant Protection Act of 2019" which was signed by Governor Newsom on October 8th, 2019 and took effect on January 1, 2020. The law limits how much rents can be increased and the allowable reasons for evicting tenants in covered units. Rents can only increase by 5 percent plus the local CPI or 10 percent whichever is lower. If a unit is already covered by Inglewood's local eviction or rent increase regulations, the unit remains subject to those local regulations and the statewide law does not remove or replace those tenant protections.

6.3.4 Household Income

In Figure 30 I analyze the median household income, again plotting the average of the post period growth of the raw data. The neighborhoods that had initially low median household income saw the greatest growth in income with stronger effects in Inglewood suggesting that this could be one of the main drivers of the observed home price appreciation after each stadium announcement. (Glaeser, 2008) note that an attractive amenity will attract the people who are willing to pay the most for it. If those people are rich, and if people like living around rich people, then the first natural amenity will be correlated with the second amenity of living around richer people.

7 Summary and Concluding Remarks

Traditionally, urban economics has perceived cities as offering advantages in production rather than in consumption. However, recent research suggests that a city's success may depend on its role as a "consumer city," driven by endogenous amenities. Over the past two decades, the United States has seen a significant increase in the construction of professional sports venues, with state and local governments investing $19 billion since 2000 to fund these projects, positioning stadiums as catalysts for economic development. Evaluating the impact of new sports facilities on home values and local economic activity can shed light on how residents perceive the value of proximity to these venues and the externalities they generate.

Existing research often inadequately captures the impact of professional sports facilities by analyzing economic development at broader geographic levels, such as counties or metropolitan statistical areas. While significant economic effects may not be evident at the metropolitan level, neighborhoods near stadiums and arenas can experience positive spillover effects that remain hidden in broader data. In this paper, I utilize a variety of rich establishment-level data sources to assess the impact of new stadium construction on employment, local foot traffic, consumer spending, establishment churn, residential property values, and overall neighborhood change in Inglewood, CA, Las Vegas, NV, and Atlanta, GA.

Using a stacked synthetic control approach, I find positive effects on home prices in

Atlanta, GA, and Inglewood, CA. I find no impact on overall employment in any city, however I do find significant employment effects for Las Vegas in service sector industries that complement with the stadium construction. I find moderate evidence of increased establishment visits in all three cities while I find moderate positive effects on overall spending in Inglewood, CA.

Overall, I find negligible change in the probability of closing for local businesses based on their proximity to the stadium. This may be due to the fact that commercial leases tend to be long term relative to residential leases. However, I do find evidence that areas in Las Vegas which experienced significant neighborhood change, businesses were more likely to close. Consistent with the predictions of a theoretical model, I find evidence that initially low price neighborhoods appreciate more than initially high price neighborhoods in Inglewood and Atlanta, GA.

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Table 1: Summary Statistics: Inglewood, CA

(1) Variable	(2) Mean	(3) Std.	(4) Min	(5) Max	(6) Tracts
HPI	186	30	119	287	118
Rent	1,434	372	648	3,422	199
HHI	56,424	30,012	15,840	187,575	199
Black	0.308	0.237	0.003	0.890	199
College	0.184	0.170	0.120	0.765	199
Jobs	1,097	2,369	15	32,804	203

(a) **Pre-Construction: Treatment**

Variable	Mean	Std.	Min	Max	Tracts
HPI	183	28	130	317	97
Rent	1,539	507	521	4,025	329
HHI	64,295	35,045	12,930	305,002	330
Black	0.053	0.080	0.000	0.716	331
College	0.304	0.232	0.208	0.819	331
Jobs	1,865	3,752	24	33,781	332

(b) **Pre-Construction: Control**

Variable	Mean	Std.	Min	Max	Tracts
HPI	356	61	236	588	118
Rent	1,701	516	971	3501	249
HHI	74,276	34,880	21,492	222,888	247
Black	0.269	0.218	0.000	0.906	249
College	0.237	0.191	0.000	0.853	249
Jobs	1,206	2,380	36	25,214	203

(c) **Post-Construction: Treatment**

Variable	Mean	Std.	Min	Max	Tracts
HPI	308	53	214	562	97
Rent	1,886	626	301	3,501	415
HHI	78,217	33,689	9,417	238,125	408
Black	0.067	0.096	0.000	0.815	417
College	0.383	0.248	0.000	0.922	417
Jobs	2,184	4,167	25	38,671	332

(d) **Post-Construction: Control**

Notes: Table 1 repots summary statistics for the FHFA HPI and ACS data used for Inglewood, California. Panel A summarizes the treatment zone (zero to five miles) before construction began using ACS 5-year data from 2011-2015. Panel B summarizes the control group (seven to ten miles) before construction began. Panel C reports the post-construction statistics for the treatment zone using ACS 5-year data form 2018-2022. Panel D reports post-construction statistics for the control group. The HPI and Jobs statistics correspond to the ACS years used.

Table 2: Summary Statistics: Las Vegas, NV

(1) Variable	(2) Mean	(3) Std.	(4) Min	(5) Max	(6) Tracts
HPI	120	24	64	183	60
Rent	1,300	407	655	3,151	110
HHI	61,481	24,529	24,889	138,238	111
Black	0.108	0.718	0.011	0.482	111
College	0.216	0.102	0.039	0.532	111
Jobs	3,400	8,377	20	79,723	124

(a) **Pre-Construction: Treatment**

Variable	Mean	Std.	Min	Max	Tracts
HPI	110	23	58	155	39
Rent	1,414	412	722	3,079	133
HHI	68,040	28,317	21,939	167,597	133
Black	0.110	0.094	0.010	0.611	133
College	0.210	0.155	0.015	0.608	133
Jobs	1,054	1,426	23	8,466	133

(b) **Pre-Construction: Control**

Variable	Mean	Std.	Min	Max	Tracts
HPI	221	38	161	343	60
Rent	1,441	392	804	3080	115
HHI	66,514	25,377	20,625	143,438	116
Black	0.132	0.093	0.007	0.519	116
College	0.257	0.113	0.034	0.693	116
Jobs	3,619	8,595	49	83,495	124

(c) **Post-Construction: Treatment**

Variable	Mean	Std.	Min	Max	Tracts
HPI	219	39	152	318	39
Rent	1,570	426	821	3,501	154
HHI	73,932	30,589	23,361	173,333	154
Black	0.111	0.091	0.000	0.478	154
College	0.243	0.167	0.020	0.647	154
Jobs	1,176	1,532	30	8,682	133

(d) **Post-Construction: Control**

Notes: Table 2 repots summary statistics for the FHFA HPI and ACS data used for Las Vegas, Nevada. Panel A summarizes the treatment zone (zero to five miles) before construction began using ACS 5-year data from 2012-2016. Panel B summarizes the control group (seven to ten miles) before construction began. Panel C reports the post-construction statistics for the treatment zone using ACS 5-year data form 2018-2022. Panel D reports post-construction statistics for the control group. The HPI and Jobs statistics correspond to the ACS years used

Table 3: Summary Statistics: Atlanta, GA

(1) Variable	(2) Mean	(3) Std.	(4) Min	(5) Max	(6) Tracts
HPI	120	14	72	156.	46
Rent	1,041	261	580	2,221	88
HHI	50,299	36,647	6,398	178,334	88
Black	0.622	0.345	0.011	1	89
College	0.362	0.269	0.016	0.877	89
Jobs	1,700	4,388	0	36,189	83

(a) **Pre-Construction: Treatment**

Variable	Mean	Std.	Min	Max	Tracts
HPI	108	20	59	158	61
Rent	1,073	261	580	2,221	61
HHI	66,795	36,390	22,528	200,592	62
Black	0.473	0.377	0.005	.995	63
College	0.395	0.248	0.025	0.882	63
Jobs	2,341	3,501	171	17,652	52

(b) **Pre-Construction: Control**

Variable	Mean	Std.	Min	Max	Tracts
HPI	175	31	82	293	46
Rent	1,104	355	364	2335	89
HHI	60,630	43,486	12,485	208,750	89
Black	0.606	0.345	0.014	1	90
College	0.409	0.267	0.041	0.890	90
Jobs	1,679	3,884	14	28,648	83

(c) **Post-Construction: Treatment**

Variable	Mean	Std.	Min	Max	Tracts
HPI	151	33	71	254	61
Rent	1,248	326	729	2,267	62
HHI	75,979	44,068	23,546	208,750	62
Black	0.475	0.359	0.003	0.972	63
College	0.445	0.251	0.045	0.887	63
Jobs	2,305	3,544	147	17,392	52

(d) **Post-Construction: Control**

Notes: Table 3 repots summary statistics for the FHFA HPI and ACS data used for Atlanta, GA. Panel A summarizes the treatment zone (zero to five miles) before construction began using ACS 5-year data from 2008-2012. Panel B summarizes the control group (seven to ten miles) before construction began. Panel C reports the post-construction statistics for the treatment zone using ACS 5-year data form 2015-2019. Panel D reports post-construction statistics for the control group. The HPI and Jobs statistics correspond to the ACS years used except for the pre-construction statistics, years 2010-2012 are used.

Table 4: Summary Statistics: 2023 Sunday Foot Traffic & Spending

(1)	(2)	(3)	(4)	(5)	(6)
Variable	Mean	Std.	Min	Max	Tracts
January-July					
Foot Traffic(T)	3,737	23,292	0	444,255	201
Foot Traffic(C)	8,222	36,843	0	731,601	330
Spending(T)	4,708	17,744	0	421,245	167
Spending(C)	6,336	17,799	0	415,103	293
August-December					
Foot Traffic(T)	1,311	6,048	0	95,548	201
Foot Traffic(C)	1,393	3,502	0	42,000	330
Spending(T)	8,202	100,797	0	2,882,301	167
Spending(C)	6,206	16,595	0	247,350	293

(a) **Inglewood, CA**

Variable	Mean	Std.	Min	Max	Tracts
January-July					
Foot Traffic(T)	39,509	213,293	.0	2,371,445	111
Foot Traffic(C)	4,758	8,621	0	75,195	126
Spending(T)	24,904	98,889	0	1,654,776	103
Spending(C)	13,351	111,006	0	2,852,218	100
August-December					
Foot Traffic(T)	34,187	177,862	0	2,007,609	111
Foot Traffic(C)	4,659	9,124	0	86,524	126
Spending(T)	33,674	172,379	0	3,242,340	103
Spending(C)	28,723	170,927	0	2,491,825	100

(b) **Las Vegas, NV**

Variable	Mean	Std.	Min	Max	Tracts
January-July					
Foot Traffic(T)	8,331	34,827	11	614,139	82
Foot Traffic(C)	11,606	32,355	56	450,485	65
Spending(T)	5,066	13,786	0	155,218	66
Spending(C)	7,885	17,392	0	195,852	56
August-December					
Foot Traffic(T)	7,655	19,726	0	176,223	82
Foot Traffic(C)	11,740	29,871	65	231,420	65
Spending(T)	3,785	8,991	0	109,444	66
Spending(C)	7,409	15,841	0	154,023	56

(c) **Atlanta, GA**

Notes: Table 4 reports Advan Sunday visits and SafeGraph Sunday spending statistics for the year 2023. January though July are the pre-football season months while August through December are the football season month. (T) and (C) represent treatment and control groups respectively.

Table 5: New Stadium Timeline

(1) City	(2) Announced	(3) Broke Ground	(4) Opening
Atlanta, GA	March, 2013	May, 2014	August, 2017
Inglewood, CA	January, 2016	November, 2016	August, 2020
Las Vegas, NV	March, 2017	September, 2017	August, 2020

Notes: Table 5 repots a timeline for each city's new stadium. Column 1 lists the name of each city where a new stadium was built. Column 2 reports when each stadium was announced. Column 3 reports when construction began in each city. Column 4 reports the opening date of each stadium. Atlanta's new stadium was build adjacent to its previous stadium while the Raiders previous stadium was in Oakland, CA. The Rams and the Chargers previous stadiums were in St Louis, MO and San Diego, CA respectively.

Table 6: Synthetic Control Estimates, Average Difference: Inglewood, CA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Home Price Index	Employment	Foot Traffic	Spending	Employment*	Foot Traffic*	Spending*
Panel A: 0-1 Mile							
$\hat{\alpha}_1$	39.750	45.077	46.957	116.356	-21.538	68.019	173.986
p-value	0.009	0.200	0.518	0.980	0.133	0.073	0.766
Panel B: 1-2 Miles							
$\hat{\alpha}_1$	40.862	-10.273	702.726	93,062.79	46.882	318.692	374.665
p-value	0.009	0.657	0.009	0.019	0.021	0.009	0.724
Panel C: 2-3 Miles							
$\hat{\alpha}_1$	27.305	-10.629	74.030	-1539.97	-12.235	74.030	833.768
p-value	0.009	0.459	0.245	0.019	0.318	0.190	0.166
Panel D: 3-4 Miles							
$\hat{\alpha}_1$	24.744	0.870	38.267	-835.386	-10.006	11.609	88.776
p-value	0.009	0.695	0.441	0.930	0.131	0.609	0.976
Panel E: 4-5 Miles							
$\hat{\alpha}_1$	20.187	33.113	-3.717	545.741	-3.279	-0.523	107.866
p-value	0.009	0.638	0.358	0.603	0.922	0.312	0.580

Notes: Table 6 presents estimates of the effect of stadium construction in Inglewood, California on the Federal Housing Financing Agency: Home Price Index, Employment, Foot Traffic and Spending using the synthetic control method outlined in Section 4. The reported estimates are the average of the treatment effects over the post treatment period. The p-values are constructed using the permutation test also described in Section 4. The asterisks(*) represents estimates restricted to the industries outlined in Table 9.

Table 7: Synthetic Control Estimates, Average Difference: Las Vegas, NV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Home Price Index	Employment	Foot Traffic	Spending	Employment*	Foot Traffic*	Spending*
Panel A: 0-1 Mile							
$\hat{\alpha}_1$		-257.347	56,805.906	-2,592,340	1,190.187	56,805.906	-991,383.726
p-value		0.971	0.009	0.920	0.009	0.009	0.131
Panel B: 1-2 Miles							
$\hat{\alpha}_1$	1.229	173.853	-512.295	-37,727.5	292.755	409.238	-727.332
p-value	0.521	0.830	0.253	0.485	0.009	0.009	0.320
Panel C: 2-3 Miles							
$\hat{\alpha}_1$	0.343	-27.644	1539.944	-28,058.48	35.342	409.238	2942.074
p-value	0.732	0.413	0.009	0.376	0.145	0.581	0.144
Panel D: 3-4 Miles							
$\hat{\alpha}_1$	2.658	31.761	-249.199	-28,058.48	66.947	-234.722	2442.087
p-value	0.295	0.264	0.009	0.376	0.009	0.009	0.237
Panel E: 4-5 Miles							
$\hat{\alpha}_1$	1.663	-69.515	-204.344	-36,425.45	-8.415	21.337	591.040
p-value	0.186	0.186	0.251	0.554	0.325	0.241	0.536

Notes: Table 7 presents estimates of the effect of stadium construction in Las Vegas, Nevada on the Federal Housing Financing Agency: Home Price Index, Employment, Median Foot Traffic and Spending using the synthetic control method outlined in Section 4. The reported estimates are the average of the treatment effects over the post treatment period. The p-values are constructed using the permutation test also described in Section 4. The asterisks(*) represents estimates restricted to the industries outlined in Table 9. FHFA HPI data are missing for Census tracts within one mile.

Table 8: Synthetic Control Estimates, Average Difference: Atlanta, GA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Home Price Index	Employment	Foot Traffic	Spending	Employment*	Foot Traffic*	Spending*
Panel A: 0-1 Mile							
$\hat{\alpha}_1$		-433.364	1,710.785	1,550.06	-148.175	561.922	-793.248
p-value		0.244	0.079	0.673	0.119	0.075	0.085
Panel B: 1-2 Miles							
$\hat{\alpha}_1$	20.560	339.433	-29,111.97	-614.359	-64.181	9335.495	566.536
p-value	0.009	0.567	0.009	0.485	0.367	0.033	0.251
Panel C: 2-3 Miles							
$\hat{\alpha}_1$	9.334	91.064	130.974	714.796	-31.844	2.757	529.965
p-value	0.027	0.765	0.106	0.732	0.362	0.453	0.493
Panel D: 3-4 Miles							
$\hat{\alpha}_1$	-4.633	-63.178	-41.746	-1,492.139	-14.653	124.854	-125.355
p-value	0.327	0.793	0.906	0.960	0.544	0.554	0.407
Panel E: 4-5 Miles							
$\hat{\alpha}_1$	-3.324	40.574	-135.336	-4,388.695	-11.803	-14.393	-673.028
p-value	0.277	0.867	0.805	0.584	0.748	0.637	0.102

Notes: Table 8 presents estimates of the effect of stadium construction in Atlanta, Georgia on the Federal Housing Financing Agency: Home Price Index, Employment, Median Foot Traffic and Spending using the synthetic control method outlined in Section 4. The reported estimates are the average of the treatment effects over the post treatment period. The p-values are constructed using the permutation test also described in Section 4. The asterisks(*) represents estimates restricted to the industries outlined in Table 9. FHFA HPI data are missing for Census tracts within one mile.

