



Birdie or Bogey? How Golf Course Construction Affects Surrounding Home Values

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**Birdie or Bogey? How Golf Course Construction
Affects Surrounding Home Values**

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Abstract

When asked to think about the how building a golf course can affect a community, many people's first thought may jump to the environmental impacts that such construction has on the surrounding area. However, the economic interplay between a course and its surrounding community can be significant. Despite this fact, the popularity of the sport of golf, and the prevalence of golf course across the U.S., relatively little is truly known about how course development may impact economic outcomes of the surrounding area. While golf enthusiasts suggest that courses serve as amenities for residents and raise home values, I find, using a novel panel dataset with newly developed difference-in-differences methods, that the effects may indeed be opposite. Specifically, my results show that the development of a golf course lowers housing values of the surrounding census tract by 2.7% of average home values. Public, private, and municipal courses lower home prices by 2.2%, 4.1%, and 2.7%, respectively. These results may help guide policy-making decision by local governments and be of interest to residents, developers, and investors as well.

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Additionally, this thesis would not have been possible with data from GolfLink.com, the U.S. Census Bureau, and Federal Housing Finance Agency, and I am thankful to those sources for the ability to use their data.

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1 Introduction

Golf is a growing game. 2021 saw 3.2 million Americans tee up a golf ball for the first time (Beditz, 2022*b*). The number of rounds played in 2022 finished 15% above the three-year average from 2017-2019 (Beditz, 2023*a*). And with this growing demand for the game comes a constant new supply of the game’s facilities. On average, the last five years have seen a new golf course open in the U.S. once every 5 days. The nation’s over 17,000 golf courses outnumber both the number of McDonald’s and number of Starbucks locations in the U.S. Despite the prevalence of the sport and the vast number of courses, there is limited economic literature exploring the ramifications of golf course development. This thesis aims to add a small contribution to that literature by exploring a specific question — how does the construction of a golf course affect home prices in the surrounding area?

For local or city governments considering tax-favored treatment, subsidies, or regulations for golf course construction, the answer to this question is important. Policymakers must weigh the trade-offs of developing a golf course along many axes — economic, environmental, social, and political. It is imperative to have full information on these trade-offs to guide policy-making decisions. If results indicate that golf courses have positive spillover effects for those in the area, perhaps their development warrants more funding from the government or regulatory lenience. If the results point the other way, perhaps golf course development needs to be taxed or otherwise restricted. Residents, developers, and real estate investors, too, may find value in understanding such effects.

The current literature that exists on golf courses and their impacts on home prices is relatively narrow in scope. Do and Grudnitski (1995) study the effect of golf courses on adjacent property values in a sample of 717 sales transactions in Rancho Bernardo, California. Using a matched-pair design comparing homes abutting courses to equivalent homes nearby without a golf course border, they found that bordering a golf course adds 7.6% to a property’s value. Grudnitski and Do (1997) build on their previous work using a multiple regression approach. Based on a sample of 314 homes on three privately owned golf courses

in Rancho Bernardo, they estimate a \$12,914 or 4.8% premium for homes bordering a course.

Nicholls and Crompton (2007) employ a hedonic pricing model similar to Do and Grudnitski (1995) to study the same effect. Their sample includes 305 residential transactions from a golf course subdivision in College Station, Texas. Their analysis suggests a 26% premium in sales prices and 19.2% premium in assessed value for homes adjacent to golf courses. They further find that assessed value declines by \$8.28 per foot further from the golf course's entrance the home is located.

Further work on this subject comes from Asabere and Huffman (1996) who examined 105 single family homes in Burlington County, New Jersey. Their results also suggest a positive effect of golf course frontage on home price, estimated at 7.9%. Importantly, the authors also examine potential negative effects from golf courses such as noise, traffic, and property damage from golf balls. They find that being located within one-tenth a mile from a golf course's front gate lowers home values by 3.7%, while being located one-half mile away lowers values by only 0.76%. This suggests that, while golf course frontage may increase values overall, there are negative effects associated with proximity to courses as well.

The most recent and broadest scope of research on this subject comes from Shultz and Schmitz (2009). They augment residential sales data with GIS-level data to study homes near 20 courses in Omaha, Nebraska. After stratifying by type of golf course they estimate a 28%, 15%, and 9% boost in property values for homes abutting private, public, and municipal courses, respectively.¹ The authors do note wide variation between individual courses' impacts, suggesting some effects may be golf-course specific.

Looking a slightly different question, Grudnitski (2003) analyze price premiums associated with homes in a golf course community — a developed housing plan that contains a golf course. This study employs a hedonic multiple regression approach on 2,311 sales transactions in Las Vegas, Nevada, and stratifies by golf course type. Their findings suggest a 12.5% and 5.7% premium in price for homes located in private and public golf course communities,

¹For more information on the different types of golf courses, see Section 2.1

respectively, compared to similar homes outside golf course communities.

This body of work leaves significant gaps in our understanding of golf course construction and its impacts on nearby home prices. Previous work has focused almost exclusively on value premiums of homes abutting golf courses or those within a golf course community. Little research has been conducted on the effect of golf courses on home prices for whole zip codes or census tracts. These studies also fail to estimate the impacts of a new golf course construction since their focus is on the amenity value of existing courses. Notably, all studies are conducted on localized, small subsets of homes and courses. Grudnitski (2003) and Shultz and Schmitz (2009) offer the widest scope, but both are still limited to a specific city. This raises concerns about the generalizability of results.

With the help of new data, my thesis attempts to address these gaps in the literature. I construct a panel dataset containing longitudinal data on home prices and golf course construction at the U.S. Census tract level from 2003-2021. I use this novel panel dataset to investigate the effects of new golf course construction on surrounding home values, a previously unexplored area of the literature. I further analyze differential impacts for different types of golf courses and expand the scope of existing research to the entire United States, as opposed to a specific community or city. Lastly, the panel dataset approach also allows me to estimate time-varying effects of golf course construction multiple years into the future.

To briefly preview results, I find that, on average, the construction of a golf course lowers home values by 6.3 HPI index points.² In a census tract with average home prices, this corresponds to a 2.7% reduction in value. After stratifying by course type, I further find that the introduction of public, private, and municipal courses lower home values by 5.2, 9.7, and 6.3 index points, respectively. Negative effects persist multiple years post-construction and increase in magnitude for the first seven years. These results may help guide policy decisions for local governments and help provide information to community members, developers, and investors for whom these effects may be important.

²See Section 3.2 for an detailed explanation of index points

2 Background

2.1 Golf Course Construction

Golf courses are typically one of three key types — public, private, or municipal. There are important distinctions between these types. Private golf courses are privately owned and operated courses that require membership to play. Typically, members pay an annual fee and can play the course at any time. Members and their guests are the only people permitted to play these courses. Public golf courses are also privately owned, but, by contrast, do not require any membership to play, rather operating on a pay-per-round fee system (Bountje et al., 2004). Municipal courses, like public courses, do not require membership. However, they are constructed, owned, maintained, and operated by public entities such as city and municipal governments. They too operate on a pay-per-round system. Other types of courses exist such as semi-private (which has a membership but still allows the public to play), but these types are rarer.

The construction of any type of golf course lies at the confluence of a number of environmental, economic, social, and regulatory factors. Environmentally, golf courses need good soil, access to water and irrigation, sufficiently flat land, and many other specific conditions to make their development possible (Salgot and Tapias, 2006; Mason-Fradette, 1994). Economically, operators of golf courses need to ensure sufficient demand for the course in a proposed location and that land prices, development costs, maintenance fees, taxes, financing costs, and other costs are sufficiently low that the course can be economically viable. Additionally, they must factor in future expectations of economic and demographic conditions in the area to ensure the large up-front costs of developing courses can be recouped with time. Social factors driving golf course development include the popularization of the sport and media coverage of professional golf (highly connected to demand for the sport), community buy-in or resistance to development, and more (Millington and Wilson, 2016). Finally, regulation and zoning laws must allow for golf courses to be developed in a given

area. Napton and Laingen (2008) discuss the complex factors that spur golf course development, stating that the history of development has been molded by “decentralization, growth of the middle class, war, economic depression, suburbanization, and the increasing role of the federal government” (p. 2).

Over the history of the United States, there have been three key booms in golf course development: one in the mid-1920s, one in the 1960s, and one in the late 1990s. Millington and Wilson (2016) explore the three booms in U.S. golf course construction. They argue that the boom in the 1920’s was spurred primarily by increases in technology; machine improvements allowed for easier movement of earth, and increases in golf club and ball technology necessitated the development of longer golf courses to accommodate longer shots. The 1960s boom, by contrast, was primarily driven by increases in television coverage and consumerism, driving more demand for the game of golf and thus, new golf courses. Finally, the 1990s brought widespread deregulation of banking that, as Millington and Wilson argue, allowed for easy development from the private sector that resulted in a boom of course construction. The 1990s boom saw nearly 4,000 courses, many of them public, constructed in a two-decade span — a drastic ramp-up that yielded an excess of facilities (Beditz, 2022*a*). The resulting course oversupply coupled with shockwaves from the Great Recession led to a cumulative 11% decline in the number of golf courses from 2006-2021 with more courses closing than being built. Most recently, the decline in golf course supply has slowed, and total courses closures in 2021 and 2022 were down 53% and 65%, respectively, from their peak in 2019 (Beditz, 2023*b*, 2022*a*).

2.2 Home Prices and Golf Courses

Residential home prices are the result of a complex combination of micro- and macroeconomic factors. On the microeconomic level, property-specific determinants include the physical characteristics of the property — square footage, age, condition, luxury, etc. Location-based drivers may include proximity to amenities like parks, schools and highways, as well as

weather, walkability, proximity to cities, and more (Albouy, 2016; Asabere and Huffman, 2009; Irwin, 2002). Government regulation, tax incentives, subsidies, and more impact home prices as well. Additionally, value can be driven by current housing market trends and buyers' perceptions of past and future demand to live in an area (Glaeser and Nathanson, 2015). Broader macroeconomic conditions, such as interest rates, unemployment, and global recessions also play a pivotal role in determining supply and demand for homes.

Golf course construction is likely to impact home prices through its influence on location specific drivers of prices. Primarily, golf courses serve as an amenity to nearby residents who can use the course. People who enjoy golfing or walking the course see a course as valuable, making nearby homes more desirable and increasing prices. Many studies have found that community amenities, public or private, raise property values for homes nearby (Asabere and Huffman, 2009; Song and Knaap, 2004; Geoghegan, Lynch and Bucholtz, 2003; Irwin, 2002). With golf courses specifically, hedonic pricing model studies find that homes closer to golf courses have higher values, suggesting an amenity effect (Nicholls and Crompton, 2007; Grudnitski, 2003; Do and Grudnitski, 1995). Real estate developers frequently include golf courses in their developments as an amenity that will increase the value of their properties (Nicholls and Crompton, 2007).

Beyond amenity values, golf courses may directly offer employment opportunities for local workers. Courses can also attract tourists to the area, which may bolster economic activity and indirectly create more jobs (Haydu, Hodges and Hall, 2008; Warnken, Thompson and Zakus, 2001). This boost in economic conditions could lead to higher prices for homes. Furthermore, high-prestige courses may increase the reputation of an area (e.g. Pinehurst, NC) which could plausibly drive up prices. Additional economic impacts may come through the effect of golf course construction on the supply of land available for residential homes. Golf courses require large swaths of land for development, which can decrease the availability of land for residential use. By constraining land supply and thus, housing supply, new golf courses may increase home prices in an area (Irwin, Jeanty and Partridge, 2014).

Municipal golf courses also may be financed from local governments' budgets, potentially leading to increased property taxes to offset their costs. All else equal, higher property taxes would be expected to drive down housing demand and prices. As a practical matter, though, one would expect the effects on home prices via public finances to be offset to some degree (or more than offset) by the fees associated with municipal courses which bolster local budgets and thereby allow for the provision of more public services.

Golf courses and their construction also have marked impacts on the environment of an area — both positive and negative. Construction of a course often generates large amounts of dust and noise, disturbs wildlife, and can taint water runoff (Salgot and Tapias, 2006). Water pollution resulting from courses' pesticide use may also have harmful effects on residents (Boyle and Kiel, 2001). These negative externalities may affect home values nearby. Additionally, the large water requirements of courses can drive water scarcity in some locations, which may drive increases in utility prices that become priced into housing markets. (Gelernter et al., 2015). However, as large porous swaths of land, golf courses can also serve a role in storm water management. Additionally, in urban and peri-urban areas, golf courses can act as a refuge for certain species of animals (Salgot and Tapias, 2006).