Table 9: 3 Digit NAICS Codes

(1)	(2)
NAICS Code	Description
455	General Merchandise Retailers
458	Clothing, Clothing Accessories, Shoe, and Jewelry Retailers
445	Food and Beverage Retailers
459	Sporting Goods, Hobby, Musical Instrument, Book, and Miscellaneous Retailers
721	Accommodation
722	Food Services and Drinking Places
711	Performing Arts, Spectator Sports, and Related Industries
712	Museums, Historical Sites, and Similar Institutions
713	Amusement, Gambling, and Recreation Industries

Notes: North American Industry Classification System 2022 definitions are used

Table 10: Probability of Closure: Inglewood, CA

	(1)	(2)	(3)	(4)	(5)
	All	Local Brand -Related	Local Brand -Unrelated	Generic -Related	Generic -Unrelated
One mile	-0.0195	0.0708	0.0279	-0.516	-0.164
	(0.0564)	(0.105)	(0.0615)	(0.337)	(0.145)
Two miles	0.0541	-0.0217	0.0873	-0.322	0.0650
	(0.0627)	(0.0704)	(0.0715)	(0.176)	(0.111)
Three miles	0.0482	-0.0233	0.0854	-0.162	-0.00497
	(0.0545)	(0.0652)	(0.0650)	(0.144)	(0.116)
Four miles	0.0274	0.0624	0.0384	-0.434*	-0.110
	(0.0401)	(0.0615)	(0.0430)	(0.203)	(0.121)
Five miles	0.0407	-0.0157	0.0811	-0.30 **	-0.0834
	(0.0517)	(0.0558)	(0.0565)	(0.106)	(0.0894)
Growth	-0.0520	0.0491	-0.0664	-0.00944	-0.0999
	(0.0601)	(0.0681)	(0.0610)	(0.0882)	(0.0819)
LI displacement	0.0160	-0.0152	0.0284	-0.193	0.0327
	(0.0473)	(0.0570)	(0.0495)	(0.126)	(0.0925)
LI concentration	-0.00610	-0.0212	-0.00636	-0.0609	0.0187
	(0.0349)	(0.0350)	(0.0384)	(0.0833)	(0.0611)
Abandonment	0.0457	0.104	0.0338	-0.0818	0.0955
	(0.0405)	(0.0541)	(0.0453)	(0.138)	(0.0692)
ACS Controls	✓	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓	✓
N	105401	18632	77126	3408	6235

Standard errors in parentheses

$* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$

Notes: Table 10 repots probit estimates of the probability of closure between 2016-2023 based on distance measures to the stadium for establishments that were in business the year before the stadium announcement in Inglewood, California. Related and Unrelated distinguish establishments that are in industries included and not included in Table 9 respectively. All standard errors are clustered at the tract level.

Table 11: Probability of Closure: Las Vegas, NV

	(1)	(2)	(3)	(4)	(5)
	All	Local Brand -Related	Local Brand -Unrelated	Generic -Related	Generic -Unrelated
One mile	-0.206	-0.158	-0.259	-0.0651	-0.138
	(0.145)	(0.138)	(0.163)	(0.157)	(0.163)
Two miles	-0.225*	-0.266*	-0.264*	-0.0332	-0.178
	(0.106)	(0.117)	(0.122)	(0.214)	(0.139)
Three miles	-0.0436	-0.128	-0.0659	0.0679	0.0437
	(0.0918)	(0.115)	(0.101)	(0.120)	(0.123)
Four miles	-0.0312	-0.124	-0.0383	-0.0479	0.0416
	(0.0747)	(0.0914)	(0.0791)	(0.130)	(0.103)
Five miles	-0.281**	-0.261*	-0.297**	-0.290	-0.184
	(0.0954)	(0.112)	(0.0955)	(0.167)	(0.124)
Growth	0.296**	-0.00426	0.409***	0.00222	0.365**
	(0.101)	(0.119)	(0.104)	(0.179)	(0.138)
LI displacement	0.376 ***	0.184	0.484 ***	0.0359	0.391***
	(0.101)	(0.120)	(0.116)	(0.115)	(0.110)
LI concentration	0.186*	0.142	0.202**	0.259*	0.172
	(0.0727)	(0.0823)	(0.0765)	(0.124)	(0.0956)
Abandonment	0.00141	-0.0328	0.0298	-1.074**	0.0421
	(0.0821)	(0.168)	(0.102)	(0.417)	(0.173)
ACS Controls	✓	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓	✓
N	49747	6732	35168	3220	4627

Standard errors in parentheses

$* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$

Notes: Table 11 repots probit estimates of the probability of closure between 2017-2023 based on distance measures to the stadium for establishments that were in business the year before the stadium announcement in Las Vegas, Nevada. Related and Unrelated distinguish establishments that are in industries included and not included in Table 9 respectively. All standard errors are clustered at the tract level.

Table 12: Probability of Closure: Atlanta, GA

	(1)	(2)	(3)	(4)	(5)
	All	Local Brand -Related	Local Brand -Unrelated	Generic -Related	Generic -Unrelated
one mile	0.170*	0.121	0.145	-0.0330	0.344
	(0.0849)	(0.151)	(0.100)	(0.250)	(0.218)
two miles	0.133	-0.0309	0.117	-0.470	0.265
	(0.0925)	(0.158)	(0.105)	(0.314)	(0.208)
three miles	0.102	-0.146	0.132	-0.300	0.00756
	(0.0912)	(0.121)	(0.0925)	(0.224)	(0.199)
four miles	0.0421	-0.0152	0.0344	0.274	-0.306
	(0.0836)	(0.121)	(0.0962)	(0.290)	(0.205)
five miles	-0.137*	-0.287***	-0.128	-0.204	-0.191
	(0.0601)	(0.0852)	(0.0683)	(0.175)	(0.180)
Growth	0.0998	0.159	0.0841	0.425*	0.106
	(0.0622)	(0.0998)	(0.0673)	(0.168)	(0.116)
LI displacement	0.119	0.121	0.128	0.456	-0.105
	(0.0633)	(0.114)	(0.0720)	(0.291)	(0.145)
LI concentration	0.0147	0.0606	0.00648	0.145	-0.0183
	(0.0479)	(0.0799)	(0.0503)	(0.143)	(0.0909)
Abandonment	-0.0118	0.0115	-0.00268	-0.553	-0.154
	(0.0530)	(0.0942)	(0.0770)	(0.321)	(0.112)
ACS Controls	✓	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓	✓
N	21546	2784	15877	838	2047

Standard errors in parentheses

$* \ p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$

Notes: Table 12 repots probit estimates of the probability of closure between 2013-2020 based on distance measures to the stadium for establishments that were in business the year before the stadium announcement in Atlanta, Georgia. Related and Unrelated distinguish establishments that are in industries included and not included in Table 9 respectively. All standard errors are clustered at the tract level.

Figure 1: Major-League Sports Venue Opening in US and Canada,1970–2020

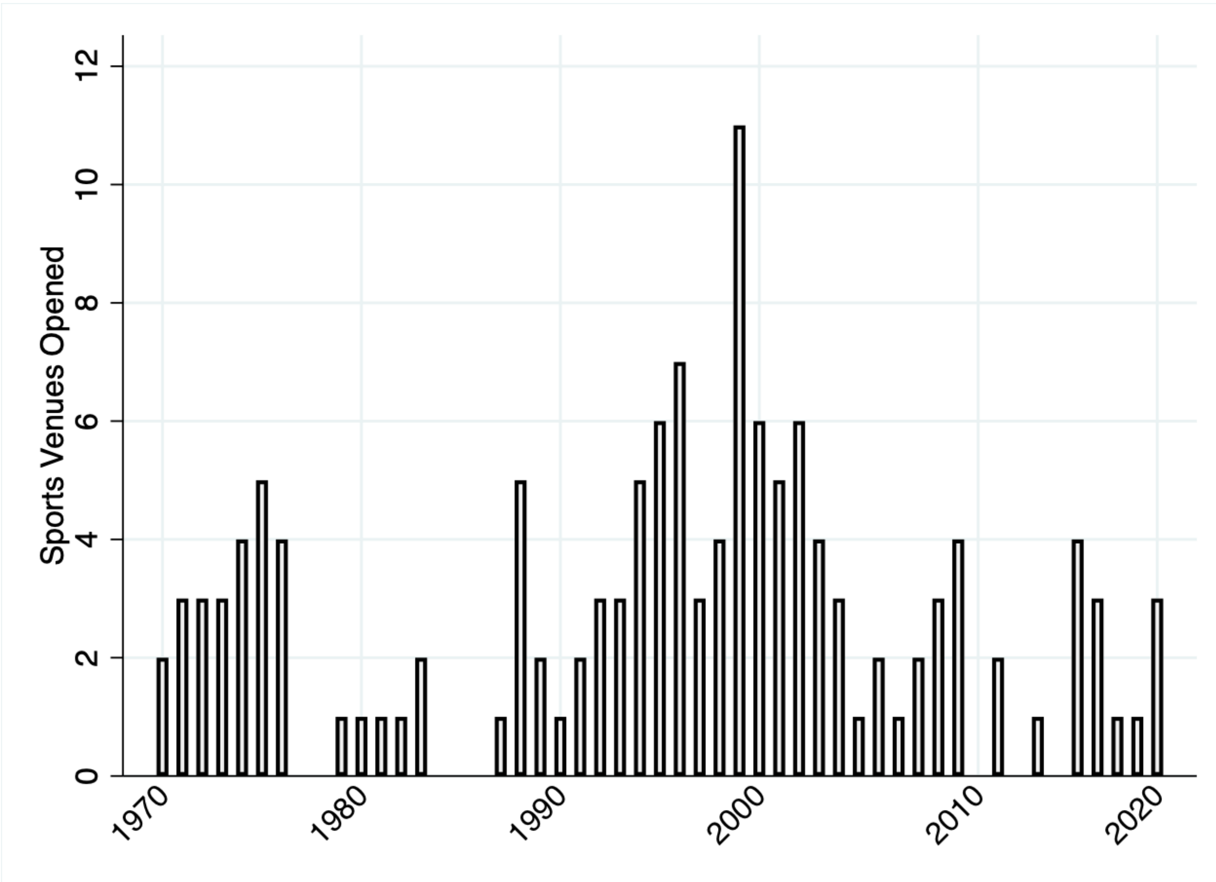
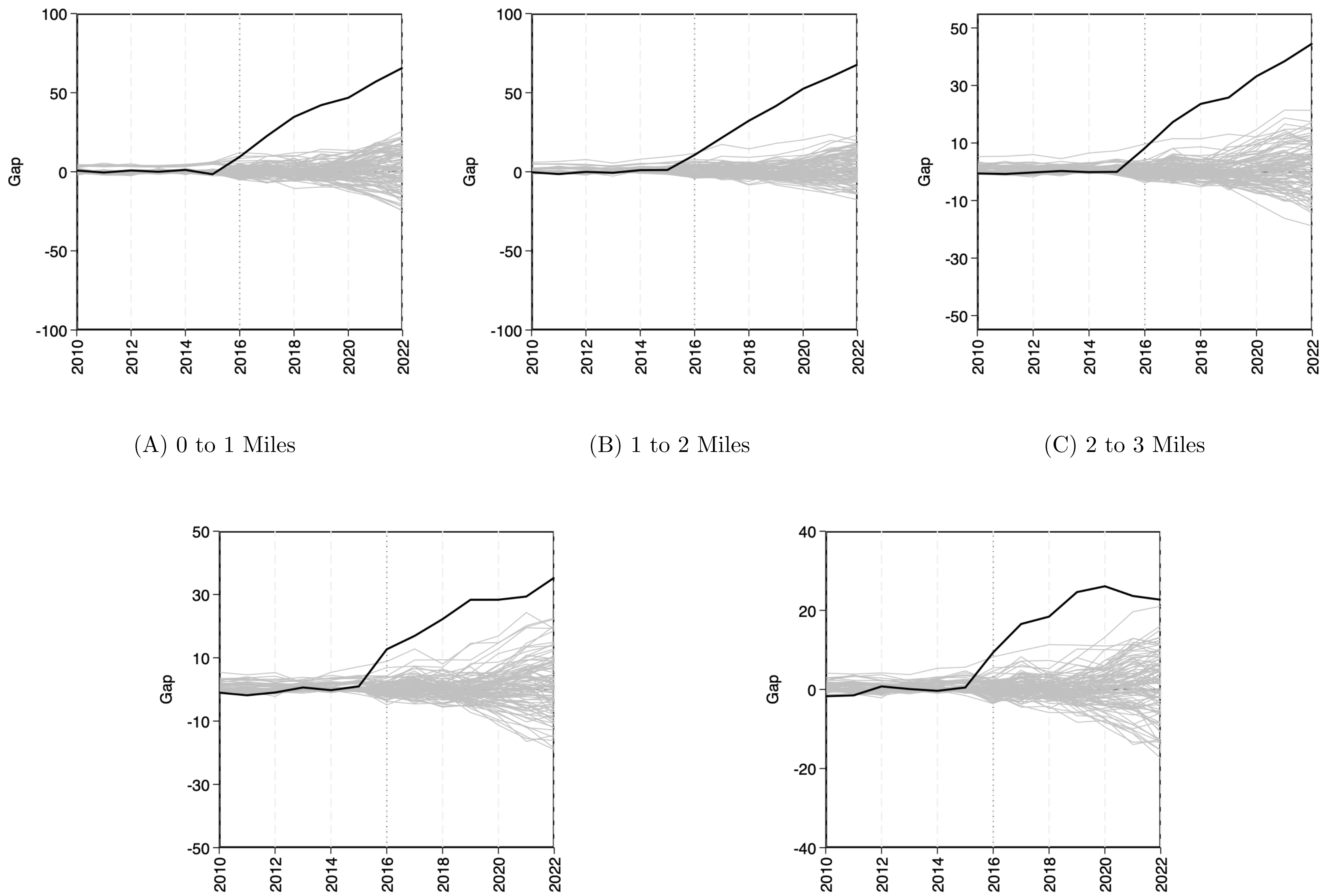


Figure 1 shows the number of new stadium and arena openings since 1970. During the 1990s through the early 2000s, roughly 50% of the 122 teams in the four major professional leagues in the United States moved into a new or substantially renovated venue (Depken et al., 2007). Fifty-seven new sporting venues were built between 2000 and 2020 and many more new facilities will likely be announced over the next 15 years. On average, teams have replaced their existing stadiums every 27 years which suggests that another wave of stadium construction might be expected within the next decade (Humphreys, 2019; Bradbury et al., 2022).

Figure 2: Inglewood, California: Home Price Index



(A) 0 to 1 Miles

(B) 1 to 2 Miles

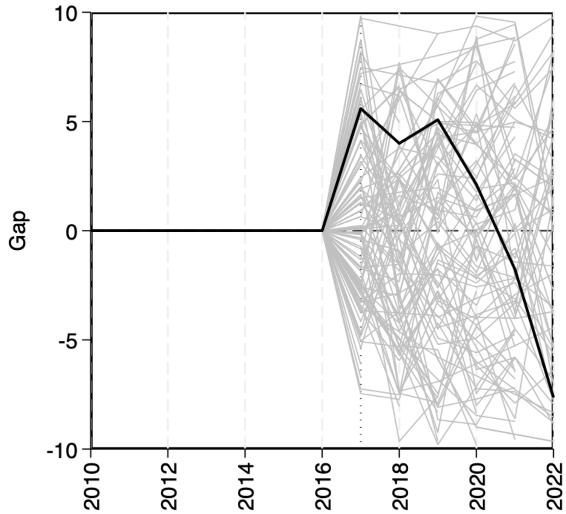
(C) 2 to 3 Miles

(D) 3 to 4 Miles

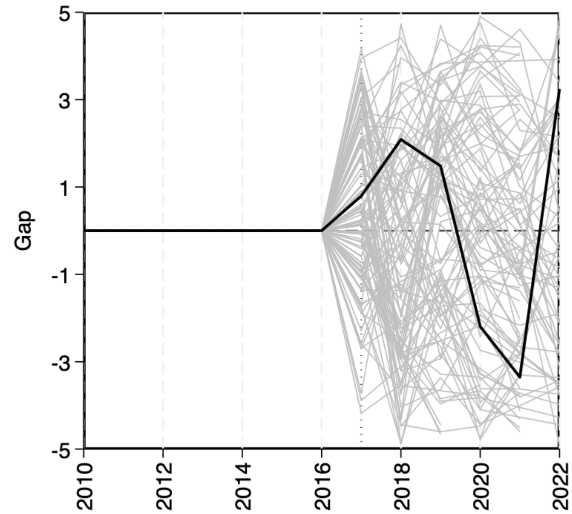
(E) 4 to 5 Miles

Notes: Figure 2 plots the synthetic control estimates for the Federal Housing Financing Agency home price index in Inglewood, California. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual Home Price index for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

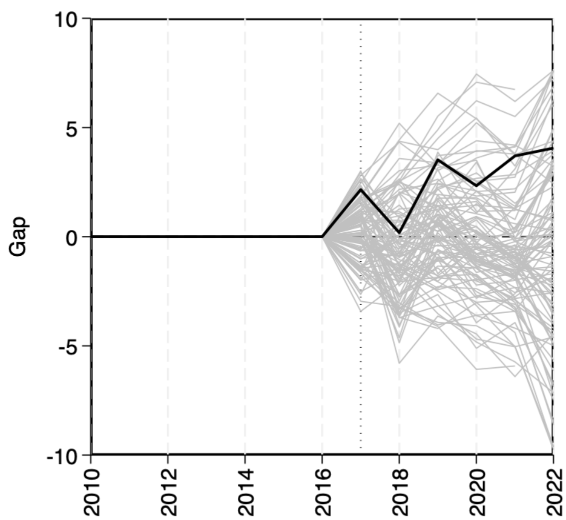
Figure 3: Las Vegas, Nevada: Home Price Index