Furthermore, the deforestation and destruction of untouched land sometimes required for construction of courses may reduce residents' access to nature and open space (Salgot and Tapias, 2006). This may lower home prices, as open space is known to be valued positively in hedonic home price models (Irwin, Jeanty and Partridge, 2014; Davis, 2011; Asabere and Huffman, 2009). Conversely, golf courses can also become sources of open space themselves. Especially in urban areas, courses can provide green grass and open walking areas to people who may not be surrounded by it. This positive open space effect could also be priced into housing decisions. An additional spillover effect of new courses may be increased traffic in an area, which can negatively impact home prices (Ossokina and Verweij, 2015).

These various mechanisms and their differing directions of influence make it difficult to reason out the net effect of building a golf course. Thus, this topic lends itself well

to empirical analysis. While hedonic models — which decompose homes into constituent attributes and use regression techniques to find the respective value of each attribute — serve well to elucidate the value of an existing golf course as an amenity, these models fall short of capturing an estimate for the *introduction* of a new course. Moreover, hedonic models can be sensitive to functional form and misspecification (Chau and Chin, 2002; Graves et al., 1988). Hedonic models are further limited by data constraints that often limit the scope of studies to small geographies and sample sizes.³ By contrast, a panel data difference-in-differences approach supports a broad scope and offers the ability to examine the introduction of a treatment. There is currently no existing literature I know of that applies this approach to the topic of golf course construction and home prices. This thesis aims to do just that.

3 Data

Data for this thesis come from three sources: GolfLink.com, the Federal Housing Finance Agency, and the U.S. Census Bureau.

3.1 Golf Course Data

Data on golf courses were obtained by scraping GolfLink.com to generate a dataset containing current U.S. golf courses and their key attributes. GolfLink is a website for players to find golf courses, tee times, and golf tournaments near them, and the site contains information on courses across the United States. GolfLink’s underlying golf course data comes from the National Golf Foundation, the leading provider of golf course statistics in the U.S., with key customers such as the PGA Tour and the USGA⁴. The initial dataset from GolfLink contained 17,108 currently open golf courses across the 50 U.S. states and D.C. that were built between the years 1878 and 2021.

³Hedonic models require detailed home-specific data that track the amenities and features that each individual home has. These data can be difficult to obtain at a national scale.

⁴This data comes from the National Golf Foundation’s website

Using the U.S. Census Bureau’s Geocoder, each golf course’s address is linked to a corresponding U.S. Census tract. If GolfLink’s listed address for a course falls within boundaries of a tract, the golf course is mapped to that tract (even if some or most of the land lies in a neighboring tract). Approximately 25% of addresses were unable to be mapped by the Geocoder as they don’t exist in the Census database for multiple reasons.⁵

To simplify the analysis, I have narrowed down the course types listed on GolfLink to the four largest categories which make up the following percentages of the dataset: 55.5% public ($n = 7157$), 25.1% private ($n = 3234$), 17.6% municipal ($n = 2269$), and 1.8% other ($n=237$). The most relevant attributes of the dataset for this thesis are the mapped census tract, year built, and type of golf course. Additionally, I include the course length, par, number of holes, and course difficulty ratings. Table 1 contains summary statistics for the numerical variables of the golf course dataset, stratified by type.

For every course type, year built ranges from the late 19th century through the present day, meaning that every type of course has existed for over 120 years. However, public courses (mean year built = 1976) were on average built later than both private courses (mean year built = 1966) and municipal courses (mean year built = 1968). This finding is consistent with the arguments of Napton and Laingen (2008) who note that private golf courses outnumbered public golf courses until the mid-1960s when golf transitioned away from a sport purely for the social elite.

A second takeaway from Table 1 is that the difficulty of the courses — measured by course rating and slope rating — is higher for private courses than for other course types. These differences may reflect private courses having features such as longer holes, more bunkers, faster greens, and other hazards that are expensive to build and maintain but more desirable for golfers. Private courses have the ability to assess members a fee for occasional course renovations, allowing them to continually improve their course’s difficult features.

⁵Reasons listed by Census Geocoder documentation include (1) non-residential or commercial address (2) recent construction (3) recently changed by Local Addressing Authority (4) in location with missing address range information (5) disclosure of address would violate U.S. Code Title 13 (“Census Geocoder Documentation”)

Table 1: Golf Course Dataset Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
<u>All Courses</u>					
Year Built	12,897	1971	31	1878	2021
Number of Holes	12,897	15.0	4.3	9	99
Par	12,487	59.2	17.4	27	75
Length	12,401	5,292.5	1,882.8	510	8,191
Slope Rating	9,326	122.6	12.1	45	155
Course Rating	9,290	65.9	13.3	22.0	140.0
<u>Public Courses</u>					
Year Built	7,157	1976	27	1880	2021
Number of Holes	7,157	14.6	4.5	9	99
Par	6,920	57.6	17.9	27	75
Length	6,870	5,081.0	1,913.0	577	8,191
Slope Rating	5,021	121.0	12.4	47	154
Course Rating	4,992	64.4	14.3	22.0	140.0
<u>Private Courses</u>					
Year Built	3,234	1966	38	1878	2021
Number of Holes	3,234	16.0	3.7	9	18
Par	3,141	63.8	15.0	27	74
Length	3,126	5,896.8	1,631.5	561	7,850
Slope Rating	2,445	128.8	9.4	57	155
Course Rating	2,440	70.0	9.0	22.0	139.0
<u>Municipal Courses</u>					
Year Built	2,269	1968	30	1890	2021
Number of Holes	2,269	14.7	4.4	9	39
Par	2,212	57.7	18.1	27	75
Length	2,191	5,083.7	1,946.9	510	7,705
Slope Rating	1,694	118.4	11.5	45	150
Course Rating	1,692	64.2	14.1	22.0	126.0
<u>Other Courses</u>					
Year Built	237	1971	31	1897	2021
Number of Holes	237	14.5	4.4	9	18
Par	214	59.7	17.0	27	72
Length	214	5,394.2	1,752.2	1,211	7,580
Slope Rating	166	125.0	10.6	86	146
Course Rating	166	65.6	13.6	30.4	76.9

Notes: This table shows summary statistics for the golf course dataset, stratified by course type. Data comes from GolfLink.com and includes all currently operational golf courses in the U.S. and D.C. Year Built is the year in which a golf course opened. Number of Holes is the number of golf holes the course contains. Par is the listed par for the golf course. Length is the total length of the golf course measured in yards. Slope Rating and Course Rating are measures of course difficulty, representing the difficulty for bogey and scratch golfers, respectively.

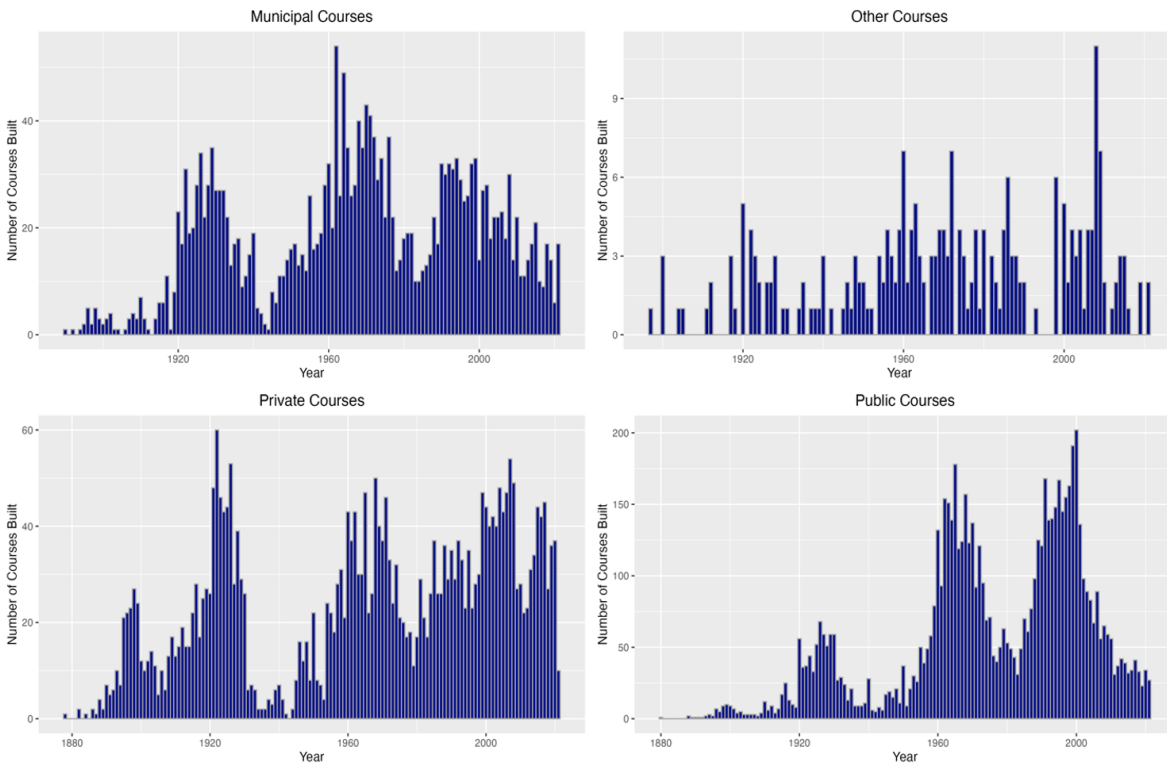
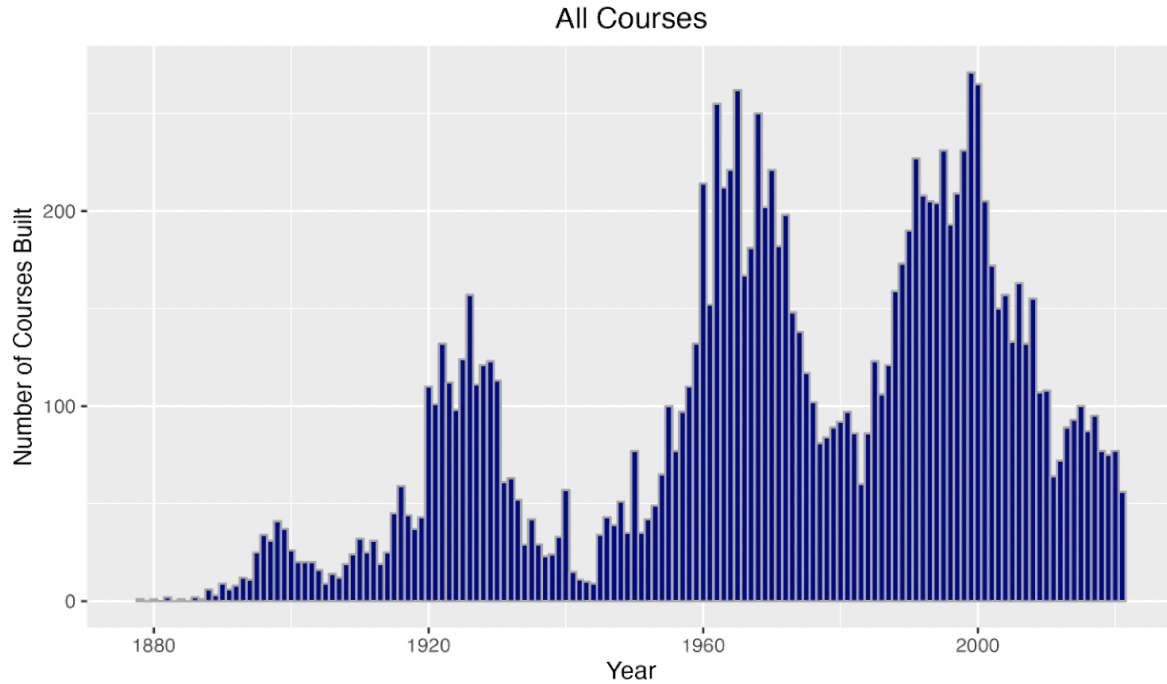


Figure 1: Histogram of Golf Course Construction Year in Golf Course Dataset

Notes: The top panel shows the distribution across years for all courses. The bottom four graphs show a breakdown by course type — public, private, municipal, and other. Data comes from GolfLink.com and includes all currently operational golf courses in the U.S. states and D.C.

Figure 1 shows the distribution of golf course construction across years. Notice the significant spikes in building in the mid 1920s, mid 1960s, and late 1990s, which correspond to the golf booms discussed in Section 2. Also noteworthy is that golf course construction has declined in the post-2000 period with a more significant decline in the construction of municipal and public courses than private courses.

3.2 Panel Dataset Creation

I combine this expansive golf course dataset with home price data from the Federal Housing Finance Association (FHFA) (Bogin, Doerner and Larson, 2019). The FHFA compiles data on home prices for each census tract ($n = 61,843$) for each year, yielding a panel dataset spanning from 1975 through 2021. FHFA’s measure of House Price Index (HPI) is a “broad measure of the movement of single-family house prices” that tracks median price levels of repeat sales for homes with mortgages backed by Fannie Mae and Freddie Mac (, n.d.). The HPI measure has a baseline value of 100 for the first year a tract is included in the dataset.⁶

A limitation of the FHFA data is that the measure excludes homes with mortgages that do not meet the eligibility requirements for Fannie Mae and Freddie Mac, such as those above certain prices⁷ or those bought by people with insufficient credit scores (Winkler, n.d.). However, because the measure is based on repeat sales, it comes with the important advantage of accounting for quality adjustments in housing markets. In addition, its granularity, long history, and national coverage enhances its value for research.

For each census tract, I construct two binary variables - *presence* and *introduction*. *Introduction* is 1 when a new golf course construction was completed in that tract in that year and 0 otherwise. *Presence* is 1 in the year of or years after a golf course is completed in a census tract (includes courses built pre-1975) and 0 otherwise. For instance, if Tract 1 had

⁶Each census tract is independently baselined to 100 based on the median home prices in FHFA data for the first year of its inclusion in the dataset. Thus, comparisons of HPI value across census tracts are not meaningful.

⁷Conforming loan limits are adjusted each year to reflect changing home prices per HERA guidelines. The 2023 national figure is \$726,200 and \$1,089,300 for high-cost areas. For reference, the 2006-2008 national limit was \$417,000. Source: FHFA Documenatation

a course built in 1990, *presence* = 1 for all years from 1990 onwards (inclusive). Note that some census tracts have *presence* = 1 for the entire span of years in my dataset (always-treated) as a result of golf courses being constructed prior to the census tract’s inclusion in the FHFA data (e.g. a course built in 1950). I construct a variable, *count*, which marks the number of courses present in a tract and increases by 1 for each new course constructed in a given census tract. This mitigates an issue with the *presence* variable, where a single golf course and multiple golf courses in a census tract are not differentially represented.

Additionally, utilizing the course type variable from the golf course dataset, I construct four binary variables to indicate the presence of a specific type of golf course in a dataset: *public*, *private*, *municipal*, and *other*. Each is set to 1 in any year that a given census tract contains the respective type golf course and 0 otherwise, much like the *presence* variable. These course type indicator variables allow for the analysis of varying treatment effects from different golf course types in Section 5.

The FHFA’s dataset does not include any covariates for census tracts. To address this problem, I use 5-year estimates from the American Community Survey Data. This data, published by the U.S. Census Bureau, includes yearly information from 2009-2021 on a wide array of demographic, economic, and social characteristics at the census-tract level. ACS 5-year estimates are “period” estimates, meaning they represent lagged 5-year moving averages.⁸ Specifically, I include the following variables from this dataset: unemployment rate, mean commute time, median household income, population, percentage over the age of 65, percentage White, percentage Black, and percentage with at least a Bachelor’s degree. Thus, I have observations for each census tract for each year from 2009-2021, where each observation is a lagged 5-year moving average for that census tract.

To extend the temporal span of this data, I combine with similar census-tract level data from the 2000 Decennial Census by matching on census tract.⁹ I then linearly impute

⁸Since the ACS began in 2005, the first 5-year estimates available are from 2009

⁹Variables obtained from the 2000 Decennial Census are the same as those from the ACS: unemployment rate, mean commute time, median household income, population, percentage over the age of 65, percentage White, percentage Black, and percentage with at least a Bachelor’s degree. Note that 2000 Census data is

covariate values for 2001-2008. Finally, I obtain land area data for each census tract from the U.S. Census Bureau’s Planning Database which I then use to construct a population density control.¹⁰ This yields a covariate dataset with observations for each year and each census tract from 2000-2021 which I then merge into my panel dataset by matching on census tract and year. Note that some tracts have missing data when there were too few survey respondents to provide reliable ACS estimates.

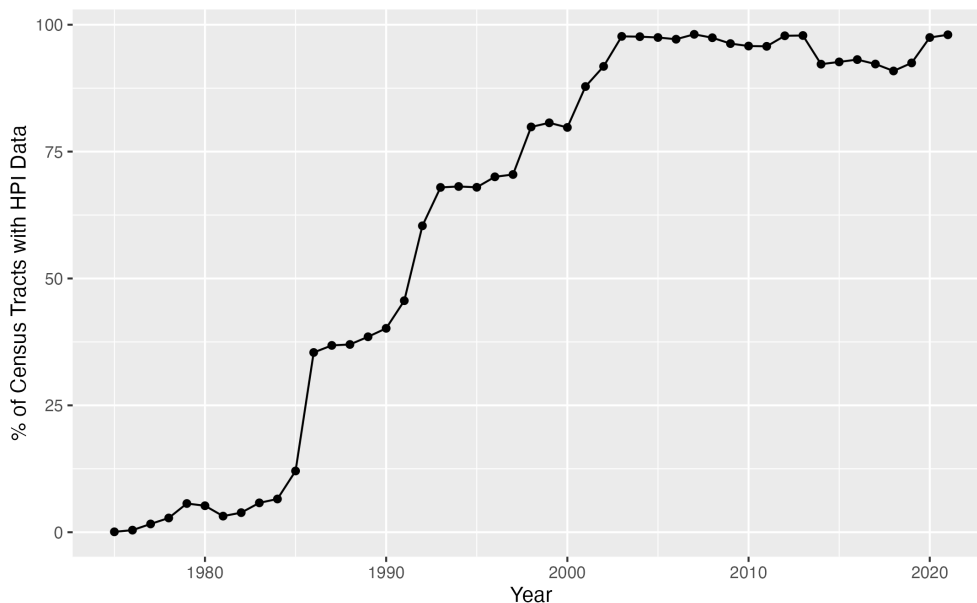


Figure 2: Plot of Percent Non-Missing Values by Year in Panel Dataset

The resulting panel dataset is unbalanced as FHFA data begins in different years for different tracts. Figure 2 plots the percentage of census tracts that have home price data for a given year. As shown in the graph, there is a steady increase in the number of tracts that contain FHFA data from 1975-2003.

Per the FHFA, the varying start dates are due to a lack of data for early years. Their repeat-sales model requires at least two transactions for a property to be included in the underlying dataset. Since residential properties tend to have multi-year periods between transactions, many census tracts in early years lack sufficient data points for inclusion in

not a period estimate like 5-year estimates from the ACS

¹⁰Population density is obtained by dividing a census tract’s population by its land area to give a measure of people per square mile. Land area is based on 2010 Census geographies

FHFA’s data. Additionally, some census tracts may be missing HPI values for certain years due to the large fluctuations in transaction volume at the census-tract level of granularity. Importantly, if these missing data are non-random and correlated with the introduction of golf courses, that could bias results. It’s plausible that newly developed communities are both more likely to have a golf course built and less likely to have previous sales transactions for inclusion in FHFA’s data.

To address potential concerns and provide consistent data, I have limited the scope of the panel dataset to only observations from 2003 to 2021. By 2003, over 95% of census tracts had FHFA data, and this number remains relatively steady across the remaining years. As such, the final dataset used in this thesis only contains observations from 2003-2021. In total, 1,990 golf courses in 1,682 census tracts were built during this time period — 47.1% public ($n = 937$), 34.5% private ($n = 687$), 15.9% municipal ($n = 316$), and 2.5% other ($n = 50$). Note the panel dataset presents a similar distribution of golf course type compared to the GolfLink golf course dataset described in Section 3.1. This suggests that the imperfect Geocoder mapping and the truncation of the data post-2002 were not significantly biased toward one golf course type.

Figure 3 displays a time-series plot of the percentage of census tracts in the dataset that contain a golf course. The vast majority of tracts do not have a course with only 1.95% of tracts containing a course by 2021. Across the 19 year span, on average 1.27% of tracts contain a golf course, 0.65% contain a public course, 0.46% contain a private course, 0.21% contain a municipal course, and 0.04% contain an “other” type course.

Finally, observations without HPI measurements were dropped, as well as those tracts who were always treated (had a golf course prior to 2003 with none built from 2003 onward), as they do not function as control or treatment groups in the difference-in-differences framework utilized in this thesis. The final dataset contains 986,948 observations, and its relevant variables are summarized in Table 2.

Important to note in Table 2 is the fact that the mean annual HPI change is 3.74 index

Table 2: Panel Dataset Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
HPI	986,948	235.5	142.9	25.7	2,300.6
Annual HPI Change	964,521	3.74	9.4	−69.0	161.2
Introduction	986,948	0.001	0.03	0	1
Presence	986,948	0.01	0.1	0	1
Public	986,948	0.01	0.1	0	1
Private	986,948	0.005	0.1	0	1
Municipal	986,948	0.002	0.05	0	1
Other	986,948	0.000	0.02	0	1
Count	986,948	0.02	0.2	0	11
Year Built	986,948	39.5	279.2	0	2021
Unemployment Rate	683,716	4.5	2.6	0.0	36.7
Mean Commute Time	683,716	25.6	6.6	5.7	106.6
Median HH Income	683,716	64,039.4	29,327.4	8,068.0	250,001.0
Over 65 Pct	683,716	14.7	6.6	0.0	96.3
Percent White	683,716	76.3	21.8	0.0	100.0
Percent Black	683,716	10.2	17.2	0.0	100.0
College Grad Pct	683,716	30.4	18.1	0.0	99.4
Population Density	655,673	4,194.6	5,406.5	0.2	83,196.1

Notes: Summary statistics for the final panel dataset spanning the years 2003-2021. HPI is the housing price index. Introduction is a binary indicator representing the construction of a golf course. Presence is a binary indicator representing the presence of a golf course. Public, Private, Municipal, and Other are binary indicator variables indicating the presence of that specific type of course. Count represents the number of golf courses present. Year Built is the most recent year in which a golf course was built in that census tract and is set to 0 in tracts with no golf courses. Mean Commute Time is measured in minutes. Median HH Income represents the median household income of households in a census tract. Over 65 Pct is the percentage of a census tract’s population over the age of 65. College Grad Pct is the percentage of a census tract’s population with at least a Bachelor’s degree. Population Density is measured in people per square mile

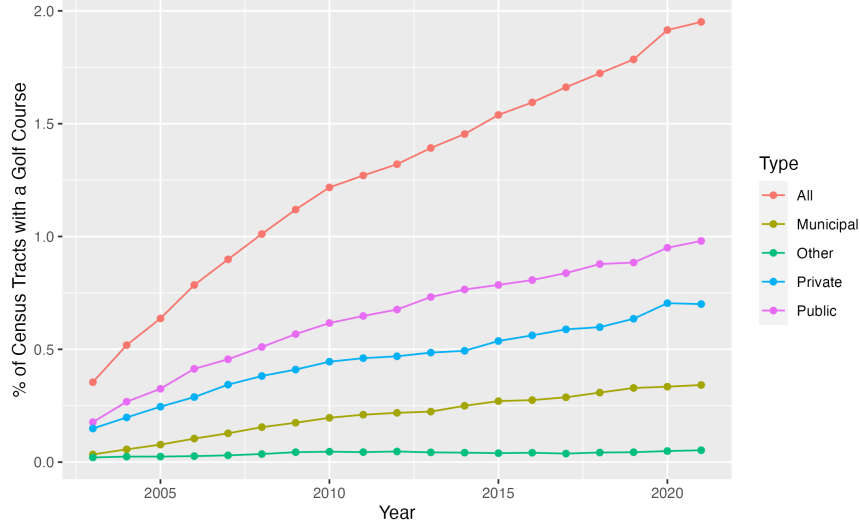


Figure 3: Percent of Census Tracts that Contain a Golf Course by Year

Notes: This figure illustrates the percentage of census tracts in my panel dataset that contain a golf course by year and stratifies by course type. Data spans 2003-2021. Note that tracts that had a golf course prior to 2003 and did not have another golf course constructed post-2003 (always-treated) are not included in the dataset.