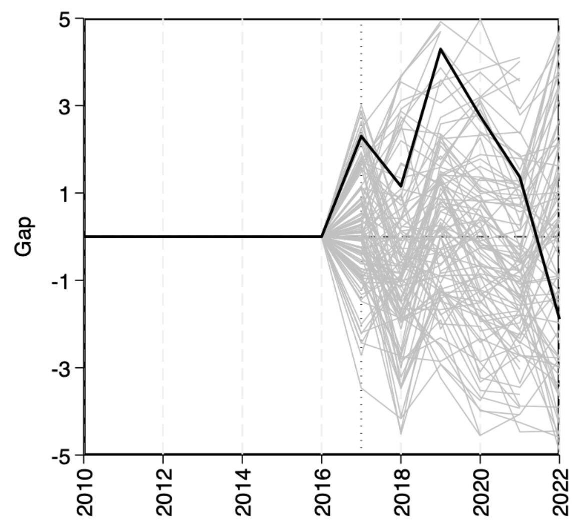
(A) 1 to 2 Miles



(B) 2 to 3 Miles



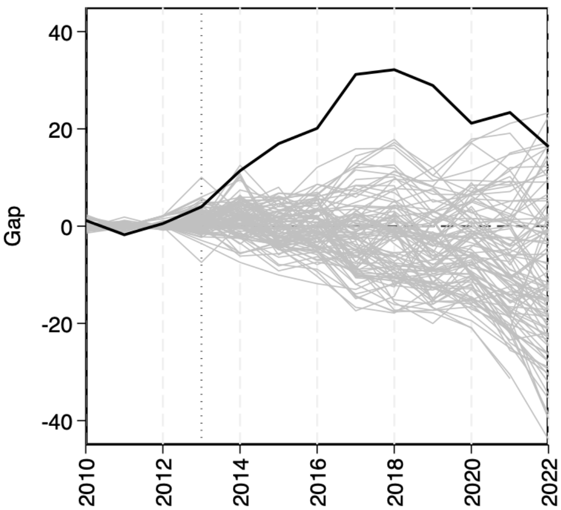
(C) 3 to 4 Miles



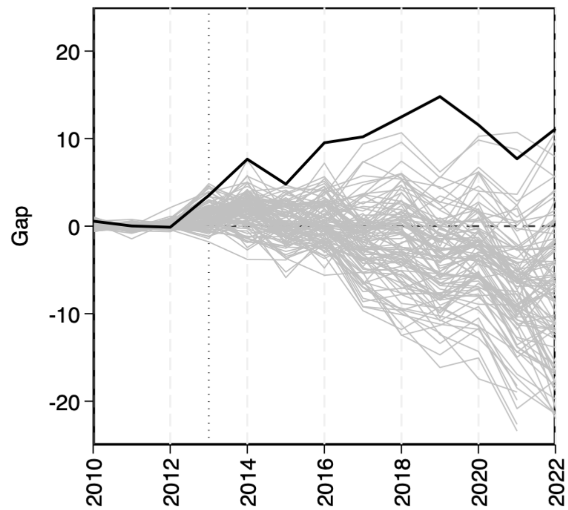
(D) 4 to 5 Miles

Notes: Figure 3 plots the synthetic control estimates for the Federal Housing Financing Agency home price index in Las Vegas, Nevada. Panels A through D plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual Home Price index for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects. Data for Census tracts within one mile mile are missing

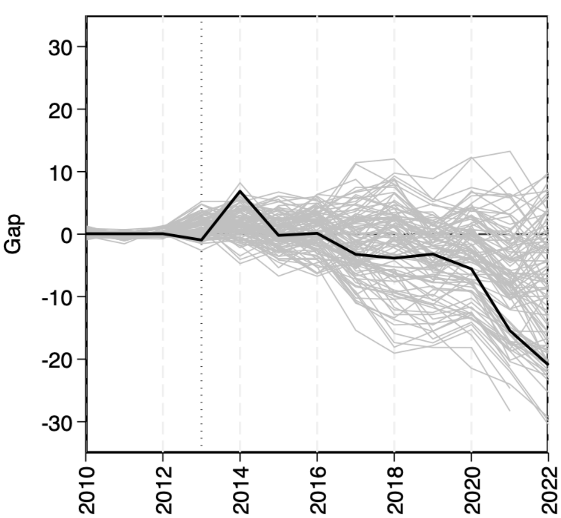
Figure 4: Atlanta, Georga: Home Price Index



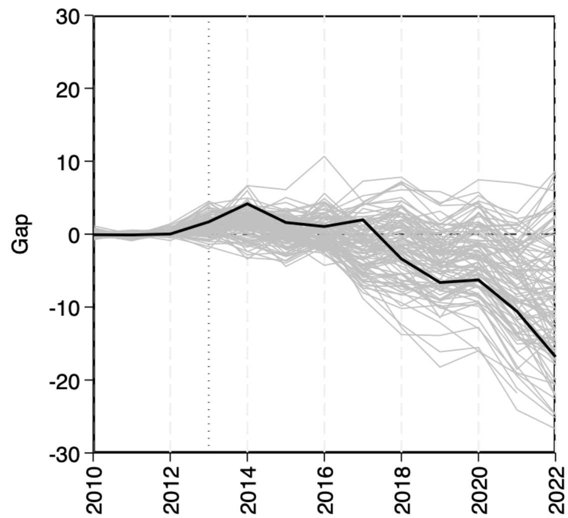
(A) 1 to 2 Miles



(B) 2 to 3 Miles



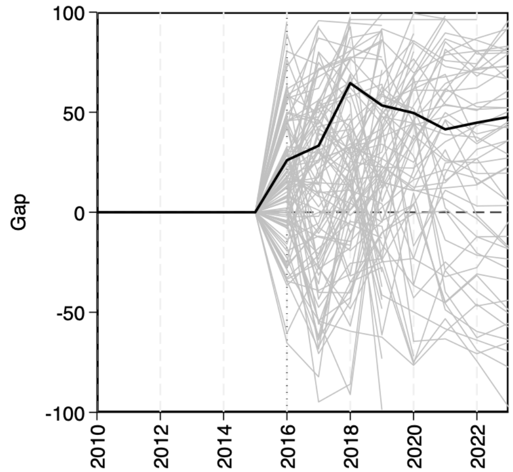
(C) 3 to 4 Miles



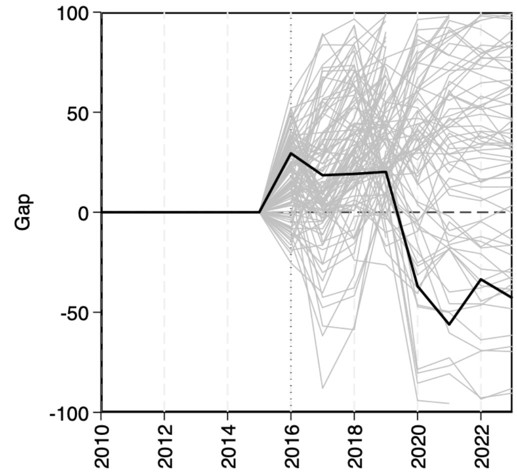
(D) 4 to 5 Miles

Notes: Figure 4 plots the synthetic control estimates for the Federal Housing Financing Agency home price index in Atlanta, Georgia. Panels A through D plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual Home Price index for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects. Data for Census tracts within one mile mile are missing

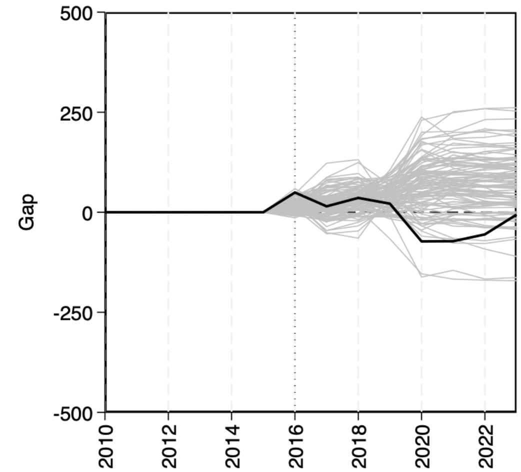
Figure 5: Inglewood, California: Jobs: Overall



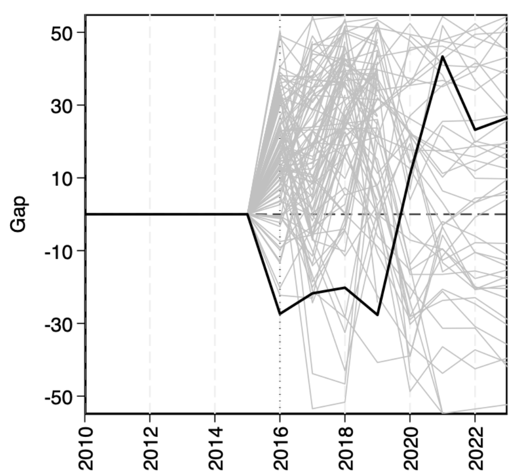
(A) 0 to 1 Miles



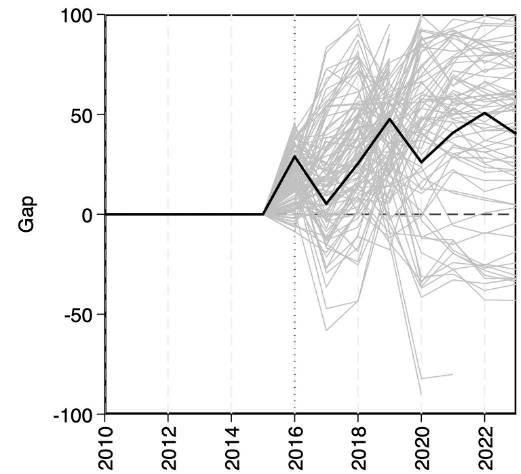
(B) 1 to 2 Miles



(C) 2 to 3 Miles



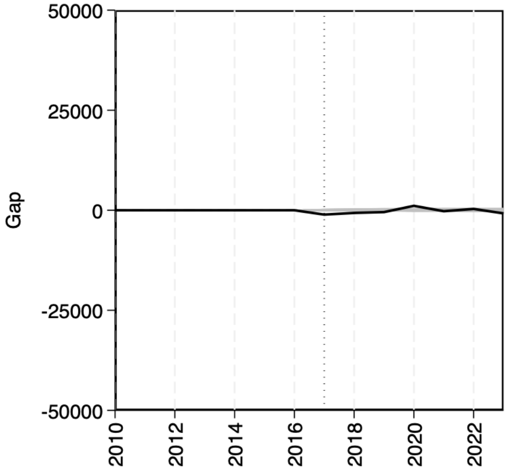
(D) 3 to 4 Miles



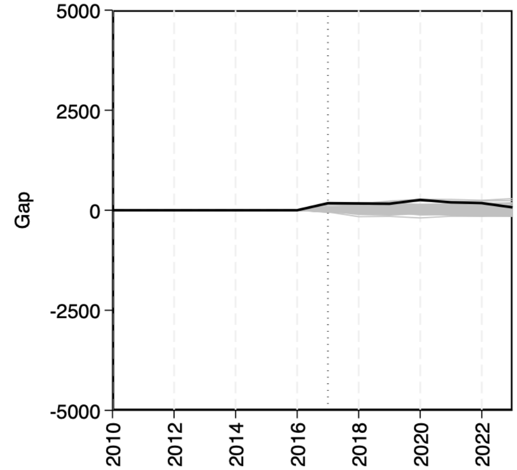
(E) 4 to 5 Miles

Notes: Figure 5 plots the synthetic control estimates for overall employment in all industries in Inglewood, California. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual employment for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

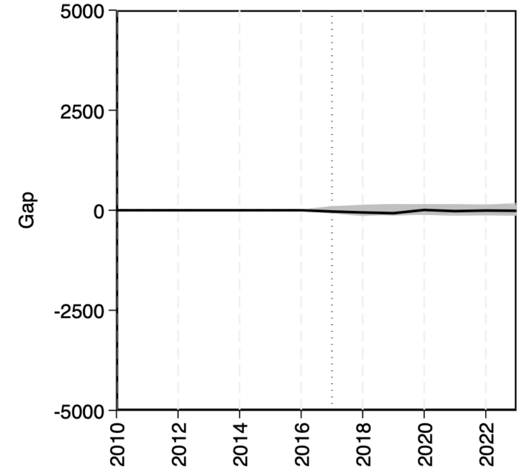
Figure 6: Las Vegas, Nevada: Jobs: Overall



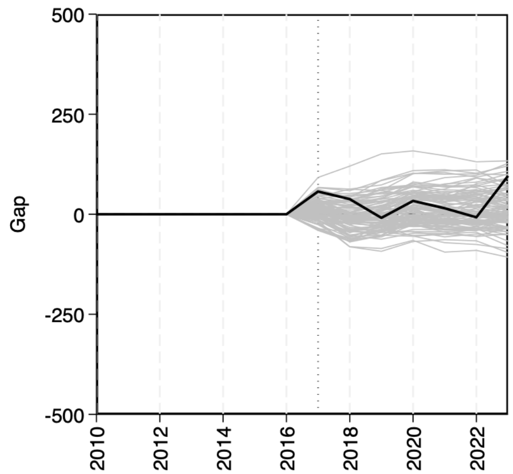
(A) 0 to 1 Miles



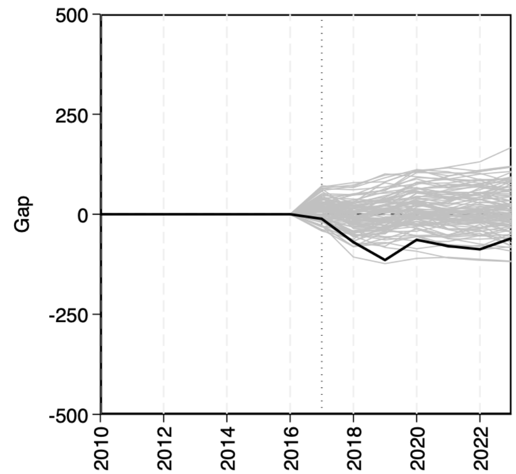
(B) 1 to 2 Miles



(C) 2 to 3 Miles



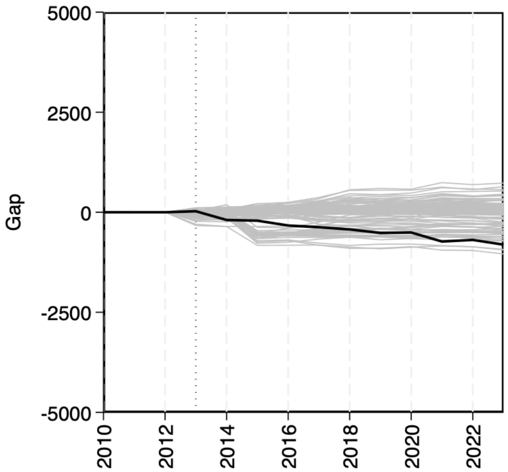
(D) 3 to 4 Miles



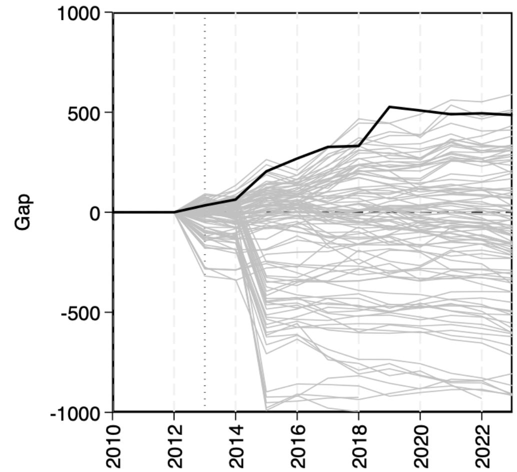
(E) 4 to 5 Miles

Notes: Figure 6 plots the synthetic control estimates for overall employment in all industries in Las Vegas, Nevada. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual employment for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

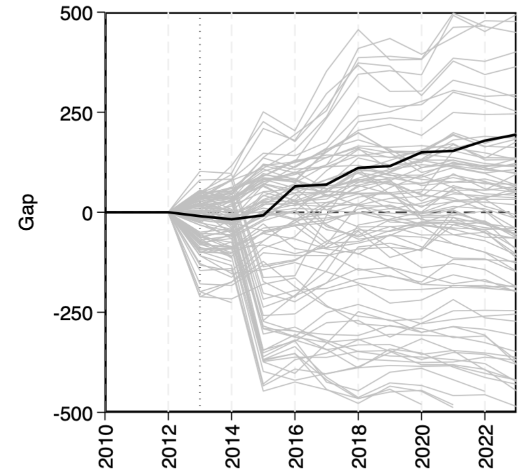
Figure 7: Atlanta, Georga: Jobs: Overall