points, showing that nominal home prices experienced significant growth over the period. Additionally, note that the standard deviation of HPI is large (142.9) relative to the mean (235.5) which may in large part be due to census tracts independently being baselined to 100 in different years. Due to the panel nature of the dataset, the mean values for binary indicator variables are relatively difficult to interpret.¹¹ Figure 3 is more instructive for examining the frequency of these indicators. However, note that since the vast majority of census tracts, especially in early years, do not have a golf course, the mean values of the indicators (*presence*, *public*, *private*, *municipal*, *other*, and *introduction*) and *count* are near zero. It is also noteworthy that some tracts have up to 11 golf courses present. Conditional on a tract having at least one course, the average count is 1.24. Finally, the demographic control data is missing in approximately 30% of observations since the ACS

¹¹The mean values of binary indicators for Presence, Public, Private, Municipal, and Other represent the fraction of census tract-year combinations where that type of golf course is present (any type in the case of Presence). The mean value of Introduction (mean=0.001) represents the average share of census tract-year combinations that have a new course was built, which can be interpreted as the observed probability that a given census tract has a golf course built in a given year. However, note that this is not entirely accurate as not every census tract has an observation for every year

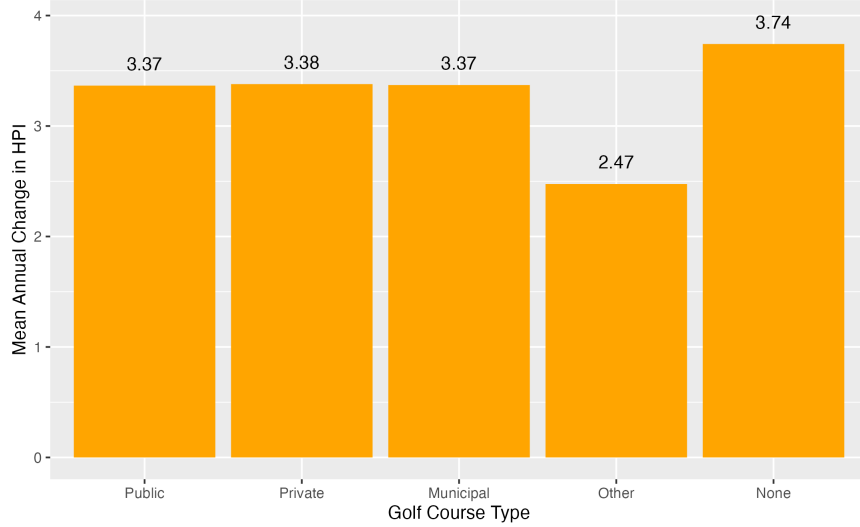


Figure 4: Mean Annual Change in House Price Index (HPI)

Notes: This figure illustrates the mean annual change in HPI stratified by the type of golf course that the census tract contains at the time. The y-axis shows mean annual change in HPI measured in index points. Data spans 2003-2021.

does not report results for tracts with insufficient survey respondents.

Figure 4 plots the mean annual change in HPI across tracts with different kinds of golf courses. Changes in home prices across the areas with public (mean=3.37), private (mean=3.38), and municipal courses (mean=3.37) are remarkably similar, while the “Other” category has a substantially lower annual HPI change (mean=2.47). Interestingly, all areas with golf courses have a lower average increase in HPI than do those tracts without a course (mean=3.74). Since the vast majority of tracts contain no golf course, the overall average change in HPI is 3.74, as reported in Table 2.

A potential limitation to this data is the lack of information on courses that may have closed over the period of interest. The GolfLink data only includes currently open courses, so courses that have closed are not included. According to data from the National Golf Foundation, 130 courses closed in 2021 (Smits, 2022). Failure to account for closing courses may bias estimates. Tracts with courses that closed would function as control units (“never-treated”) despite having been treated for part of the period of interest which may incorrectly

shrink the magnitude of estimates.¹²

4 Methodology

A fundamental concern in this study is the endogeneity of golf course development. It is likely that rising home prices spur golf course development. In addition, other characteristics that drive developers to develop courses in a given area may also raise home prices. For instance, arrival of nearby businesses, improvements in school quality, or changes in regulations may cause a census tract to be more economically viable for development of a golf course while also raising home prices. Additionally, there may be concerns of endogeneity of treatment timing, where census tracts who received golf courses may lead nearby census tracts to develop one. Due to these factors, golf course development may likely be correlated with the error term in a basic OLS regression of home prices on golf course presence, and thus lead to inconsistent estimates.

To attempt to address these endogeneity concerns, I utilize a staggered difference-in-differences approach to analyze the effects of golf course development on census tract home prices. As a baseline, I first use a two-way fixed effects (TWFE) model to estimate this effect. I then utilize what I call a “grouped difference-in-differences” model following Callaway and Sant’Anna (2020) to deal with concerns around “forbidden comparisons” in the traditional staggered difference-in-differences framework that lead to inconsistent TWFE estimates. Using this newer methodology, I provide evidence in support of the parallel trends assumption necessary to make the estimates of effects causal.

To begin, I employ a standard two-way fixed effects (TWFE) staggered difference-in-differences approach. TWFE allows for temporally-fixed, spatially-variant and temporally-variant, spatially-fixed differences between observations. This estimation allows for multiple units and multiple treatment timings and has been viewed as more robust than DiD with

¹²Another potential limitation is the dropout of FHFA data. Despite efforts to limit to only time periods where the data is robust, there are some tracts that drop out during the study ($\approx 95\%$ complete data)

a single treatment period by mitigating concerns around contemporaneous trends (Baker, Larcker and Wang, 2022). Using the previously described *presence* indicator variable, the following TWFE regression estimates the effect of the introduction of a golf course on home prices.¹³

$$hpi_{it} = \alpha + \beta \cdot presence_{it} + \eta \cdot X_{it} + \delta_i + \lambda_t + \epsilon_{it} \quad (1)$$

Here, α is a constant. The δ_i and λ_t represent spatial and time fixed effects, respectively, that are included to control for geographic-specific or temporal-specific variations in HPI. The outcome variable, hpi_{it} , is the house price index for tract i in year t . The $presence_{it}$ indicates whether tract i had a golf course present in year t . X_{it} is a vector of demographic controls for tract i in year t . Control variables used in this thesis are: unemployment rate, mean commute time, median household income, population density, percentage over the age of 65, percentage White, percentage Black, and percentage with at least a Bachelor's degree. The coefficient of interest is β which encapsulates the average treatment effect of the construction a golf course on home prices. This TWFE framework assumes a singular β for all census tracts and years, requiring that effects are homogeneous across tracts and time. If the positive amenity value of golf courses dominates other determinants of home prices, as might be suggested by earlier literature, one would expect β to be positive (Asabere and Huffman, 2009; Song and Knaap, 2004; Irwin, 2002).

I also expand this regression to include the indicator variables for the presence of different types of golf courses, which provides heterogeneous effects across golf course types:

$$hpi_{it} = \alpha + \beta_1 \cdot public_{it} + \beta_2 \cdot private_{it} + \beta_3 \cdot municipal_{it} + \beta_4 \cdot other_{it} + \eta \cdot X_{it} + \delta_i + \lambda_t + \epsilon_{it} \quad (2)$$

¹³Note that the by construction, the $presence_{it}$ variable is equivalent to the interaction term in traditional 2x2 DiD designs $TREAT_i \cdot POST_t$ and thus under certain assumptions, β is equivalent to the estimates from 2x2 DiD regressions (Baker, Larcker and Wang, 2022)

To elucidate the effects of treatment intensity effects, I use this TWFE approach with the *count* and *count*² variables. Equation 3 allows for non-linear treatment effects based on the number of golf course a census tract receives:

$$hpi_{it} = \alpha + \beta_1 \cdot count + \beta_2 \cdot count^2 + \eta \cdot X_{it} + \delta_i + \lambda_t + \epsilon_{it} \quad (3)$$

Importantly, difference-in-differences only estimates an average treatment effect if several assumptions hold. First, it must be true that the treatment group and control groups exhibit parallel trends. That is, pre-intervention, units in the control group must exhibit the same trends in home prices as those tracts in the treatment group, although the actual HPI levels can be different. Additionally, there must be no anticipation of treatment, meaning there should be no causal effects before the construction of a course. In practical terms, this demands that actors do not price impending golf course construction into current home values. Finally, it must be that units remain treated once they undergo treatment — that is, after a golf course opens in a tract, it does not close during the period of interest.

However, as Callaway and Sant’Anna (2020) point out in their recent paper, conducting the standard TWFE regression with staggered treatment timings can lead to “forbidden comparisons.” Good comparisons are those between newly treated and never treated and newly treated and not-yet-treated units. By contrast, “forbidden comparisons” are those between newly treated units with already treated units. When there is treatment effect heterogeneity — when treatment effects depends on the time elapsed post-treatment — and staggered treatment timing, these forbidden comparisons lead to biased estimates under a traditional TWFE approach and can even produce estimates with the opposite sign to the true effect (Baker, Larcker and Wang, 2022; Callaway and Sant’Anna, 2020; de Chaisemartin and D’Haultfoeuille, 2021; Sun and Abraham, 2021). It is likely that the reaction of home prices to golf course construction changes over time, and thus these “forbidden comparisons” are an issue.

To address these concerns, Callaway and Sant’Anna suggest a variation on the staggered

difference-in-difference framework that utilizes treatment “groups,”¹⁴ to eliminate such “forbidden comparisons” and yield robust estimators. See Eq. 4 for the potential outcomes definition of “group-time” average treatment effects as provided by Callaway and Sant’Anna (Callaway and Sant’Anna, 2022b).

$$ATT(g, t) = E[Y_t(g) - Y_t(0) | G = g] \quad (4)$$

This methodology provides “group-time” ATTs that allow for heterogeneous treatment effects across treatment groups and time. Each $ATT(g, t)$ represents the effect of participating in the treatment for group g at time t . For instance, $ATT(2013, 2016)$ would be the treatment effect experienced in 2016 by those tracts who received a golf course in 2013. This methodology only allows good comparisons and eliminates comparisons with already treated groups.¹⁵ In this thesis, both never-treated and not-yet treated census tracts are used as control units.

As Callaway and Sant’Anna’s framework relies on a single independent variable, I run separate regressions for each type of golf course, with either the *presence* variable or the respective indicator for each course type. Both unconditional and conditional specifications are examined for each type of golf course.¹⁶ Specifically, their model requires time-invariant covariates. However, the demographic characteristics included in my panel dataset are time-variant. Callaway and Sant’Anna describe how this is dealt with in their regression model:

For time varying covariates, the did package sets the value of the covariate to be equal to the value of the covariate in the “base period” where, in post-treatment periods the base period is the period immediately before observations in a particular group become treated (when there is anticipation, it is before anticipation

¹⁴Groups are based on the year of treatment

¹⁵Callaway and Sant’Anna’s estimator does this by uses a two-step estimation method that uses propensity scores to re-weight the “long differences” in the outcome variable (Baker, Larcker and Wang, 2022). For more details on their estimator and the intuition behind it, refer to Callaway and Sant’Anna (2020) and Baker, Larcker and Wang (2022)

¹⁶Controls included are the same as those in the TWFE model (listed earlier in Section 4

effects start too), and in pre-treatment periods the base period is the period right before the current period (Callaway and Sant’Anna, 2022*a*)

The same assumptions that are required in the TWFE regression are required in the Callaway and Sant’Anna model, albeit with minor adjustments. First, once a treatment group has been treated, we assume that it remains treated. Naturally, the time period of treatment varies across census tracts, but it must be assumed that once a tract receive a golf course, it continues to have that course for the entire treatment period. Next, the parallel trends assumption must hold between the treatment group and the control groups: never-treated and not-yet-treated units¹⁷ Finally, there must also be no anticipation of treatment.¹⁸

Evidence in support of the parallel trends and no anticipation assumptions required for TWFE and group-time ATT models will be analyzed further in the next section. However, the assumption requiring treated units to stay treated can reasonably be assumed from the nature of my dataset construction. Since, by construction, only golf courses that are currently operational are included in the dataset, their corresponding census tracts must have had and still have those courses since their year of introduction. After all, golf courses do not move around move around too much. And while some courses closed during the period of study, these courses do not appear in GolfLink’s data and thus are treated as control units. While this may affect results,¹⁹ it does not violate the assumption since all treated units in the dataset remain treated for the entire time.