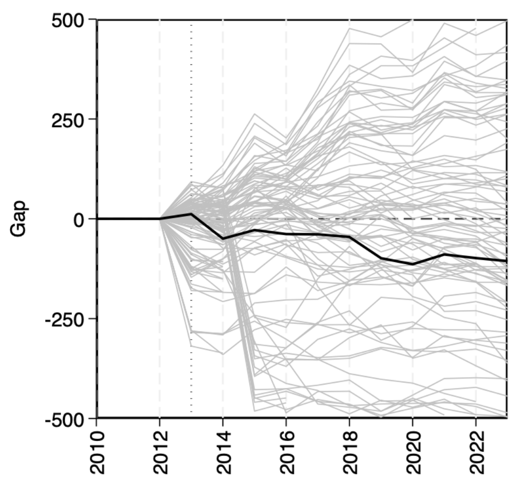
(A) 0 to 1 Miles



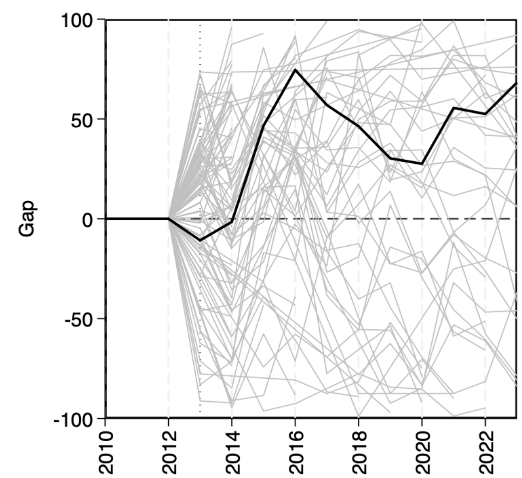
(B) 1 to 2 Miles



(C) 2 to 3 Miles



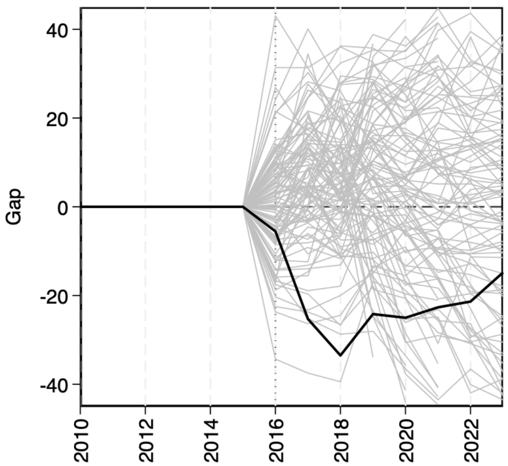
(D) 3 to 4 Miles



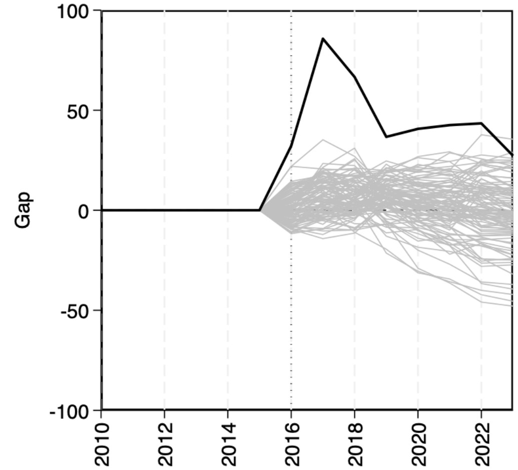
(E) 4 to 5 Miles

Notes:Notes: Figure 7 plots the synthetic control estimates for overall employment in all industries in Atlanta, Georgia Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual employment for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

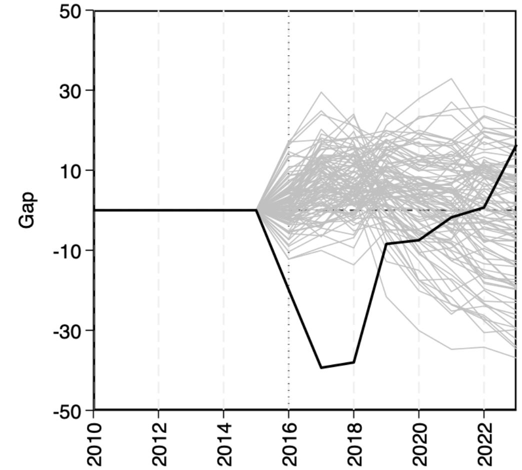
Figure 8: Inglewood, California: Jobs: Specific NAICS



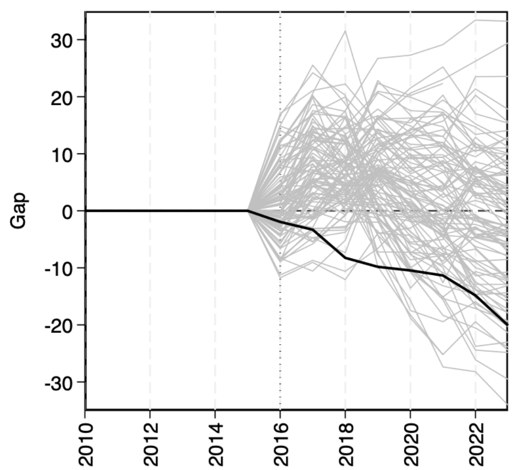
(A) 0 to 1 Miles



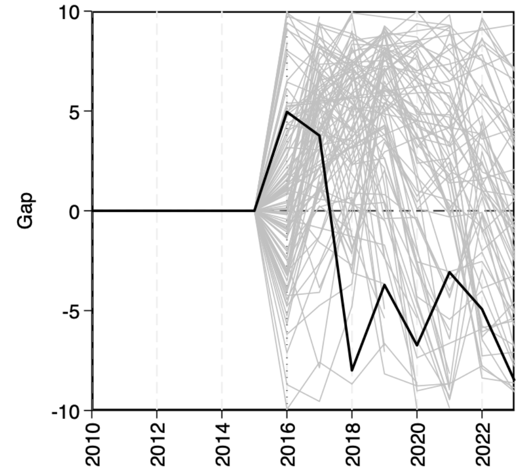
(B) 1 to 2 Miles



(C) 2 to 3 Miles



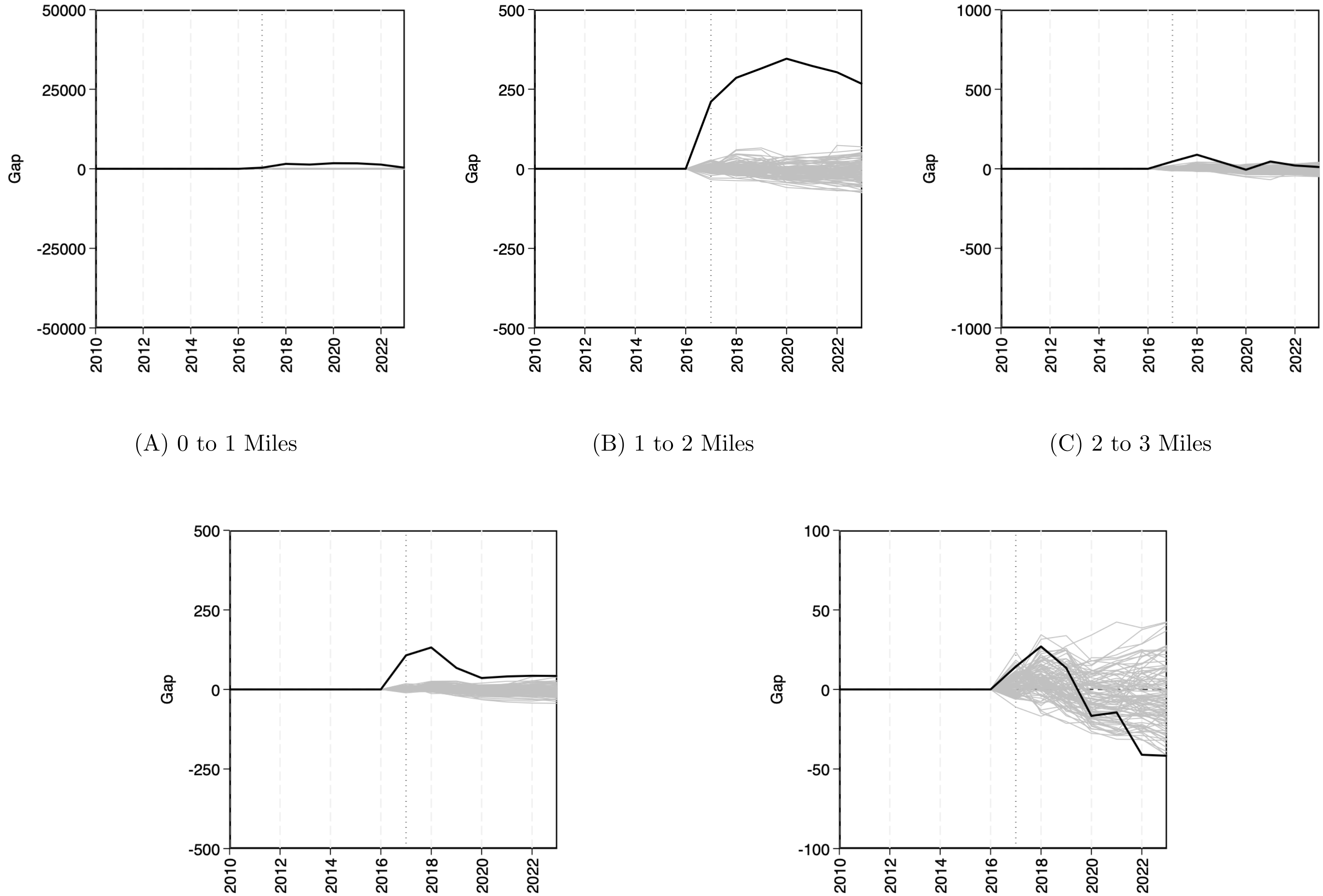
(D) 3 to 4 Miles



(E) 4 to 5 Miles

Notes: Figure 8 plots the synthetic control estimates for employment in the industries specified in Table 9 for Inglewood, California. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual employment for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

Figure 9: Las Vegas, Nevada: Jobs: Specific NAICS



(A) 0 to 1 Miles

(B) 1 to 2 Miles

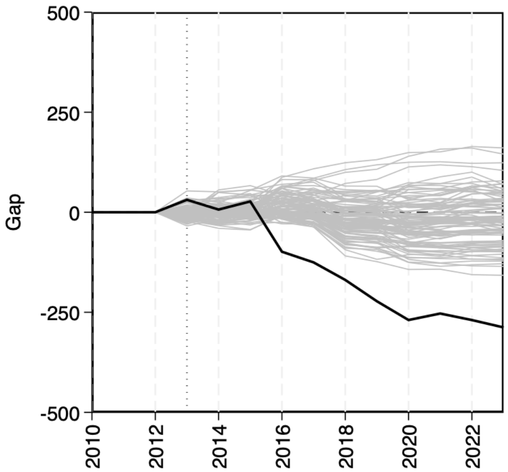
(C) 2 to 3 Miles

(D) 3 to 4 Miles

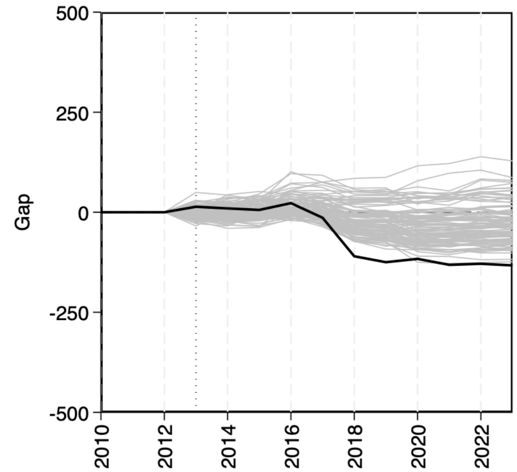
(E) 4 to 5 Miles

Notes: Figure 9 plots the synthetic control estimates for employment in the industries specified in Table 9 for Las Vegas, Nevada. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual employment for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

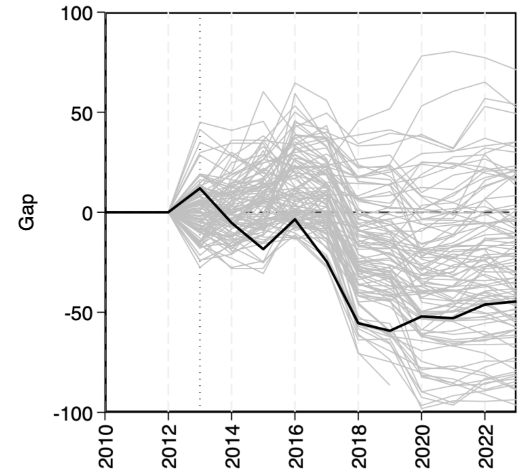
Figure 10: Atlanta, Georgia: Jobs: Specific NAICS



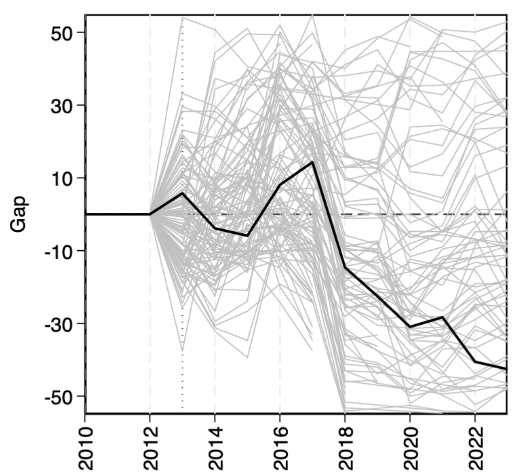
(A) 0 to 1 Miles



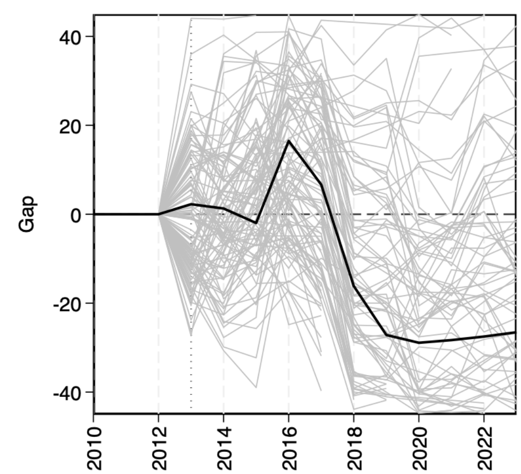
(B) 1 to 2 Miles



(C) 2 to 3 Miles



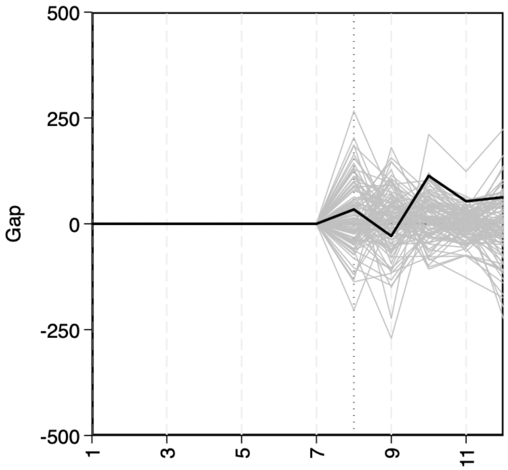
(D) 3 to 4 Miles



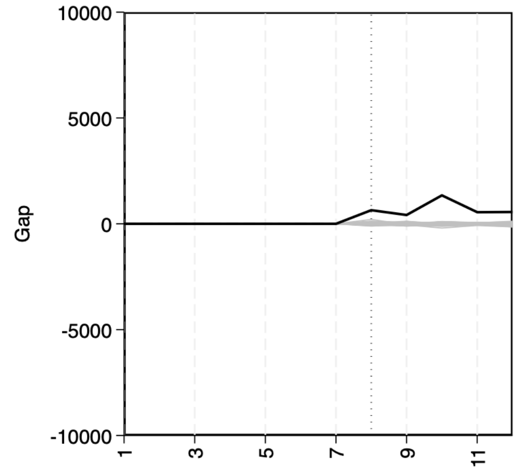
(E) 4 to 5 Miles

Notes: Figure 10 plots the synthetic control estimates for employment in the industries specified in Table 9 for Atlanta, Georgia. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual employment for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

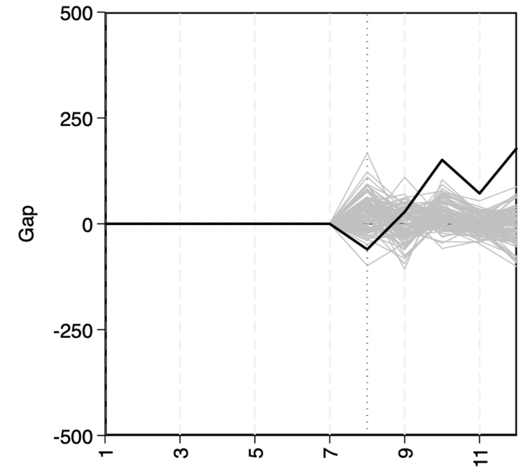
Figure 11: Inglewood, California: 2023 Monthly Sunday Foot Traffic: Overall



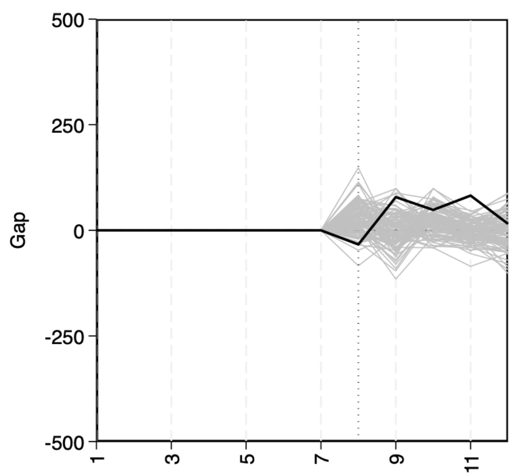
(A) 0 to 1 Miles



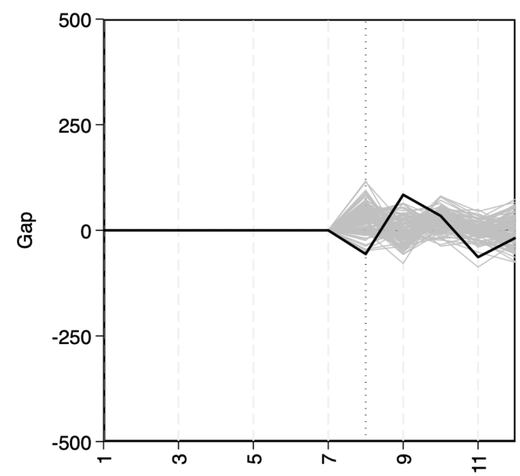
(B) 1 to 2 Miles



(C) 2 to 3 Miles



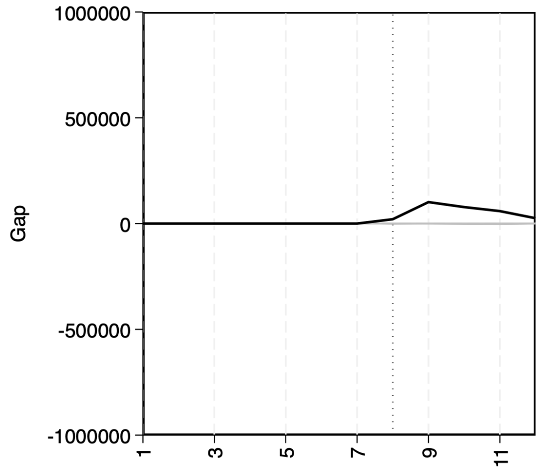
(D) 3 to 4 Miles



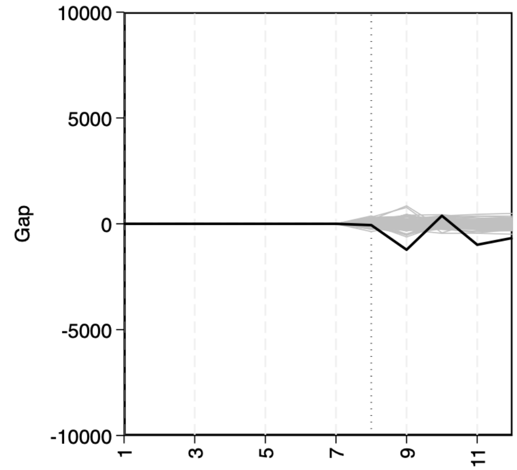
(E) 4 to 5 Miles

Notes: Figure 11 plots the 2023 monthly synthetic control estimates for Sunday establishment visits in all industries in Inglewood, California. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual number of visits for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