¹⁷Callaway and Sant’Anna’s estimator allows for parallel trends to hold after conditioning on covariates. They label their parallel trends assumptions “Conditional Parallel Trends Based on a ‘Never-Treated’ Group” and “Conditional Parallel Trends Based on ‘Not-Yet-Treated’ Groups”

¹⁸Technically this assumption is overly strict. Callaway and Sant’Anna provide an empirical method for handling anticipation periods and require the assumption of “Limited Treatment Anticipation”. This assumption requires a known number of anticipation periods. But without a known number of anticipation periods, I set the value to 0 in my models meaning that I assume no anticipation. I provide support for this assumption in Section 5

¹⁹See the last paragraph of Section 3.2 for a discussion of how course closures may affect results

5 Empirical Results

5.1 Two-Way Fixed Effects Models

Table 3 reports results from the TWFE models. Columns 1 and 2 report results of regressions per Equations 1 and 2, respectively, while Columns 3 and 4 report results from the same regressions but including state-time interaction fixed effects. State-time fixed effects allow for differential time evolution in HPI across different states. Columns 1 and 3 report a single coefficient for the presence of a golf course (of any type), while stratified results in Columns 2 and 4 show coefficients for each type of course — public, private, municipal, or other. More detailed robustness checks for these regressions can be found in the Appendix.

Across both specifications (Columns 1 and 3), the coefficient on *presence* is negative and statistically significant at the 5 percent level. This suggests that the presence of a golf course, or, equivalently, the construction of a new golf course to a tract, lowers home values of the tract relative to control tracts.²⁰ Including state-year fixed effects decreases the magnitude of the effect by 37% ($\hat{\beta} = -8.725$ vs. $\hat{\beta} = -5.471$) and explains a larger share of the variation in HPI ($R^2 = 0.921$ vs. $R^2 = 0.9544$). The more flexible specification, that with state-year fixed effects, produces a coefficient on presence of -5.471. This suggests that the introduction of golf course leads to a decrease in home values of 5.471 index points, corresponding to 2.3% of the mean HPI value in the dataset²¹ (mean HPI = 235.5), or 1.46 times the magnitude of the average annual HPI change (mean change = 3.74).^{22,23}

²⁰It is the case that “the presence of a golf course” can be replaced with “the construction of a new golf course” since these are equivalent under the setup. There are no always-treated groups, and so once a golf course is built in a tract, that tract goes from not having a golf course to having one. TWFE estimates the effect of “participating in the treatment,” and by nature, “participating in the treatment” equivalently means having had a new golf course constructed or having a golf course present

²¹Note that this does not mean that home prices decrease on average by 2.3%. Rather, it suggests that the average value of home prices decrease by 2.3%. This could also be interpreted as saying that the a census tract with the mean HPI will on average experience a 2.3% decline in home values

²²To get a back-of-the-envelope estimate of the dollar value of this effect, we could use the median sales price of homes in the U.S. reported in the Federal Reserve Economic Data, currently listed at \$467,700. A 2.3% change corresponds to a \$10,757 decrease in value

²³Note that measuring results relative to the standard deviation of HPI (SD=142.9) is somewhat misleading. The standard deviation is large due to the fact that each individual census tract is baselined to 100 independently in different years by the FHFA. Thus, newly included census tracts may have values close

Table 3: Two-Way Fixed Effects Regression Results

Dependent Variable:	HPI			
Model:	(1)	(2)	(3)	(4)
<i>Variables</i>				
Presence	-8.725*** (2.646)		-5.471** (1.969)	
Public		-16.99*** (3.085)		-12.90*** (2.506)
Private		-5.296 (4.380)		-0.2273 (3.672)
Municipal		0.8634 (5.130)		0.6727 (3.110)
Other		-16.76** (6.434)		-23.64*** (7.212)
<i>Controls</i>				
Demographic Controls	Yes	Yes	Yes	Yes
<i>Fixed-effects</i>				
Census Tract	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State-Year			Yes	Yes
<i>Fit statistics</i>				
Observations	655,673	655,673	655,673	655,673
R ²	0.92148	0.92149	0.95444	0.95444
Within R ²	0.07746	0.07753	0.05824	0.05834

Clustered (census tract & year) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports estimates from two-way fixed effects regressions. Columns (3) and (4) include state-year interaction fixed effects. Demographic controls are included in all regressions. The outcome variable is housing price index (HPI). Presence is an indicator for presence of a golf course in given census tract for a given year. Public, private, municipal, and other are indicators for the presence of the respective type of golf course. Standard errors are shown in parentheses are clustered by census tract and year

The stratified results reported in Columns 2 and 4 of Table 3 show the differential effects by golf course type. Estimates of coefficients on *public* and *other* are significant at the 1 percent level across both specifications with values in Column 4 reported as -12.9 and -23.6 for *public* and *other*, respectively. These correspond to a 5.5% and 10.0% decrease from the mean HPI, respectively, or 3.45 times and 6.31 times the average annual HPI change. Coefficients on *private* and *municipal* are not statistically significant and have estimates close to zero with wide confidence intervals. Importantly, these results suggest that building public golf courses, more so than building private and municipal courses, can be detrimental to home prices in the surrounding area.

I also test the intensity of treatment by running TWFE models using *count* and *count*² as the primary right-hand side variables per Equation 3. Using the non-linear *count*² term allows for differential impacts depending on the number of courses present. The results of this regression are reported in Table 4, both with and without state-year fixed effects.

Estimates of the coefficient on *count* suggest what was seen from TWFE regressions holds in the intensive margin; that is, the introduction of a golf course tends to decrease home prices. Additionally, results suggest that the more courses there are previously present, the larger the effect is.²⁴ Effects are statistically significant for both *count* and *count*² in Column 1 but are insignificant in Column 2, perhaps due to the increased statistical demands when including state-year fixed effects. Column 1 reports a coefficient on *count* of -5.423 and a coefficient on *count*² of -1.499. Taking the derivative of *hpi* with respect to *count* yields the marginal change in HPI for each additional golf course constructed: $\frac{\delta hpi}{\delta count} = -5.423 - 2.998 * count$. Plugging in values, we find that adding the first course decreases home prices by -5.42 index points while adding a second course to a tract decreases HPI by -8.42 index points. Each additional course present increases the marginal effect of the next course by approximately 3 index points. These non-linear trends in the impact of golf

to 100 while those that have been in data for many years may have values as high as 2,300. This renders standard deviation-based interpretations of coefficients quite small and somewhat meaningless

²⁴Further support for these results using a regression on indicators of count can be found in the Appendix

Table 4: Treatment Intensity Regression Results

Dependent Variable: Model:	HPI	
	(1)	(2)
<i>Variables</i>		
Count	-5.423** (2.507)	-3.370 (1.951)
Count ²	-1.499*** (0.5141)	-0.6527 (0.3981)
<i>Controls</i>		
Demographic Controls	Yes	Yes
<i>Fixed-effects</i>		
Census Tract	Yes	Yes
Year	Yes	Yes
State-Year		Yes
<i>Fit statistics</i>		
Observations	655,673	655,673
R ²	0.92149	0.95444
Within R ²	0.07755	0.05827

Clustered (census tract & year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table reports estimates from regressions on the *count* and *count*² variables. Count representing number of golf courses present in a census tract in a given year. Count² is the square of the count variable allowing for non-linear treatment effects. Column 1 reports estimates without state-year fixed effects while Column 2 includes state-year fixed effects. Standard errors are shown in parentheses are clustered by census tract and year

course construction suggest that having more golf courses not only continues to hurt home prices, but that it begins to compound. Perhaps this could be due to negative externalities of golf courses, like traffic, multiplying the more courses there are in a small area. While one course may increase traffic to an area by a little, adding a second or third course could compound those effects.

5.2 Grouped Difference-in-Differences Models

Following Callaway and Sant’Anna, I produce a model estimating a group-time average treatment effect, $ATT(g, t)$, for all time periods t and treatment groups g .²⁵ As such, each model yields 324 parameters of interest (18 years $\cdot$ 18 years).²⁶ While each individually is difficult to generalize, Callaway and Sant’Anna propose different aggregations of these coefficients that can provide interpretations similar to those produced by traditional difference-in-differences (Callaway and Sant’Anna, 2020).

The first of the aggregations is a simple averaging of all $ATT(g, t)$ ’s across all groups g and time periods t , using a weighted average by number of observations in that group and time period. This produces a single coefficient similar to those produced by TWFE models in Section 5.1 that is homogeneous across treatment groups and time. This can be considered the overall parameter of interest and represents the causal effect of golf course construction on home prices if the necessary assumptions hold. However, Callaway and Sant’Anna caveat that this estimate may overly rely on early treatment groups since they are present in more post-treatment periods (Callaway and Sant’Anna, 2020).

Table 5 displays the results of the ten different grouped DiD models I run. Two models were run for each course type, one with demographic controls included and one without. In Table 5, notice that estimates are negative across all course types and that estimates are

²⁵Callaway and Sant’Anna’s model allows for doubly robust, inverse probability weighting, and outcome regression estimation of these effects. Per suggestions in their documentation, I use the doubly robust method of estimation for all models

²⁶While the time period of the panel spans 2003-2021, there are no $ATT(g, t)$ estimates for 2003 as there is no pre-treatment period to compare post-treatment periods to (i.e. they are always treated)

Table 5: Summary Table of Grouped DiD Regression Estimates

Course Type	Controls	Estimate	Std. Error	P-Value	[95%	Conf. Int]
All	N	−6.430**	1.399	0.000	−9.159	−3.701
All	Y	−6.268**	2.277	0.006	−10.707	−1.828
Public	N	−3.985**	1.946	0.041	−7.780	−0.190
Public	Y	−5.196*	2.791	0.063	−10.639	0.247
Private	N	−8.583**	1.843	0.000	−12.176	−4.989
Private	Y	−9.735**	2.892	0.001	−15.375	−4.096
Municipal	N	−7.017**	1.748	0.000	−10.425	−3.610
Municipal	Y	−6.265**	2.723	0.021	−11.576	−0.955
Other	N	−5.943**	1.521	0.000	−8.908	−2.978
Other	Y	−6.772**	2.445	0.006	−11.539	−2.004

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Summary of coefficients from simple aggregation of $ATT(g,t)$'s from grouped DiD model per Callaway and Sant'Anna. Each estimate is the result of taking a weighted average of $ATT(g,t)$'s across all groups g and times t (weighted by number of observations in that group and time period). Estimates are reported for regressions run on all courses as well as on each of the four course types individually. Additionally, each model was run with and without demographic controls, as is indicated in the Controls column. Bootstrapped standard errors listed in Std. Error Column

significantly different from 0 at the 5 percent level in all but the controlled specification for public golf courses.

The two overall estimates (all course types) of $\hat{\beta} = -6.430$ and $\hat{\beta} = -6.268$ suggest that the construction a golf course causes home prices in an area to fall. Using the estimate from the regression including covariates suggests that, on average, building a course lowers home prices by approximately 6.3 index points, or 2.7% of the mean HPI of the data. Additionally, the magnitude of this effect is 1.7 times the average annual change in HPI for tracts in the dataset, suggesting the observed effect is economically significant.

The construction of private courses ($\hat{\beta} = -9.735$), municipal courses ($\hat{\beta} = -6.265$), and other course types ($\hat{\beta} = -6.772$) all negatively affect home prices as well, with private courses having the largest effect. Coefficients for each of these estimates are statistically significant at the 5 percent level and correspond to 4.1%, 2.7%, and 2.9% of the mean HPI, respectively. Point estimates of the coefficient on *public* are also negative and suggest the same direction of effect in both the uncontrolled ($\hat{\beta} = -3.985$) and controlled ($\hat{\beta} = -5.196$) regressions, but the controlled specification’s estimate is only marginally statistically significant ($p = 0.063$). Finally, note that controlling for observables decreases the magnitude of effects for all courses and municipal courses, but increases the size of estimates for public, private and other course types.

These results are interesting and both support and refine findings from the TWFE models. The negative direction and significance of the overall effect aligns with that found in TWFE models. However, the magnitude of this effect is 15% larger in this specification than the TWFE specification ($\hat{\beta}_{TWFE} = -5.471$ vs. $\hat{\beta}_{CSA} = -6.268$). This suggests that the TWFE models underestimated the true effect by failing to account for “forbidden comparisons.” That is, by using already treated groups as comparison units, the TWFE models diminished the true difference between treatment and control groups and thus reported smaller effects.²⁷

²⁷Technically, eliminating forbidden comparisons can push results in either direction (closer or further from zero). Doing so would only push estimates closer to zero if the TWFE estimate had the opposite sign of the true ATE. In this case, it seems that the TWFE model produced estimates with the correct sign (negative) but was underestimating the true effect and elimination

Public courses ($\hat{\beta}_{TWFE} = -12.9$) and “other” course types ($\hat{\beta}_{TWFE} = -23.6$) had previously shown the largest and most significant negative coefficients in TWFE models, while private and municipal courses had coefficients that were statistically insignificant from zero. Using Callaway and Sant’Anna’s estimator, all course types except public have significant results at the 5 percent level. Furthermore, private courses have the largest effect, followed by “other” courses, municipal courses, and lastly public courses. This suggests that eliminating “forbidden comparisons” between newly treated and already treated groups has a larger effect for public courses. Perhaps this is because they are the most frequent and thus, tracts containing public course make up the largest share of already-treated tracts. Due to the aforementioned advantages of Callaway and Sant’Anna’s approach over TWFE models,²⁸ I proceed with these model and their estimates as my primary results moving forward.