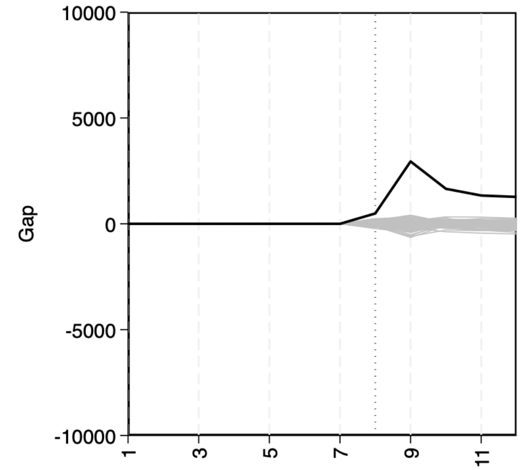
Figure 12: Las Vegas, Nevada: 2023 Monthly Sunday Foot Traffic: Overall



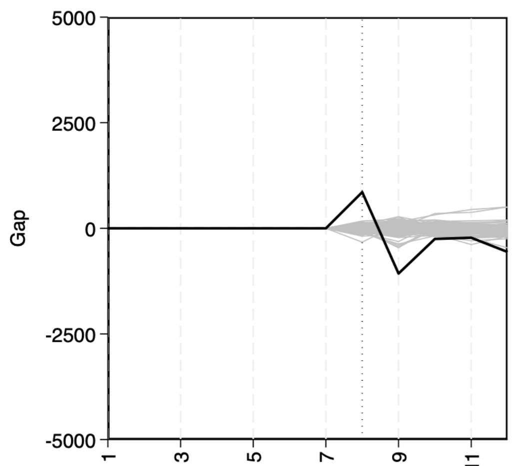
(A) 0 to 1 Miles



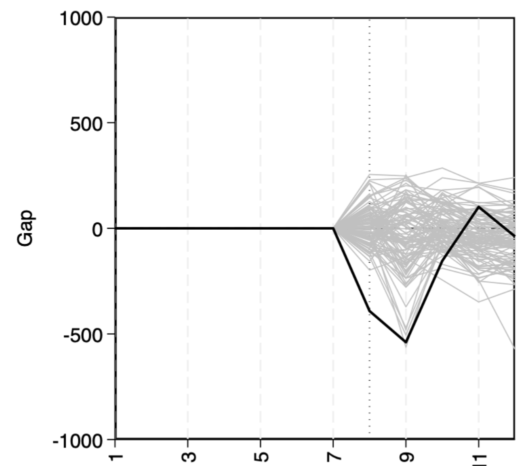
(B) 1 to 2 Miles



(C) 2 to 3 Miles



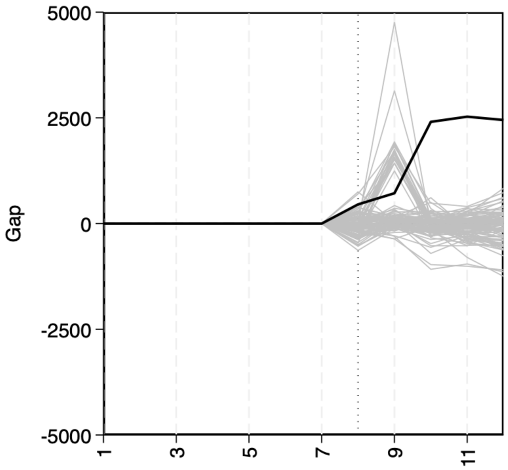
(D) 3 to 4 Miles



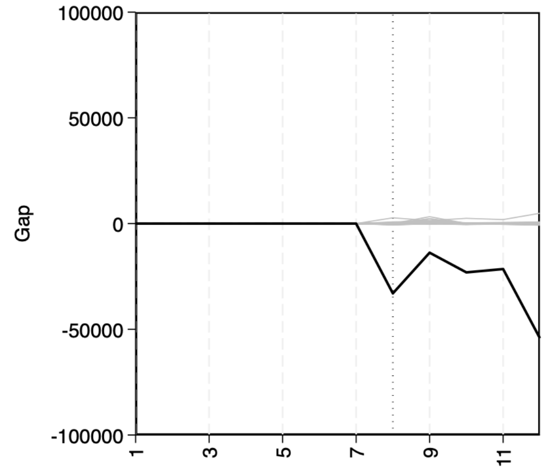
(E) 4 to 5 Miles

Notes: Figure 12 plots the 2023 monthly synthetic control estimates for Sunday establishment visits in all industries in Las Vegas, Nevada. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual number of visits for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

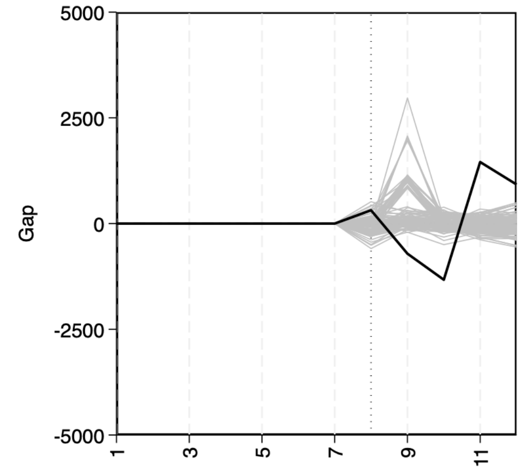
Figure 13: Atlanta, Georgia: 2023 Monthly Sunday Foot Traffic: Overall



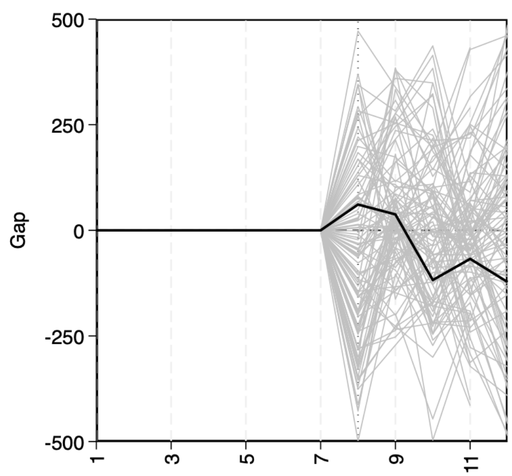
(A) 0 to 1 Miles



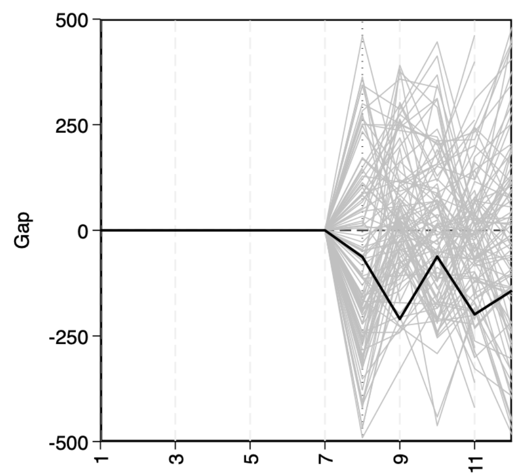
(B) 1 to 2 Miles



(C) 2 to 3 Miles



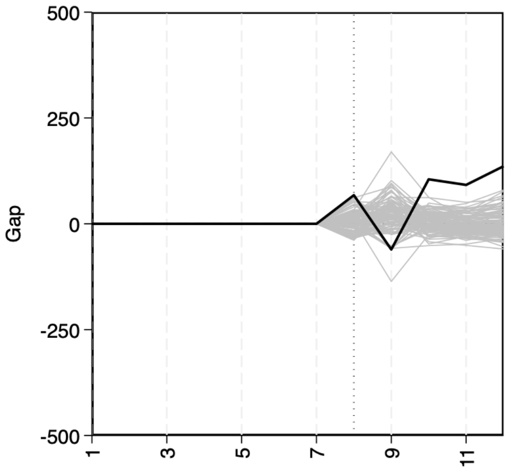
(D) 3 to 4 Miles



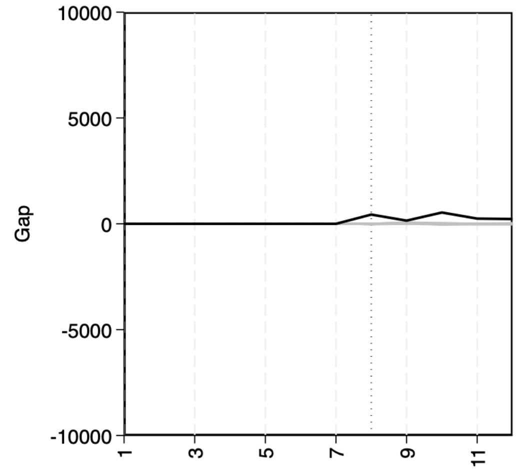
(E) 4 to 5 Miles

Notes: Figure 13 plots the 2023 monthly synthetic control estimates for Sunday establishment visits in all industries in Atlanta, Georgia Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual number of visits for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

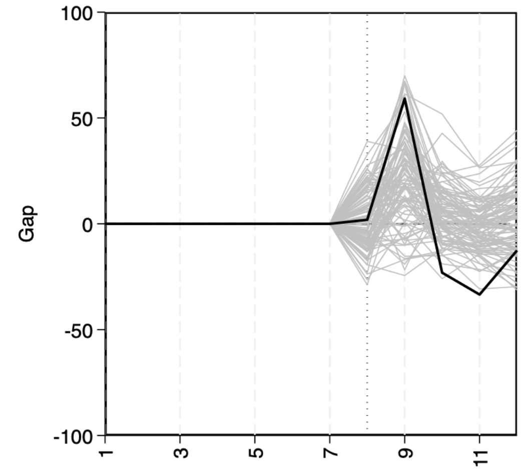
Figure 14: Inglewood, California: 2023 Monthly Sunday Foot Traffic: Specific NAICS



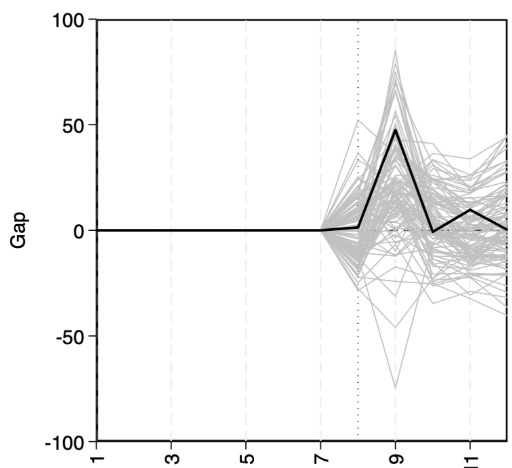
(A) 0 to 1 Miles



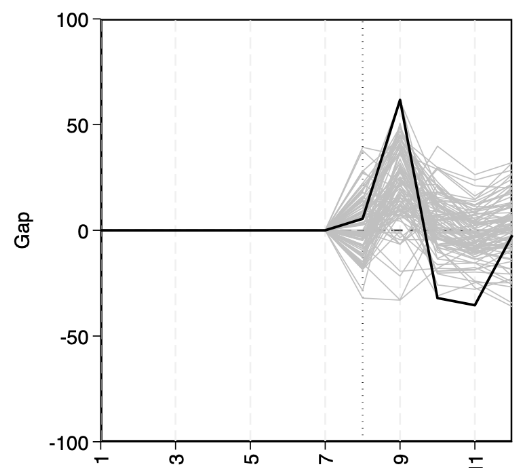
(B) 1 to 2 Miles



(C) 2 to 3 Miles



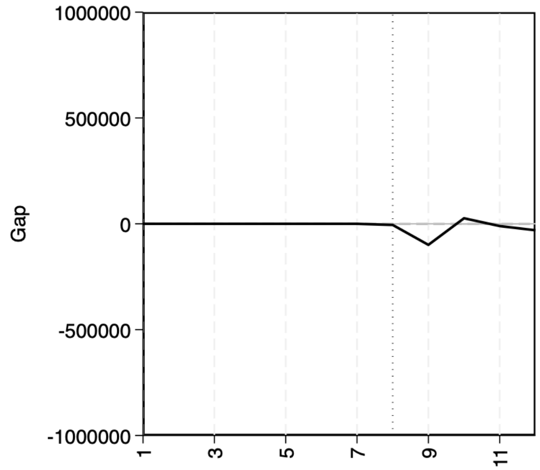
(D) 3 to 4 Miles



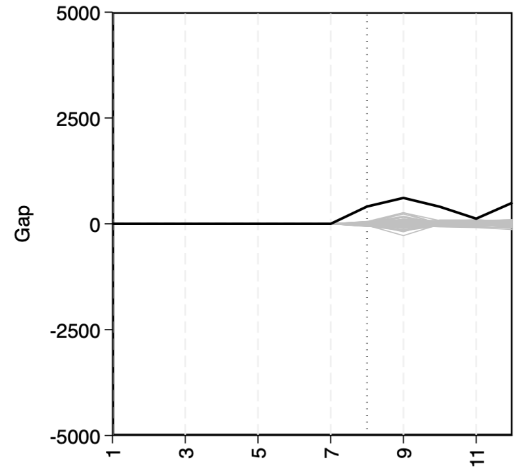
(E) 4 to 5 Miles

Notes: Figure 14 plots the 2023 monthly synthetic control estimates for Sunday establishment visits for the industries specified in table 9 for Inglewood, California. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual number of visits for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

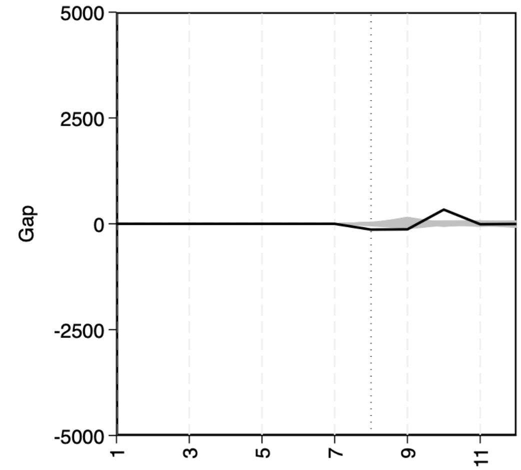
Figure 15: Las Vegas, Nevada: 2023 Monthly Sunday Foot Traffic: Specific NAICS



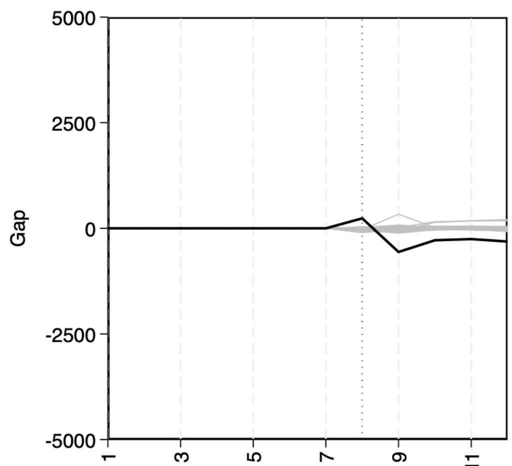
(A) 0 to 1 Miles



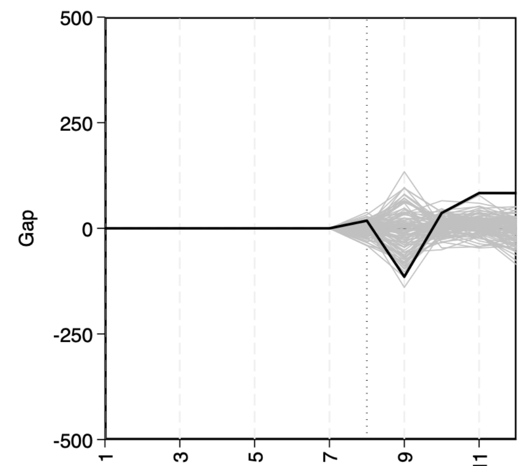
(B) 1 to 2 Miles



(C) 2 to 3 Miles



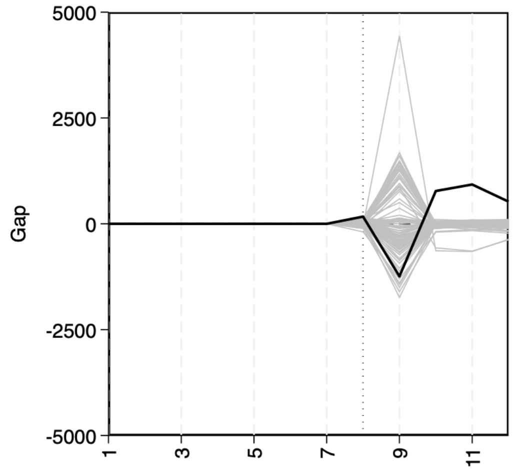
(D) 3 to 4 Miles



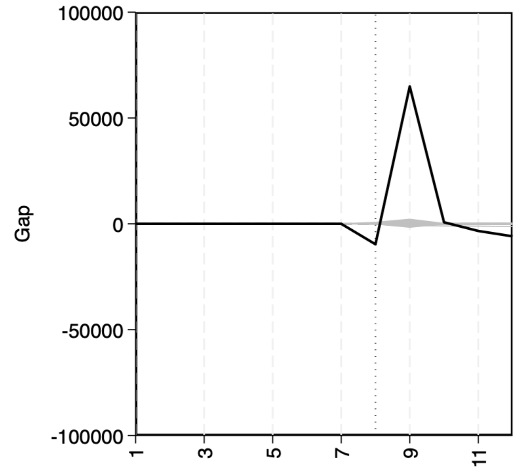
(E) 4 to 5 Miles

Notes: Figure 15 plots the 2023 monthly synthetic control estimates for Sunday establishment visits for the industries specified in table 9 for Las Vegas, Nevada. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual number of visits for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

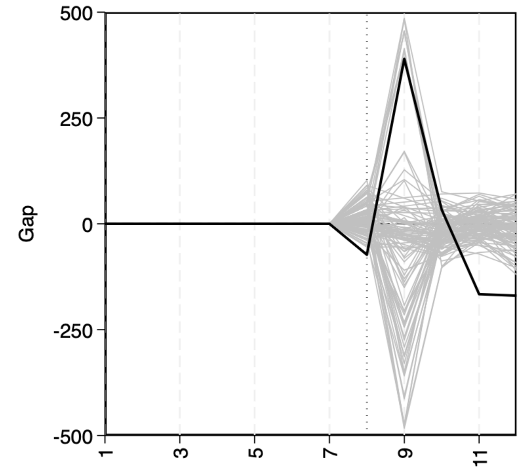
Figure 16: Atlanta, Georgia: 2023 Monthly Sunday Foot Traffic: Specific NAICS



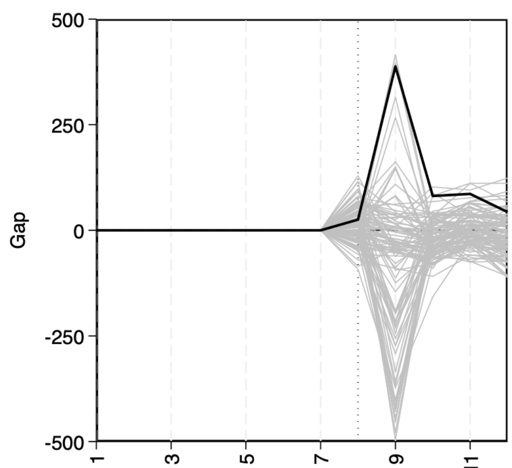
(A) 0 to 1 Miles



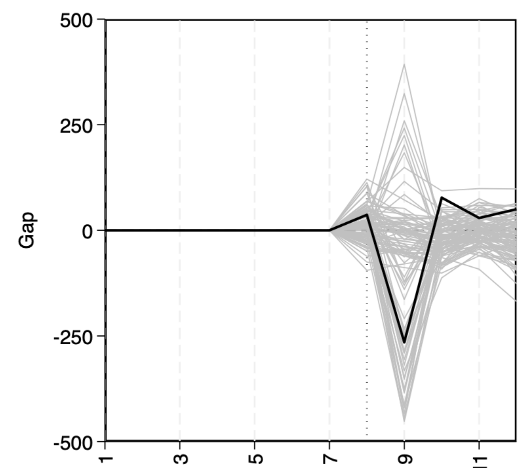
(B) 1 to 2 Miles



(C) 2 to 3 Miles



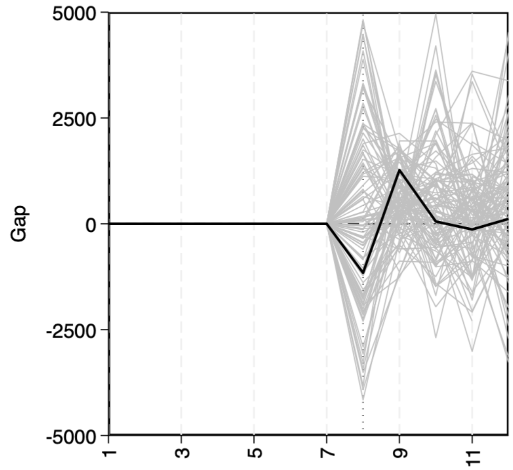
(D) 3 to 4 Miles



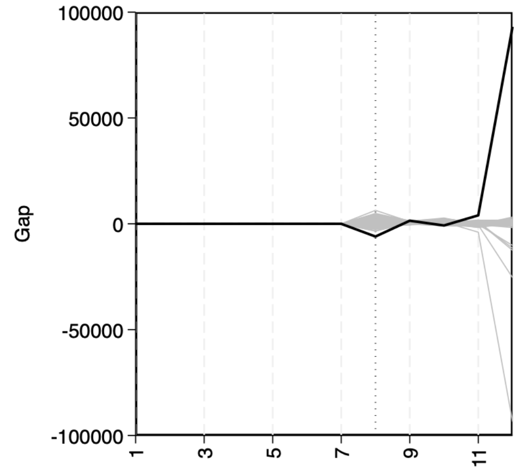
(E) 4 to 5 Miles

Notes: Figure 16 plots the 2023 monthly synthetic control estimates for Sunday establishment visits for the industries specified in table 9 for Atlanta, Georgia. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual number of visits for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

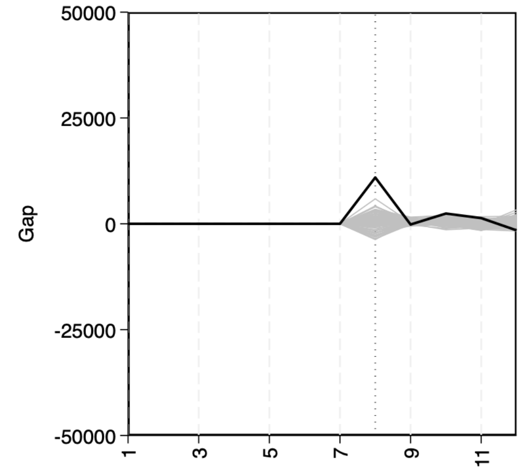
Figure 17: Inglewood, California: 2023 Monthly Sunday Spending: Overall



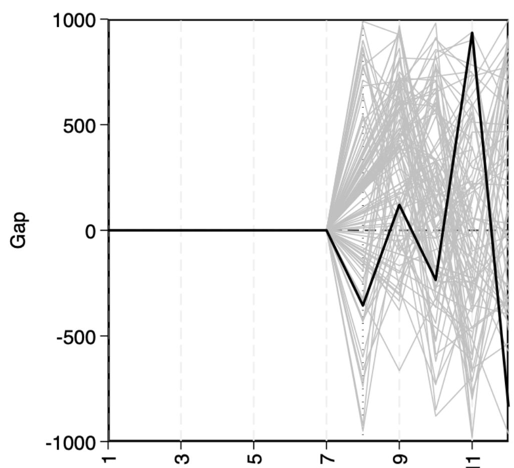
(A) 0 to 1 Miles



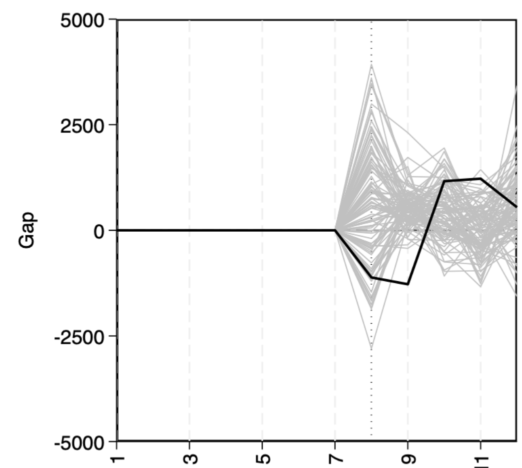
(B) 1 to 2 Miles



(C) 2 to 3 Miles



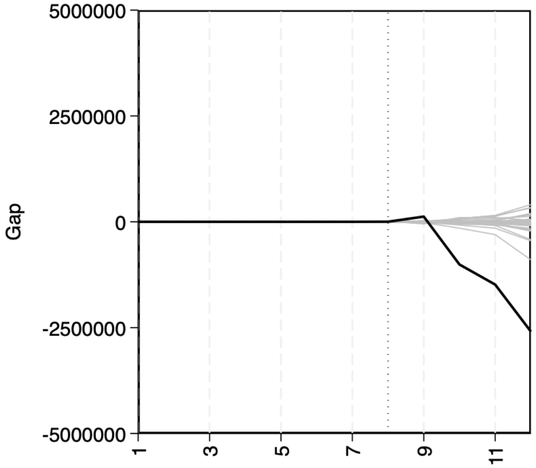
(D) 3 to 4 Miles



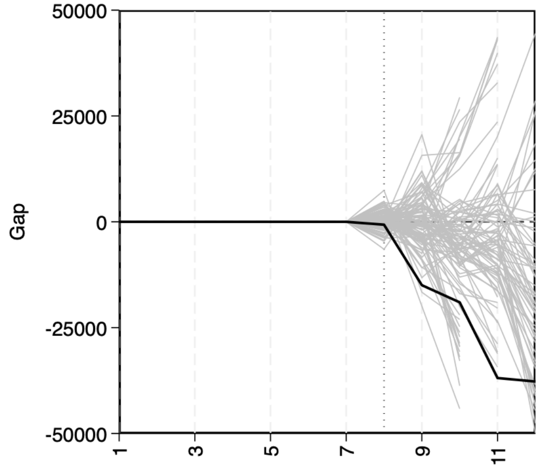
(E) 4 to 5 Miles

Notes: Figure 17 plots the 2023 monthly synthetic control estimates for Sunday establishment spending in all industries in Inglewood, California. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual amount of spending for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

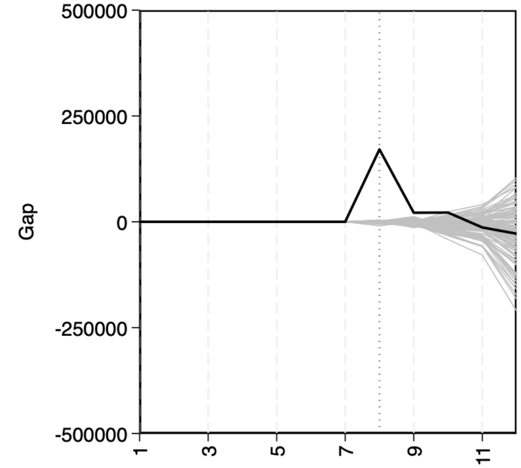
Figure 18: Las Vegas, Nevada: 2023 Monthly Sunday Spending: Overall



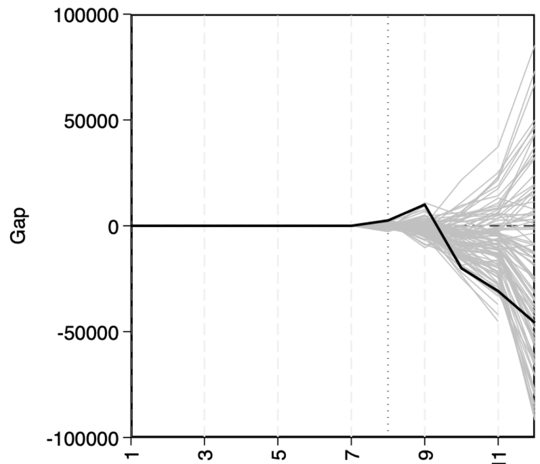
(A) 0 to 1 Miles



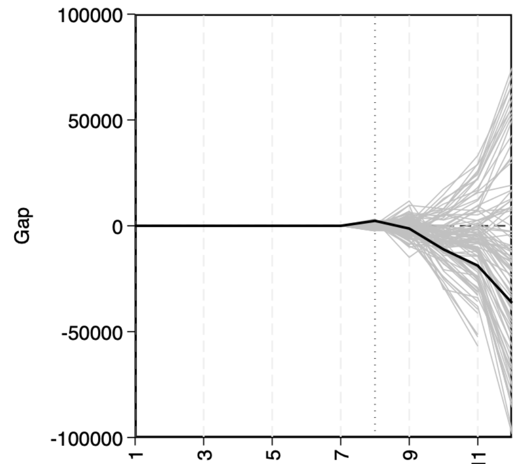
(B) 1 to 2 Miles



(C) 2 to 3 Miles



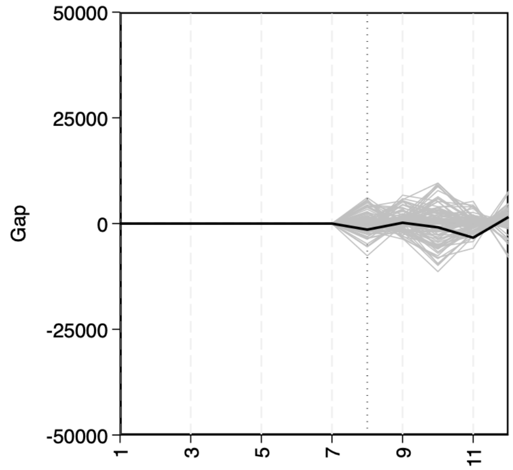
(D) 3 to 4 Miles



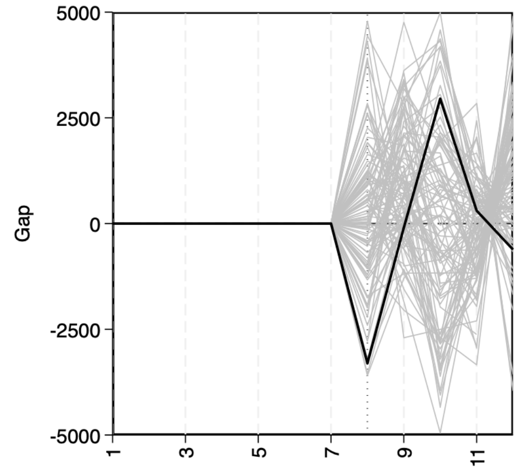
(E) 4 to 5 Miles

Notes: Figure 18 plots the 2023 monthly synthetic control estimates for Sunday establishment spending in all industries in Las Vegas, Nevada. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual amount of spending for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

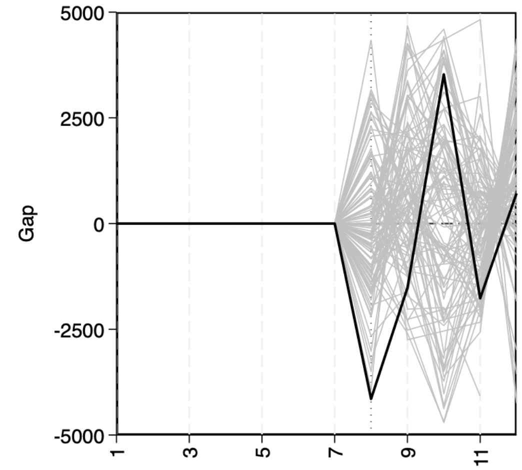
Figure 19: Atlanta, Georgia: 2023 Monthly Sunday Spending: Overall



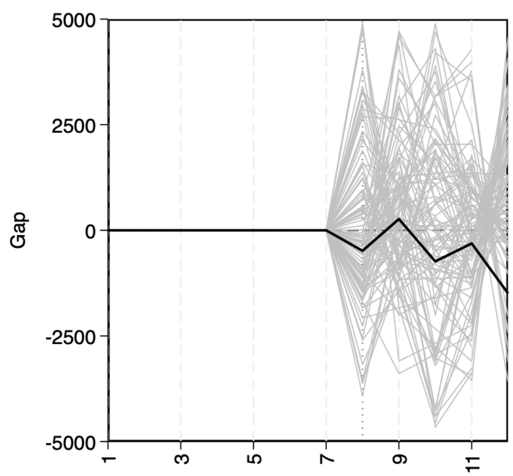
(A) 0 to 1 Miles



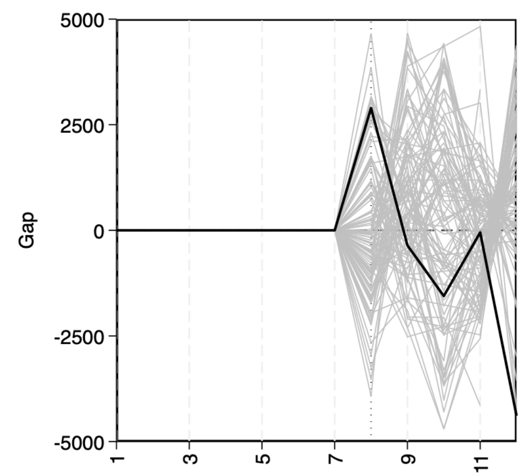
(B) 1 to 2 Miles



(C) 2 to 3 Miles



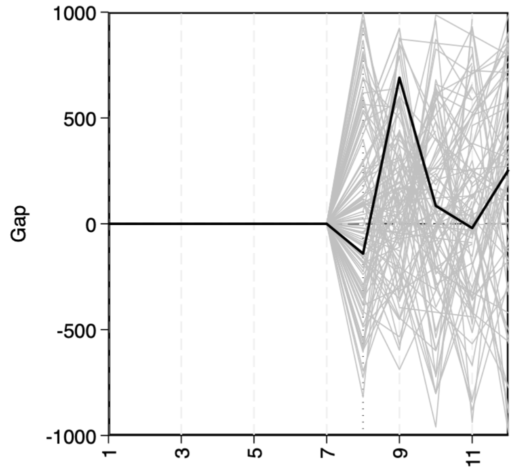
(D) 3 to 4 Miles



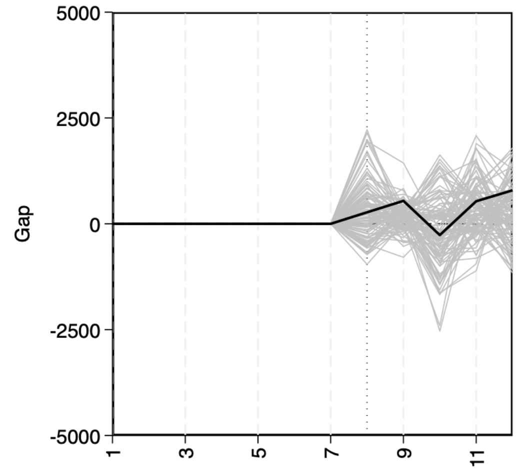
(E) 4 to 5 Miles

Notes: Figure 19 plots the 2023 monthly synthetic control estimates for Sunday establishment spending in all industries in Atlanta, Georgia. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual amount of spending for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