Another informative view of $ATT(g, t)$ ’s is the event-study aggregation; this is done by averaging $ATT(g, t)$ ’s across all groups g for each event-time pre- and post-treatment. This produces a result similar to a dynamic specification of a TWFE model.²⁹ Plotting the coefficients from this event-study aggregation shows the evolution of pre- and post-treatment ATTs spanning from -17 years to +17 years relative to the introduction of a golf course. Callaway and Sant’Anna argue this is perhaps the most informative of the aggregation methods — especially because it provides evidence to test the parallel trends assumption (Callaway and Sant’Anna, 2022b). Figures 5 through 6d show this event-study aggregation for each of the controlled (i.e. covariates included) models reported in Table 5.³⁰

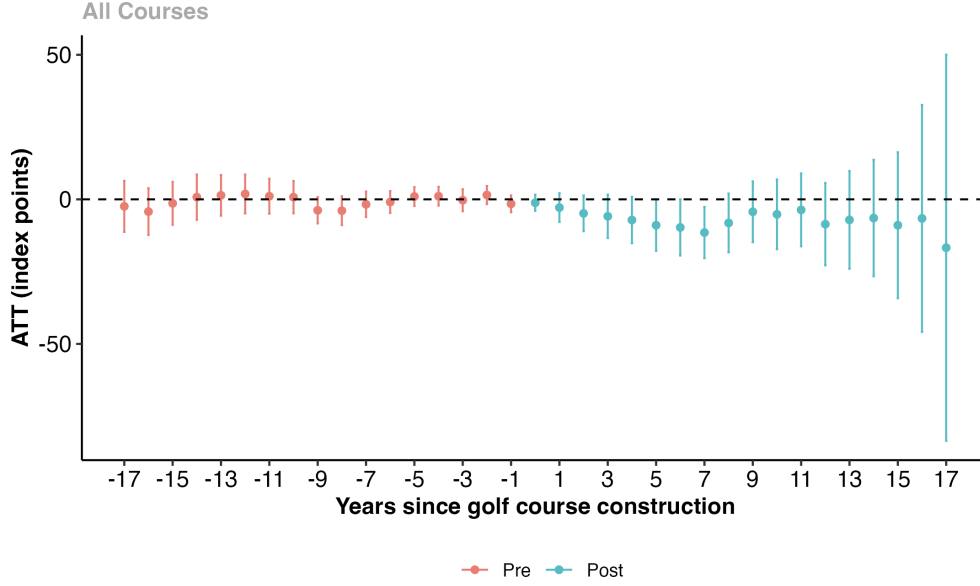
There are a couple interesting takeaways from these figures. First and foremost, we see good evidence of parallel trends with all pre-treatment periods (shown in red) being statistically insignificant. Not only do the standard errors overlap zero for every pre-treatment period, but the estimates themselves tend to bounce above and below zero, indicating the

²⁸See 4 for a detailed description of the advantages of this methodology over TWFE

²⁹Note that a this thesis does not present a dynamic specification of a TWFE model

³⁰See Table 11 the Appendix for the uncontrolled event-study aggregation of $ATT(g, t)$ ’s from the model run on all course types. Note similar behavior for most post-treatment periods and similar satisfaction of parallel trends.

Figure 5: Event-Study Aggregation of $ATT(g,t)$'s for All Course Types



Notes: This figure shows the event-study aggregations of ATTs produced by grouped difference-in-differences regression per Callaway and Sant’Anna. The outcome variable is House Price Index (hpi) and the independent variable is indicator for the presence of any type of golf course ($presence$). The x-axis displays the event-time in terms of years relative to golf course construction. The y-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with vertical bars.

parallel trends assumption may hold. Specifically, this suggests that trends in HPI between the treatment and control groups were insignificantly different prior to the construction of a golf course. Additionally, in pre-treatment periods immediately preceding the introduction of a course, no statistically significant effects are found, suggesting that the no anticipation assumption holds;³¹ that is, any anticipation of impending golf course construction does not lead to a change in home values prior to the opening of the course compared with control groups.³² Callaway and Sant’Anna also note that these event-study pre-treatment tests are still valid even with selective treatment timing (which is likely present in golf course development), a common pitfall in traditional event-study pre-treatment testing (Callaway and Sant’Anna, 2022c). The satisfaction of parallel trends and no anticipation assumptions

³¹As a robustness check, Tables 12 and 13 in the Appendix contains models that account for 1 year and 2 year anticipation periods. Results of these do not vary drastically from model reported with no anticipation

³²However, it could be true that there is indeed an anticipatory effect but that it occurs with a lag due to gradual turnover of housing stock and thus shows up in post-treatment periods

Figure 6: Event Study Aggregations across Different Types of Courses

(a) Event-Study Aggregation of ATT(g,t)'s for Public Courses



(b) Event-Study Aggregation of ATT(g,t)'s for Private Courses

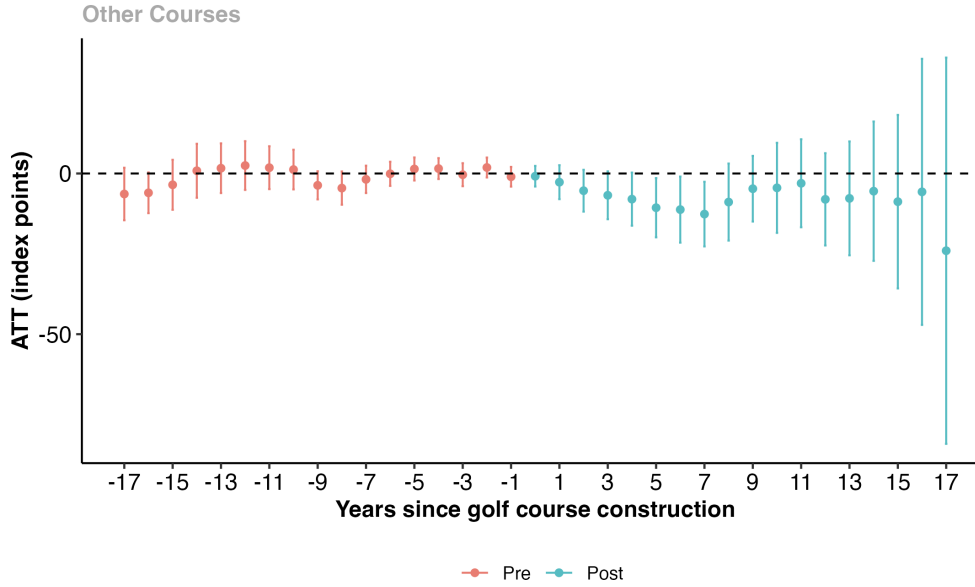


Figure 6: Event Study Aggregations across Different Types of Courses (cont.)

(c) Event-Study Aggregation of $ATT(g,t)$'s for Municipal Courses



(d) Event-Study Aggregation of $ATT(g,t)$'s for Other Course Types



Notes: This figure shows the event-study aggregations of ATTs produced by grouped difference-in-differences regression per Callaway and Sant'Anna. The outcome variable is House Price Index (*hpi*). Panel (a) shows results for public courses. Panel (b) shows results for private courses. Panel (c) shows results for municipal courses. Panel (d) shows results for other course types. The x-axis displays the event-time in terms of years relative to golf course construction. The y-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with vertical bars.

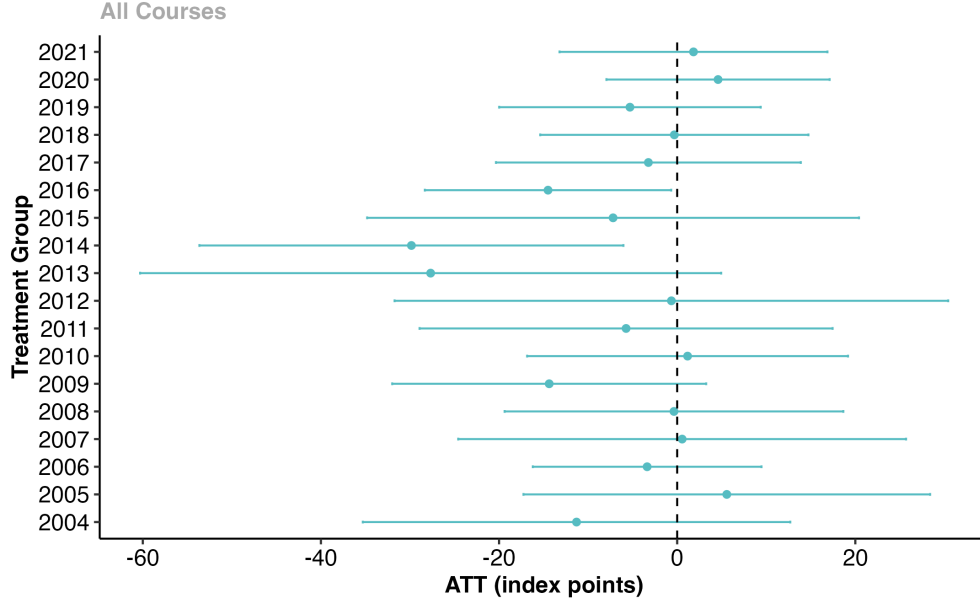
supports the group-time treatment estimates' causal interpretation.

Another important trend in Figures 5 through 6d is what is shown in blue. Across all graphs, the post-treatment point estimates trend downward for the first seven years. There is variation across course types in the degree to which this happens as well as the statistical significance of the estimates. Specifically, private courses exhibit the most statistically significant coefficients post-treatment (count = 5) while public courses exhibit the fewest (count = 0). Figure 5, which displays event-study results from the model with all courses, shows statistically significant coefficients at 5 year ($ATT = -8.95$) and 7 year ($ATT = -11.48$) horizons. Prior to 5 years, point estimates consistently trend downwards with relatively small confidence intervals that just barely cross zero. These results indicate that courses overall have negative impacts on home prices and that those impacts continue to increase in magnitude for the first seven years post-treatment.

Between the 7- and 9-year event horizons, point estimates are still negative but trend upward with confidence intervals that cross zero. At even longer event-time horizons, point estimates level off (slightly negative for most course types) and remain relatively constant (with some fluctuation). Meanwhile, standard errors for these estimates increase dramatically and results become further statistically insignificant. This is to be expected in a staggered difference-in-differences approach as the longer the post-event time horizon, the fewer units are in the sample. For instance, the only units in the +17 event horizon estimation are those that were treated in 2004, which greatly limits statistical power.

Figure 7 shows ATTs aggregated by treatment group (year of treatment) – that is, each group's effect is averaged across all post-treatment periods. For instance, the point in the graph for Group 2004 represents the average treatment effect across all post-treatment periods for those census tracts that received a golf course in 2004. There is large variation in these group estimates ranging from +5.6 for tracts treated in 2005 to -29.8 for tracts treated in 2014. Confidence intervals are wide and only two groups have statistically significant estimates — 2014 ($ATT = -29.8$) and 2016 ($ATT = -14.5$). The wide variance and lack

Figure 7: Group Aggregation of $ATT(g,t)$'s - All Courses



Notes: This figure shows the average treatment effect by treatment group produced by aggregating $ATT(g,t)$'s across all event times for each treatment group, per Callaway and Sant'Anna. Each data point represents the average treatment effect across all post-treatment periods experienced by tracts that received a golf course in a given year. The outcome variable is House Price Index (*hpi*) and the independent variable is indicator for the presence of any type of golf course (*presence*). The y-axis displays the year of treatment. The x-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with horizontal bars.