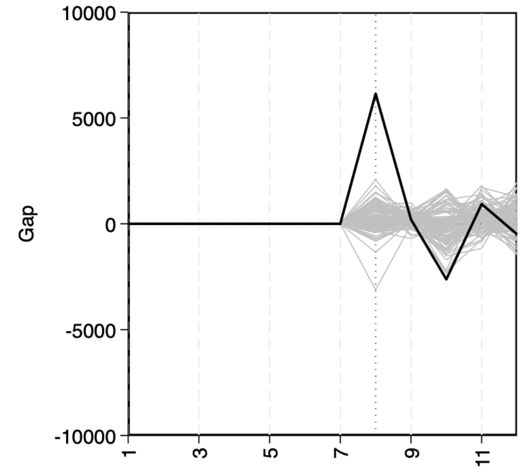
Figure 20: Inglewood, California: 2023 Monthly Sunday Spending: Specific NAICS



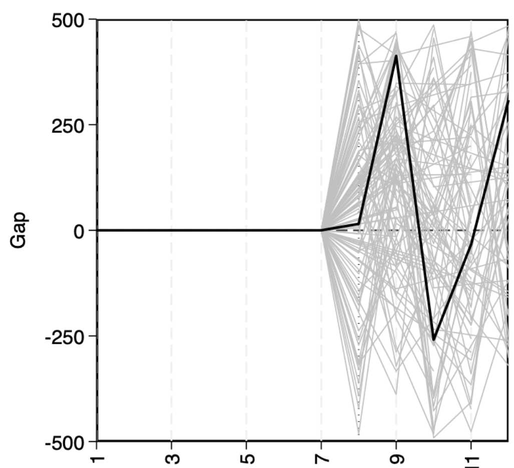
(A) 0 to 1 Miles



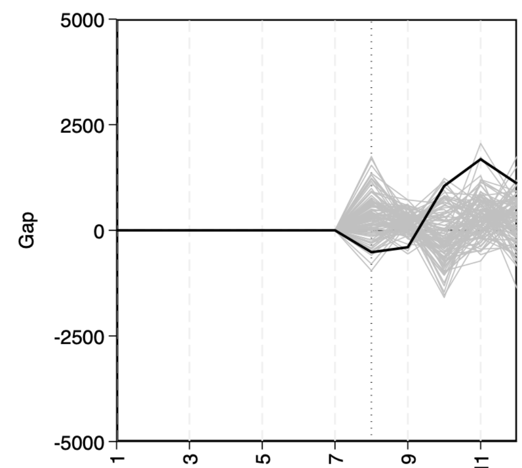
(B) 1 to 2 Miles



(C) 2 to 3 Miles



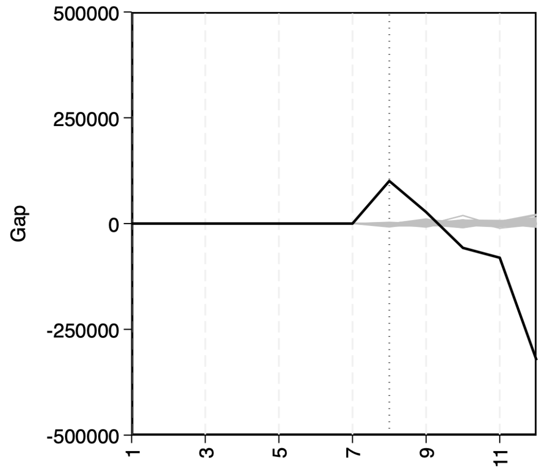
(D) 3 to 4 Miles



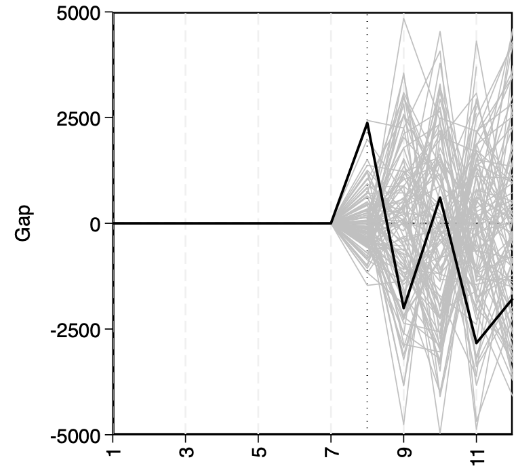
(E) 4 to 5 Miles

Notes: Figure 20 plots the 2023 monthly synthetic control estimates for Sunday establishment spending for the industries specified in table 9 for Inglewood, California. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual amount of spending for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

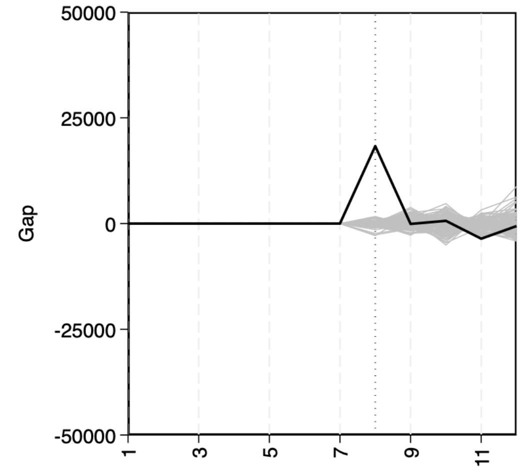
Figure 21: Las Vegas, Nevada: 2023 Monthly Sunday Spending: Specific NAICS



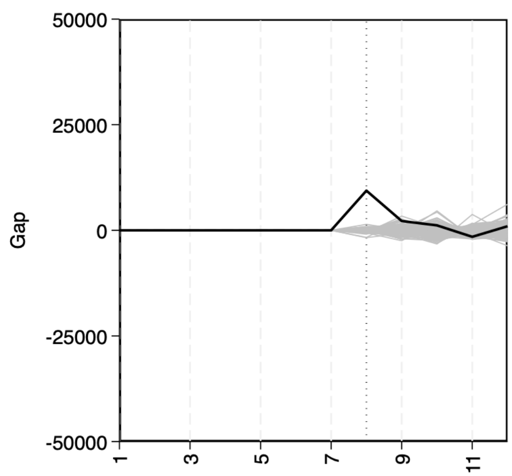
(A) 0 to 1 Miles



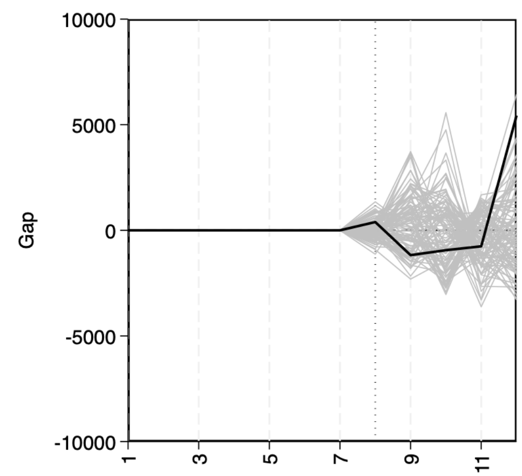
(B) 1 to 2 Miles



(C) 2 to 3 Miles



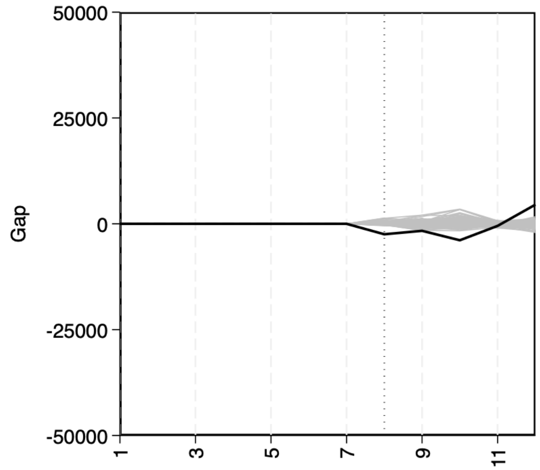
(D) 3 to 4 Miles



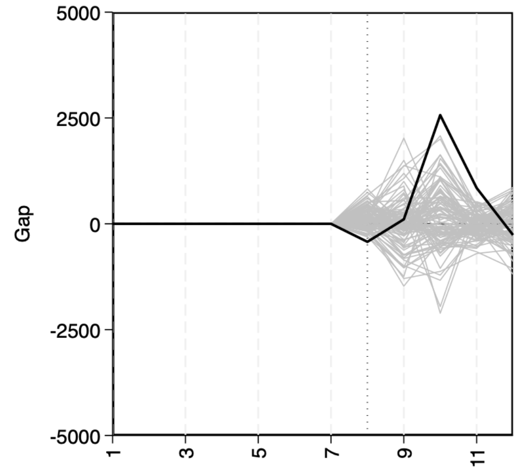
(E) 4 to 5 Miles

Notes: Figure 21 plots the 2023 monthly synthetic control estimates for Sunday establishment spending for the industries specified in table 9 for Las Vegas, Nevada. Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual amount of spending for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

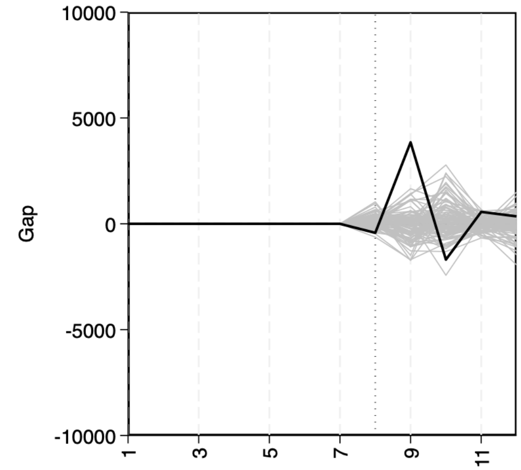
Figure 22: Atlanta, Georgia: 2023 Monthly Sunday Spending: Specific NAICS



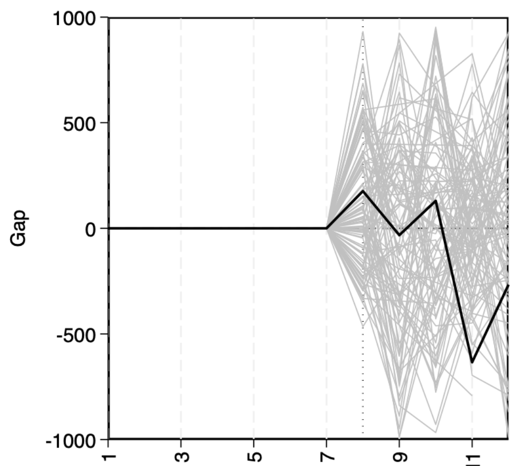
(A) 0 to 1 Miles



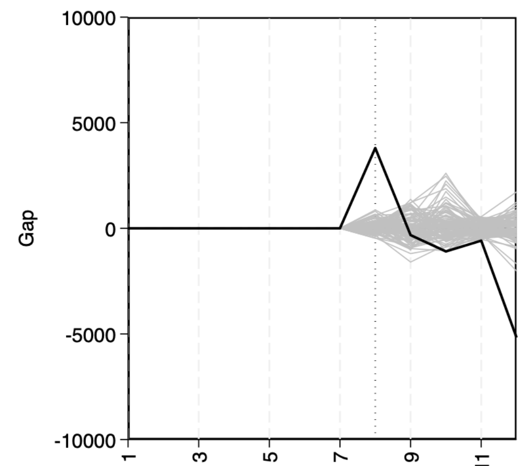
(B) 1 to 2 Miles



(C) 2 to 3 Miles



(D) 3 to 4 Miles



(E) 4 to 5 Miles

Notes: Figure 22 plots the 2023 monthly synthetic control estimates for Sunday establishment spending for the industries specified in table 9 for Atlanta, Georgia Panels A through E plot synthetic control estimates for Census tracts within one to five miles respectively. The vertical gray bar indicate the year of the stadium announcement. The solid black lines plot the actual amount of spending for the city using the average effect for the Census tracts within each distance measure. The gray lines are paths of random samples of 100 placebo average treatment effects.

Figure 23: Census Tract Classification

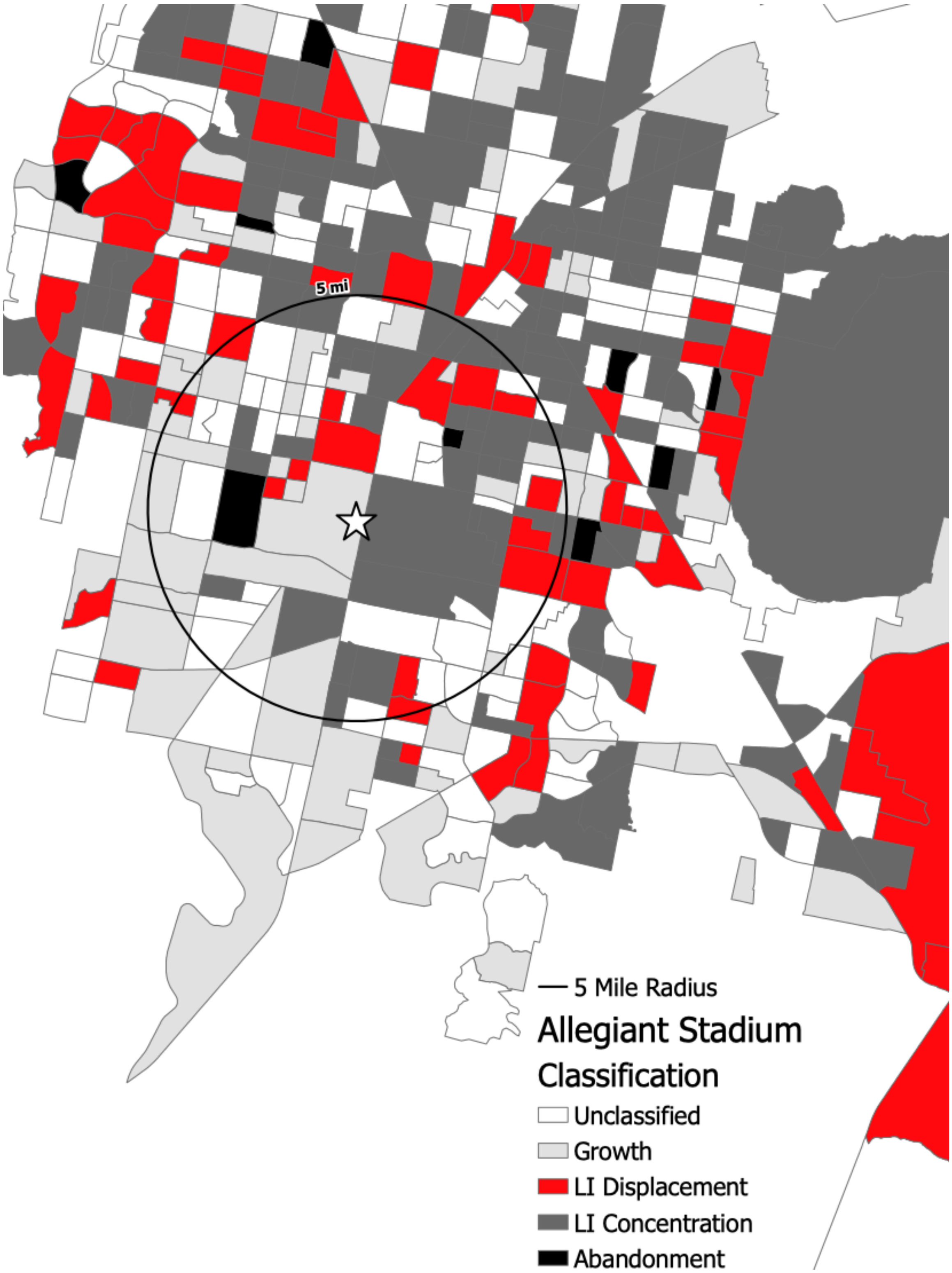
	Expanding	Declining
Low-Income Population Growth	**Growth**	**Low-Income Concentration**
Low-Income Population Decline	**Low-Income Displacement**	**Abandonment**

Note: I follow (Institute on Metropolitan Opportunity, 2019; LaPoint, 2023) and first classify a tract as expanding or declining. The second step examines the changing low-income population share in an area.