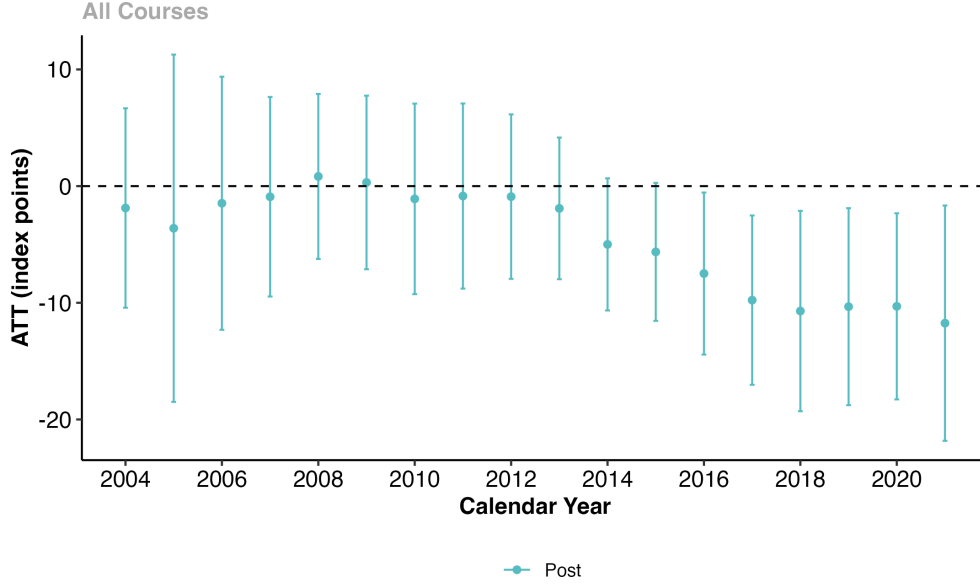
of significance could be due to the fact that relatively few courses are constructed per year. However, it would be interesting to research further whether there were reasons motivating differential impacts for courses built in the 2013-2016 period, where estimates are the most negative. Perhaps these periods had an influx of courses that were viewed negatively by the community, mismanaged by owners, or otherwise had disproportionately large negative impacts on surrounding home prices.³³

Finally, Callaway and Sant'Anna's model allows for aggregation of $ATT(g,t)$'s by calendar time. This is done by averaging $ATT(g,t)$'s across all groups g that have been treated by a given year t (i.e. $g \leq t$).³⁴ Results of this calendar time aggregation are shown in

³³See the Figures 9a through 9d for group-aggregation plots stratified by course type. Results are similar.

³⁴This means that the number of treated groups comprising each estimate increases with calendar year

Figure 8: Calendar-Time Aggregation of $ATT(g,t)$'s - All Courses



Notes: This figure shows the average treatment effect by calendar year produced by averaging $ATT(g,t)$'s across all treated groups in a given year. Each data point represents the average treatment effect experienced by treated census tracts in that year. The outcome variable is House Price Index (*hpi*) and the independent variable is indicator for the presence of any type of golf course (*presence*). The x-axis displays the calendar year. The y-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with vertical bars.

Figure 8.³⁵ Each data point represents the average treatment effect experienced by treated census tracts in the given calendar year. Figure 8 shows that estimates of the ATT are near zero (and not significant) through 2012, experience a decline from 2012-2018, and remain negative and statistically significant from 2016-2021 with a ATT fluctuating near -10 index points. The 2012-2018 decline may suggest that conditions during this period made golf course development become increasingly detrimental to home prices nearby, perhaps due to growing environmental concern or other shifts in consumer behavior. However, this decline is also likely a reflection of two dynamics explored in previous graphs: (1) increasing effect magnitude with time elapsed post-treatment (shown in Figure 5) and (2) more negative effects for treatment groups in 2013-2016 (shown in Figure 7). As calendar time increases,

³⁵See the Figures 10a through 10d in the Appendix for group-aggregation plots stratified by course type. Results are similar

previously treated census tracts experience larger negative effects, pulling down the average; at the same time, the inclusion of 2013-2016 treatment groups during this period further brings down the average.

6 Discussion

This thesis utilizes a novel panel data approach to provide an expansive, up-to-date analysis on the effects of golf course construction on home values. Results obtained using the recently published “group-time” ATT estimator by Callaway and Sant’Anna suggest that the construction of a golf course lowers home prices in the same census tract by approximately 6.3 index points,³⁶ or roughly a 2.7% reduction in value for a census tract with average home prices.³⁷ This observed decrease has economic significance, as its magnitude is 1.7 times the average annual change in HPI. The direction and statistical significance of this result is robust across a variety of specifications. Additionally, my methodology accounts for previous concerns around “forbidden comparisons” present in traditional TWFE models that may bias estimates.

I further find that construction of public, private, municipal, and “other” golf courses lower home prices by 5.2, 9.7, 6.3, and 6.8 index points, respectively, corresponding to 2.2%, 4.1%, 2.7%, and 2.9% average declines in value for census tracts with an average HPI. Notably, effects for public courses are only marginally statistically significant ($p = 0.063$). Furthermore, using event-study aggregations proposed by Callaway and Sant’Anna, I find the negative effects of course construction increase in magnitude for multiple years into the future. Specifically, statistically significant effects are seen at 5-years and 7-years post-construction, estimated at -9.0 and -11.5 index points, respectively.³⁸

³⁶Note that the average number of post-treatment periods experienced by census tracts that had a golf course constructed between 2003-2021 is 10.01; thus, as an simplified approximation, we could say that, on average, the 6.3 index point decline in home values is realized over a 10 year period

³⁷This follows from the fact that the observed 6.3 index point decrease is 2.7% of the mean HPI. A census tract with mean HPI would thus, on average, experience a 2.7% decrease in HPI

³⁸These estimates come from the model with all course types included. While other point estimates in this

These findings are seemingly at odds with existing literature and would probably surprise many golf enthusiasts. Previous research into golf courses' effects on home prices has consistently found positive premiums up to 26% for homes bordering golf courses or those in golf course communities (Nicholls and Crompton, 2007). However, this body of work has notable limitations and differs from my thesis in key ways that may explain the disparity in results and give credence to the methodology used in this paper.

Specifically, previous studies use hedonic pricing models to find the value of bordering an existing golf course, whereas my thesis uses a panel data approach to explore how new golf course construction affects a broader local area. These are fundamentally different questions and thus my results may capture factors that were outside the scope of previous work. Hedonic models can also be sensitive to functional form and variable selection (Chau and Chin, 2002; Graves et al., 1988). A particular concern would be that golf course proximity is correlated with an unobservable such that a hedonic model's estimated coefficient is also capturing other determinants of home prices. These concerns are mitigated under my panel data difference-in-differences approach. Furthermore, previous studies are limited to small geographies, often focusing on properties in metropolitan areas. My thesis expands the scope to the entire United States, producing results that are more representative and generalizable.

Finally, the timeframe explored by existing research is limited to the late 1990s and 2000s, with the most recent paper published in 2009 (Shultz and Schmitz, 2009). My thesis examines a more recent timeframe (2003-2021) in which there may plausibly be shifts in consumer preferences and changes in background factors. For instance, growing concern for the environment in the past decades may have altered perceptions of golf course development. Particularly with undeveloped land more sacred than in previous decades, people may now be more opposed to living near a course whose construction may involve cutting down trees, polluting water runoff, and destroying natural habitats.

event-study are not statistically significant, early period estimates have tight confidence intervals that only barely cover zero. Effects 1-year, 2-year, and 4-years post-treatment are estimated at -2.8, -4.8, and -7.15 index points, respectively. Estimates beyond seven years become statistically insignificant and confidence interval become wide

At the same time, there are also limitations associated with the data and methodology used in this paper. Because my data source only contained information on golf courses operational as of 2021, my analysis does not include golf courses that were open for part of my sample period but closed before the end of it. Failure to include these courses leads to comparisons between treated units and “untreated” units that were actually treated for part of the period of interest. This limitation may bias estimates and should do so in a way that pushes estimates closer to zero. Additionally, since the use of golf courses is not restricted to only residents of the course’s home census tract, spillover effects into neighboring census tracts may lead to imperfect control units. Failure to account for these spillovers should also push estimates closer to zero. Additionally, like in 2x2 DiD designs, there may still be concerns around contemporaneous trends — unobservable changes that are may be correlated with golf course development and housing prices.

Methodological concerns aside, this thesis does not posit a definitive explanation for the findings of negative effects of golf course construction on home prices. However, there are a few plausible explanations that may be partially responsible for these results.

One potential explanation may be that the negative externalities of new golf courses — traffic, noise, environmental destruction, water scarcity, etc. — are more important for residents than the positive externalities — amenity value, open space, tourism, green infrastructure, etc. Residents who do not golf may derive little amenity value from a new course and care more about its negative factors. Another plausible explanation could be that the construction of courses on its own may not push down home prices, but rather that alternative use of such land in control tracts raises home prices by a larger amount. Golf courses require significant amounts of land that could otherwise be used for residential development, commercial use, conversion to public parks, or other amenities that raise nearby home values. Additionally, negative effects found using my 2003-2021 sample could be due to the oversupply of courses that resulted from the 1990s boom in construction Beditz (2022*a*). Fledgling courses that opened in an era of oversupply could become eyesores as opposed

to amenities and thus detract from home values nearby. However, the construction of my dataset required courses to be currently operational, so this dynamic would only influence results if such courses were still operational under weak circumstances.

7 Conclusion

The thesis examines the question of how golf course development affects nearby home values. Using a nationally-representative panel dataset and new methodology, I find that home values are significantly reduced by the construction of a golf course and that the detrimental effects increase in magnitude for multiple years post-construction. I also show that these negative effects are consistent across public, private, and municipal courses.

These results may help inform local governments considering policy decisions surrounding golf course development. Municipal governments may recognize that golf course construction could lead to depressed home prices for residents and lower property tax revenues in the following years. Perhaps these governments should consider more regulation on the development of golf courses and ensure community buy-in before such construction. Additionally, tax dollars spent on municipal course construction, maintenance, and operation could perhaps be better allocated to other projects that raise the wealth of areas as opposed to hurting it. Residents, too, may consider these results before allowing a new golf course to enter their area, especially those who do not plan to use the course themselves.

Future research should be aimed at corroborating the findings found within this thesis as well as following up on work to elucidate differential impacts based on course type. Significant work also is needed at understanding the mechanisms at play that may lead to the effects seen in this paper.

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Appendix

Table 6: Two-Way Fixed Effects Roubustnes Checks Regression Results

Dependent Variable: Model:	(1)	(2)	(3)	HPI		(6)	(7)	(8)
<i>Variables</i>								
Presence	-6.433** (2.393)		-3.871* (1.882)		-8.725*** (2.646)		-5.471** (1.969)	
Public		-14.88*** (3.207)		-12.37*** (2.808)		-16.99*** (3.085)		-12.90*** (2.506)
Private		0.7257 (3.213)		4.387 (3.033)		-5.296 (4.380)		-0.2273 (3.672)
Municipal		2.336 (3.748)		3.539 (2.796)		0.8634 (5.130)		0.6727 (3.110)
Other		-7.652 (5.842)		-10.82** (4.550)		-16.76** (6.434)		-23.64*** (7.212)
<i>Controls</i>								
Demographic Controls					Yes	Yes	Yes	Yes
<i>Fixed-effects</i>								
Census Tract	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year			Yes	Yes			Yes	Yes
<i>Fit statistics</i>								
Observations	986,948	986,948	986,948	986,948	655,673	655,673	655,673	655,673
R ²	0.91219	0.91220	0.94829	0.94830	0.92148	0.92149	0.95444	0.95444
Within R ²	6.25×10^{-5}	0.00017	3.83×10^{-5}	0.00022	0.07746	0.07753	0.05824	0.05834

Clustered (census tract & year) standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: This table shows estimates from TWFE regressions to be used as robustness checks. Even numbered regressions contain coefficients stratified by golf course type, while odd numbered regressions show a single coefficient for the presence of any type of golf course. The outcome variable is House Price Index (*hpi*). The independent variable is Presence, an indicator for presence of any kind of golf course. Public, private, municipal, and other are indicators for the presence of the respective kind of golf course. Columns (5)-(8) include demographic controls and columns (3),(4),(7), and (8) include state-year fixed effects. Standard errors are clustered on census tract and year and are reported in parentheses.