Figure 24: Inglewood, CA: Neighborhood Change Classification

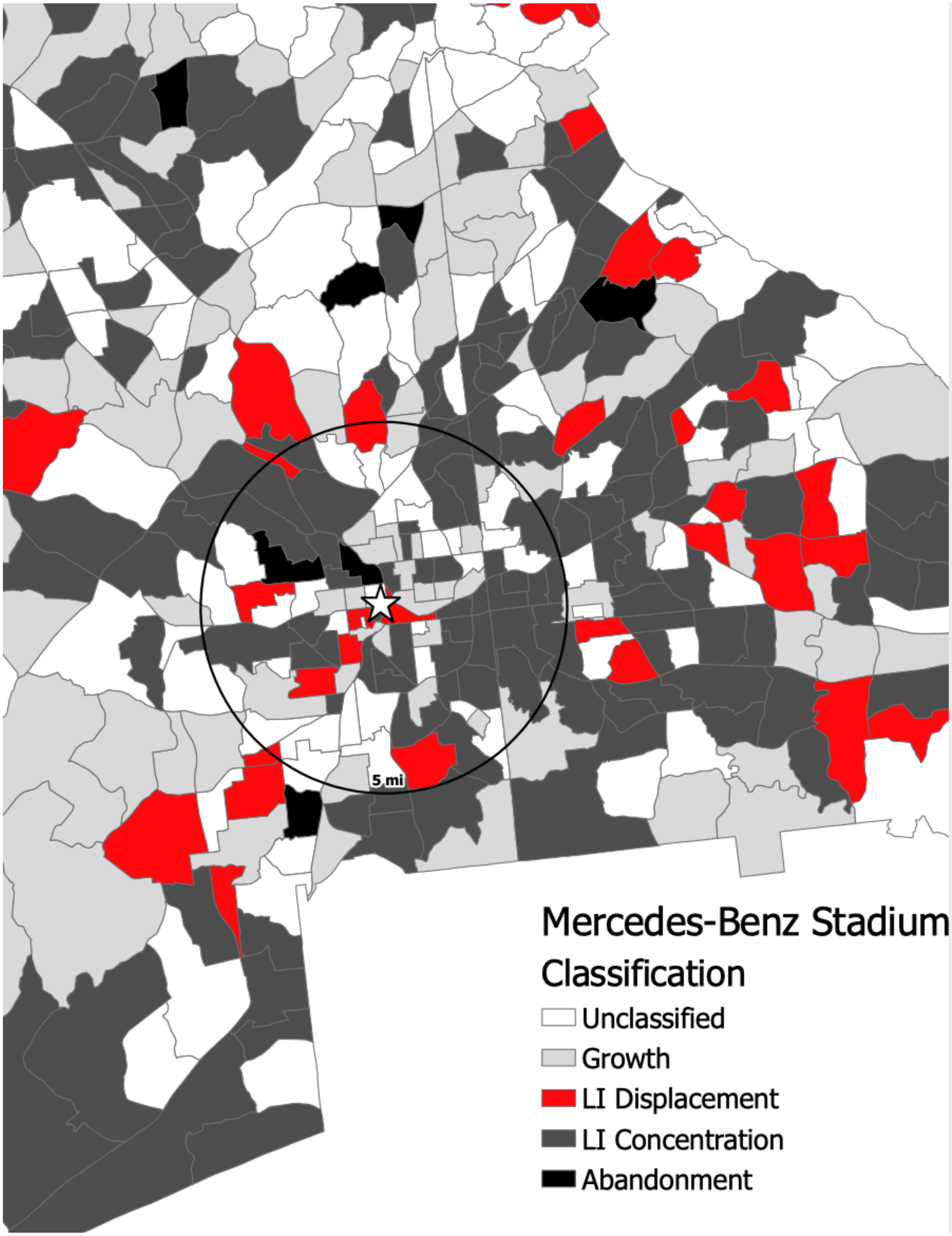
Note: For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article

Figure 25: Las Vegas, NV: Neighborhood Change Classification



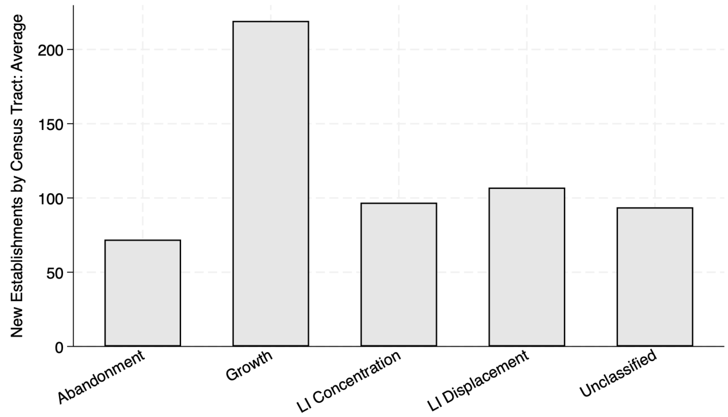
Note: For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article

Figure 26: Atlanta, GA: Neighborhood Change Classification

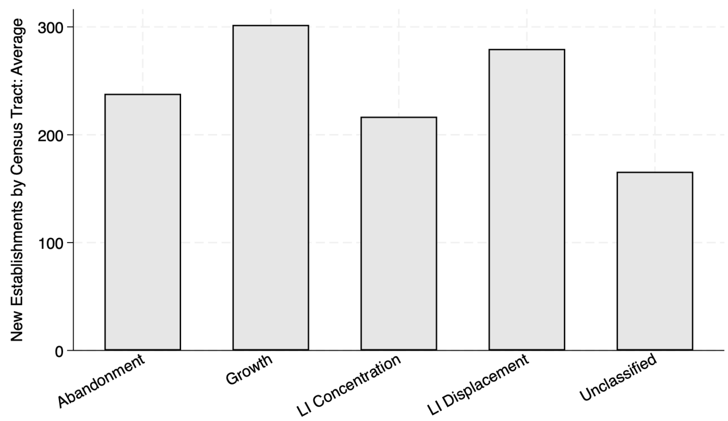


Note: For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article

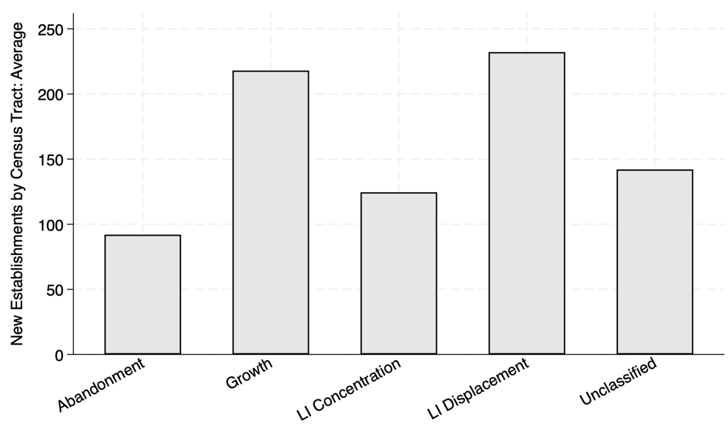
Figure 27: New Establishments per Census Tract: Average



(A) Inglewood, CA



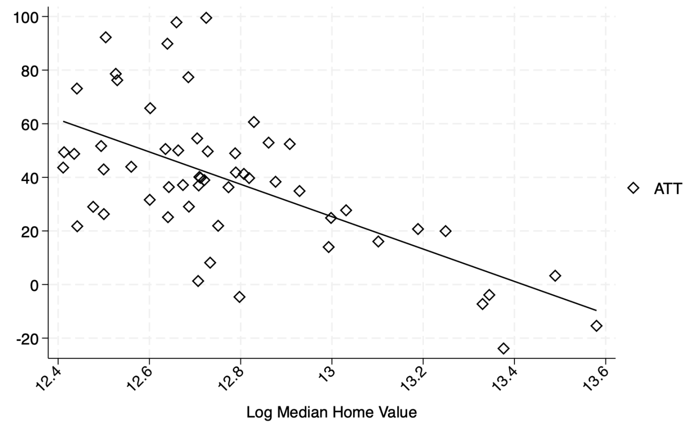
(B) Las Vegas, NV



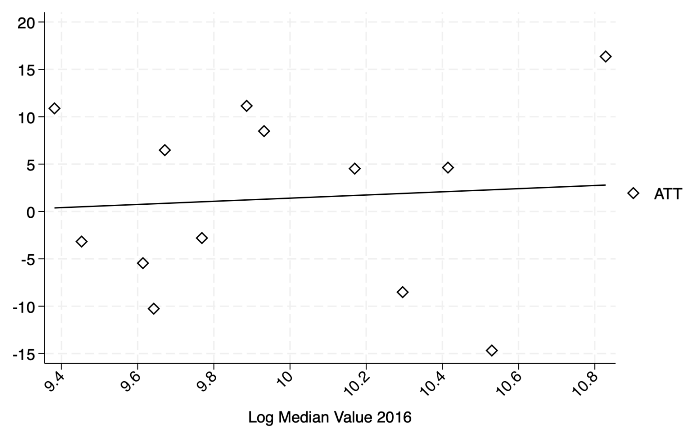
(C) Atlanta, GA

Notes: Figure 27 shows the average number of new establishments within 3 miles of each new stadium since its announcement through the end of 2023 broken down by that Census tract's classification. Panel A corresponds to Inglewood, California, Panel B corresponds to Las Vegas, Nevada and Panel C corresponds to Atlanta, Georgia

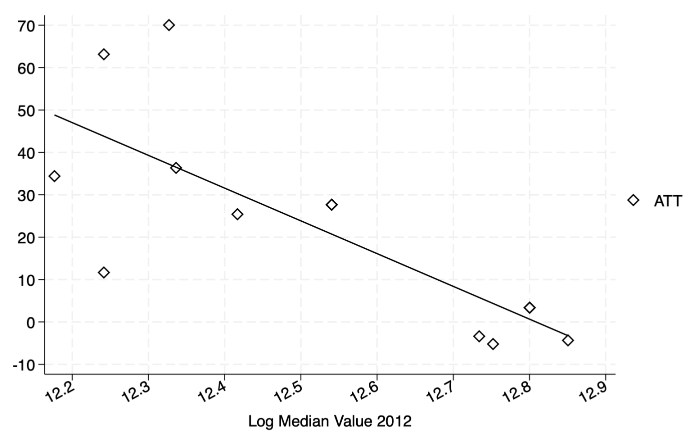
Figure 28: Housing Price Growth versus Initial Housing Price



(A) Inglewood, CA



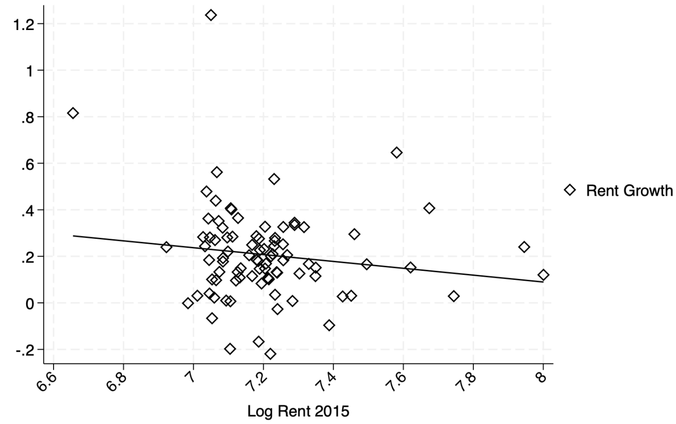
(B) Las Vegas, NV



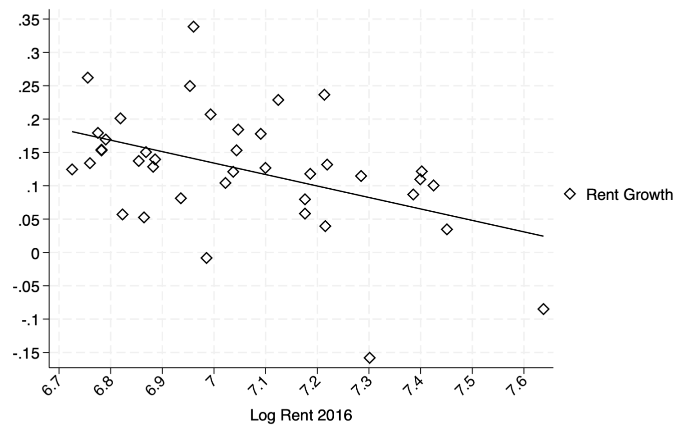
(C) Atlanta, GA

Notes: Figure 28 shows the initial house price in a Census tract the year before the stadium announcement versus the subsequent time average of the house price growth Average Treatment on the Treated. Panel A corresponds to Inglewood, California, Panel B corresponds to Las Vegas, Nevada and Panel C corresponds to Atlanta, Georgia.

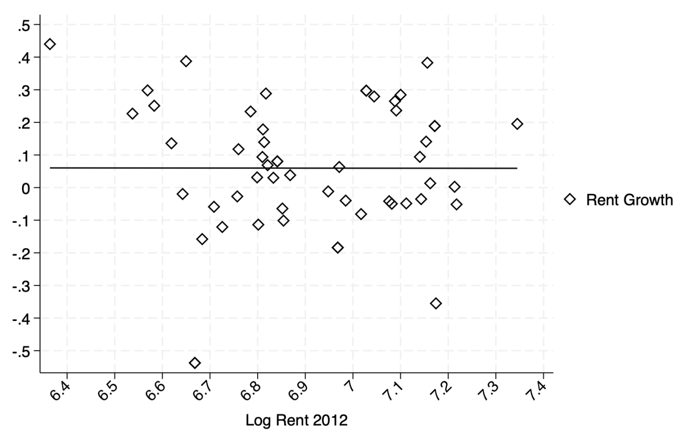
Figure 29: Rent Growth versus Initial Rent



(A) Inglewood, CA



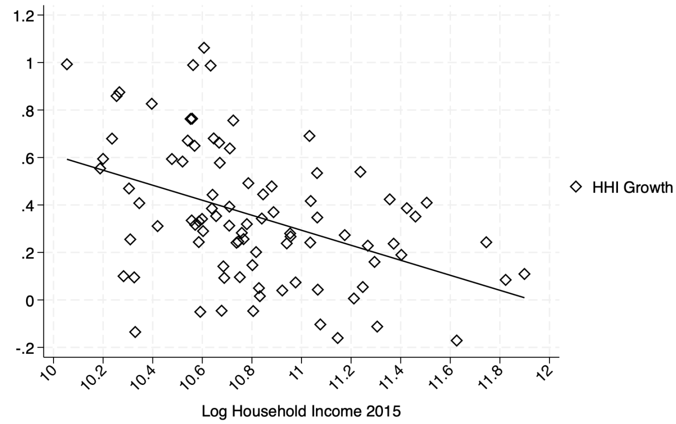
(B) Las Vegas, NV



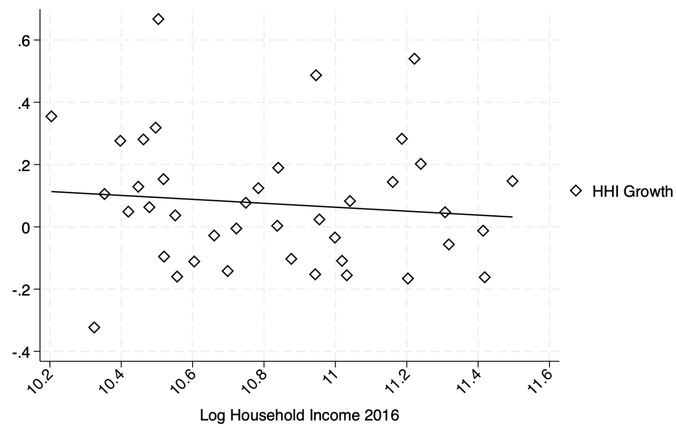
(C) Atlanta, GA

Notes: Figure 29 analyzes rental costs. On the x-axes I show each Census tracts rental cost ACS 5-year average the year before the stadium announcement versus the y-axes that plot the subsequent 5-year average for the years mentioned in section 3. Panel A corresponds to Inglewood, California, Panel B corresponds to Las Vegas, Nevada and Panel C corresponds to Atlanta, Georgia

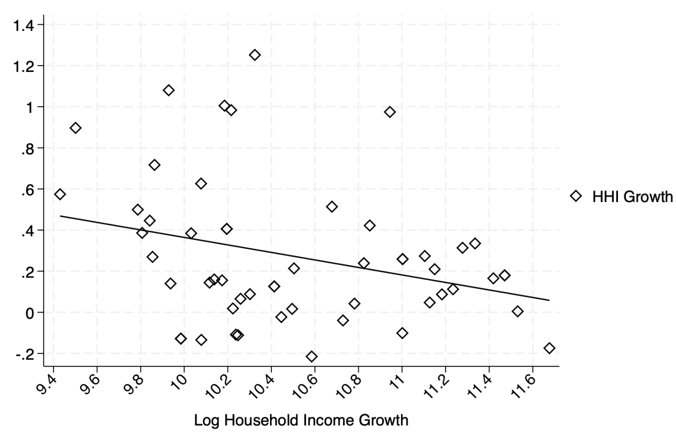
Figure 30: Household Income Growth versus Initial Household Income



(A) Inglewood, CA



(B) Las Vegas, NV



(C) Atlanta, GA

Notes: Figure 30 analyzes the median household income. On the x-axes I show each Census tracts median household income ACS 5-year average the year before the stadium announcement versus the y-axes that plot the subsequent 5-year average for the years mentioned in section 3. Panel A corresponds to Inglewood, California, Panel B corresponds to Las Vegas, Nevada and Panel C corresponds to Atlanta, Georgia