Table 7: Robustness Checks with Controls

Dependent Variable: Model:	(1)	(2)	(3)	(4)	HPI (5)	(6)	(7)	(8)	(9)
<i>Variables</i>									
Presence	-5.471** (1.969)	-5.532** (1.972)	-5.370** (1.951)	-4.158* (2.142)	-5.602** (1.969)	-5.357** (1.978)	-5.410** (1.998)	-5.404** (2.007)	-5.267** (2.036)
Unemployment Rate	-0.5292*** (0.1032)		-0.5213*** (0.1033)	-0.6081*** (0.1360)	-0.5149*** (0.1047)	-0.5386*** (0.1030)	-0.4973*** (0.1055)	-0.5932*** (0.1003)	-0.6362*** (0.0994)
Mean Commute Time	0.6407*** (0.1117)	0.6372*** (0.1114)		0.7641*** (0.1330)	0.6327*** (0.1137)	0.6395*** (0.1120)	0.6606*** (0.1129)	0.6264*** (0.1116)	0.6717*** (0.1132)
Median HH Income	0.0008*** (0.0001)	0.0008*** (0.0001)	0.0008*** (0.0001)		0.0008*** (0.0001)	0.0008*** (0.0001)	0.0008*** (0.0001)	0.0008*** (0.0001)	0.0009*** (0.0002)
Population Density	0.0027*** (0.0004)	0.0027*** (0.0004)	0.0027*** (0.0004)	0.0037*** (0.0005)		0.0026*** (0.0004)	0.0030*** (0.0004)	0.0029*** (0.0004)	0.0024*** (0.0004)
Percent Over 65	0.1485 (0.0883)	0.1652* (0.0883)	0.1438 (0.0874)	0.0616 (0.0964)	0.0648 (0.0895)		0.0952 (0.0854)	0.1779* (0.0924)	0.0681 (0.0831)
Perctet White	-0.5118*** (0.0792)	-0.5066*** (0.0787)	-0.5191*** (0.0799)	-0.5346*** (0.0896)	-0.5307*** (0.0798)	-0.5070*** (0.0776)		-0.2086*** (0.0481)	-0.4831*** (0.0765)
Percent Black	-0.8882*** (0.1060)	-0.9025*** (0.1054)	-0.8810*** (0.1053)	-1.003*** (0.1319)	-0.8954*** (0.1068)	-0.8919*** (0.1075)	-0.4681*** (0.0535)		-0.9706*** (0.1215)
Pct College Grad	1.063*** (0.1625)	1.074*** (0.1616)	1.071*** (0.1616)	1.524*** (0.2216)	1.035*** (0.1584)	1.058*** (0.1612)	1.044*** (0.1582)	1.102*** (0.1689)	
<i>Fixed-effects</i>									
Census Code	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Fit statistics</i>									
Observations	655,673	655,673	655,673	655,673	683,716	655,673	655,673	655,673	655,673
R ²	0.95444	0.95441	0.95437	0.95336	0.95575	0.95444	0.95429	0.95425	0.95396
Within R ²	0.05824	0.05772	0.05680	0.03583	0.05584	0.05815	0.05510	0.05431	0.04834

Notes: This table shows robustness checks on the TWFE regression and the effects of control variables on estimates. All regressions include state-year fixed effects in addition to TWFE. The outcome variable is House Price Index (*hpi*). The independent variable is Presence, an indicator for presence of any kind of golf course. Each individual control variable is dropped out one at a time as you move rightward in the regression table. Mean Commute Time is measured in minutes. Median HH Income represents the median household income of households in a census tract. Over 65 Pct is the percentage of a census tract's population over the age of 65. College Grad Pct is the percentage of a census tract's population with at least a Bachelor's degree. Population Density is measured in people per square mile. Standard errors are clustered on census tract and year and are reported in parentheses. *Signif. Codes:* ***: 0.01, **: 0.05, *: 0.1

Table 8: Treatment Intensity Regression Results - Indicator on Count

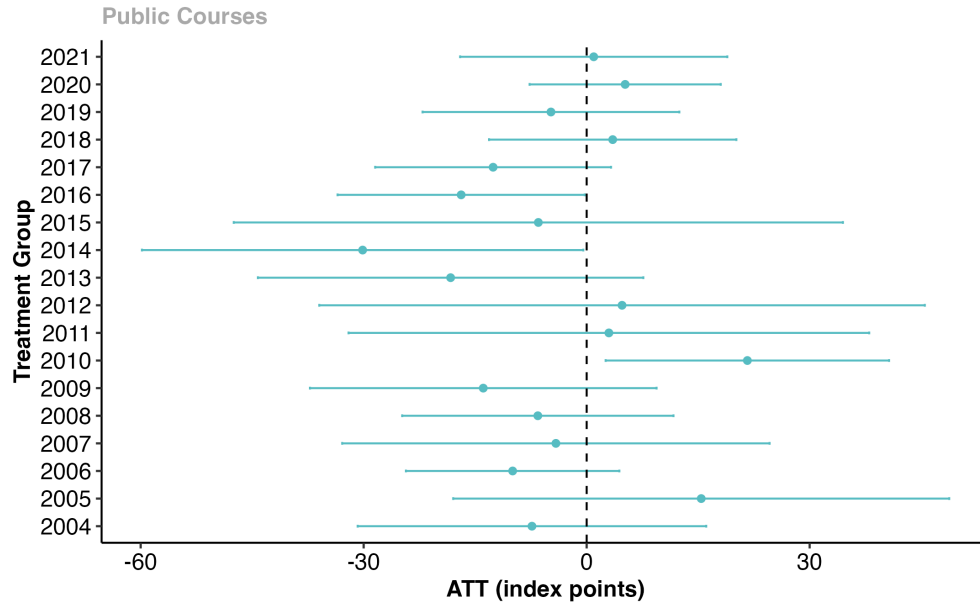
Dependent Variable:	HPI					
	NO TWFE		TWFE			
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
Constant	235.6*** (0.1448)	355.9*** (1.509)				
Count=1	-7.131*** (1.487)	-32.08*** (1.624)	-5.949*** (1.469)	-3.710*** (1.298)	-9.245*** (2.158)	-5.447*** (1.834)
Count=2	2.204 (3.232)	-48.65*** (3.553)	-11.40*** (2.670)	-5.747** (2.430)	-14.86*** (4.228)	-3.659 (3.291)
Count=3	-20.25*** (4.704)	-71.24*** (5.220)	-15.98*** (5.115)	-6.438 (4.296)	-23.42*** (8.080)	-9.995 (6.105)
Count=4	12.49 (10.54)	-128.3*** (11.06)	-30.13*** (6.406)	-13.58*** (4.933)	-52.64*** (9.914)	-26.05*** (7.516)
Count=5	23.72 (22.88)	-59.65*** (21.46)	-52.18*** (14.67)	-22.45*** (6.713)	-110.7*** (19.97)	-57.45*** (9.393)
Count=6	34.22 (50.53)	-36.22 (44.88)	-66.44*** (12.34)	-25.39*** (6.310)	-144.4*** (23.96)	-69.78*** (13.33)
Count=7	-70.39* (38.19)	-92.82* (47.98)	-193.4*** (10.60)	-202.4*** (5.594)	-296.6*** (20.74)	-268.1*** (10.16)
Count=8	-56.04 (58.34)	-58.00 (89.77)	-83.02*** (10.62)	-36.56*** (5.456)	-193.3*** (20.76)	-102.2*** (10.06)
Count=9	-22.04 (63.91)	-197.6*** (56.78)	-103.2*** (16.95)	-50.91*** (14.14)	-216.9*** (20.68)	-115.0*** (10.20)
Count=10	-59.26 (101.1)		-57.96*** (10.62)	-9.155* (5.505)		
Count=11	-103.3 (71.45)	-110.1 (73.29)	-61.47*** (10.62)	-39.27*** (5.494)	524.1 (6,737,316.6)	-51.56 (5,840,310.5)
<i>Controls</i>						
Demographic Controls		Yes			Yes	Yes
<i>Fixed-effects</i>						
Census tract			Yes	Yes	Yes	Yes
Year			Yes	Yes	Yes	Yes
State-year				Yes		Yes
<i>Fit statistics</i>						
Observations	986,777	683,567	986,777	986,777	683,567	683,567
R ²	2.49×10^{-5}	0.32832	0.91220	0.94829	0.92371	0.95576
Within R ²			9.66×10^{-5}	4.57×10^{-5}	0.07361	0.05593

Signif. Codes: ***p < 0.01, **p < 0.05, *p < 0.10

Notes: This table shows estimates from regressions both with and without TWFE testing the intensity of treatment. Columns (1) and (2) do not include census tract and year fixed effects while Columns (3) through (6) do. The outcome variable is House Price Indexx (*hpi*). Each independent variable is a binary indicator for the *count* variable with each representing whether a given census tract contains that many golf courses. The constant is reported in Columns (1) and (2) because there are no fixed-effects. Columns (5)-(8) include demographic controls and columns (3),(4),(7), and (8) include state-year fixed effects. Standard errors are clustered on census tract and year in columns (3)-(6) but not clustered in Column(1) and (2). These standard errors are reported in parentheses.

Figure 9: Group Aggregations across Different Types of Courses

(a) Group Aggregation of $ATT(g,t)$'s for Public Courses



(b) Group Aggregation of $ATT(g,t)$'s for Private Courses

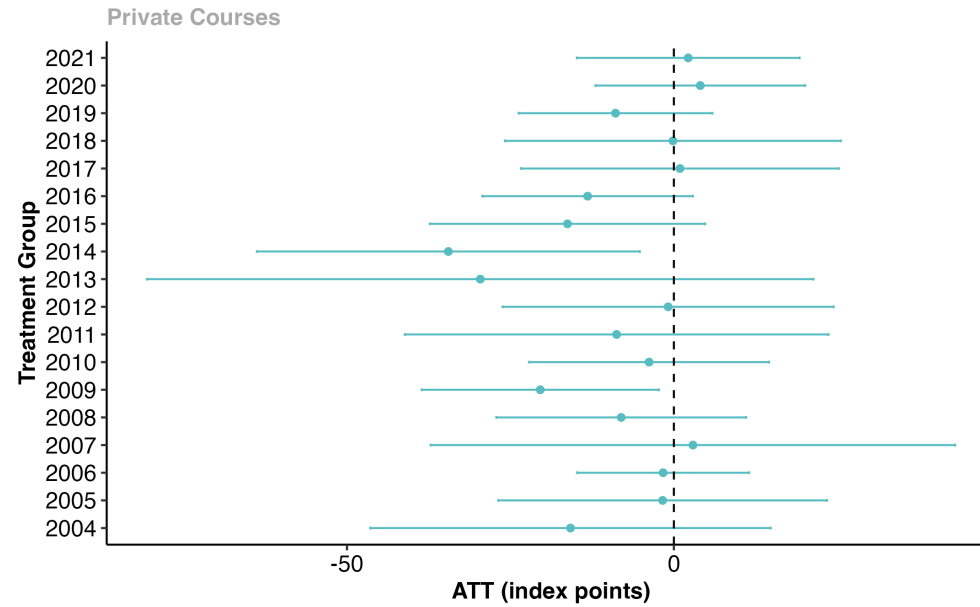
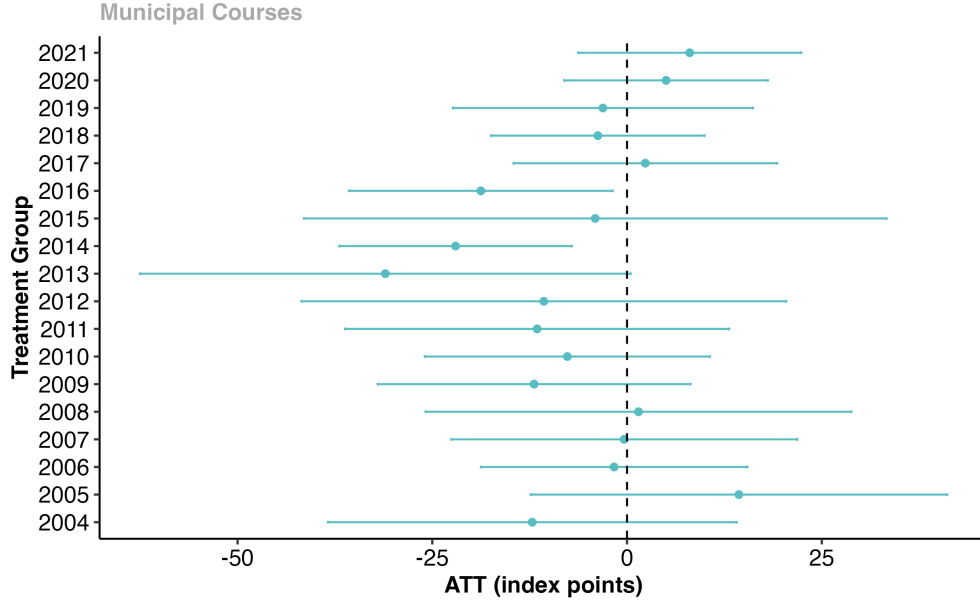
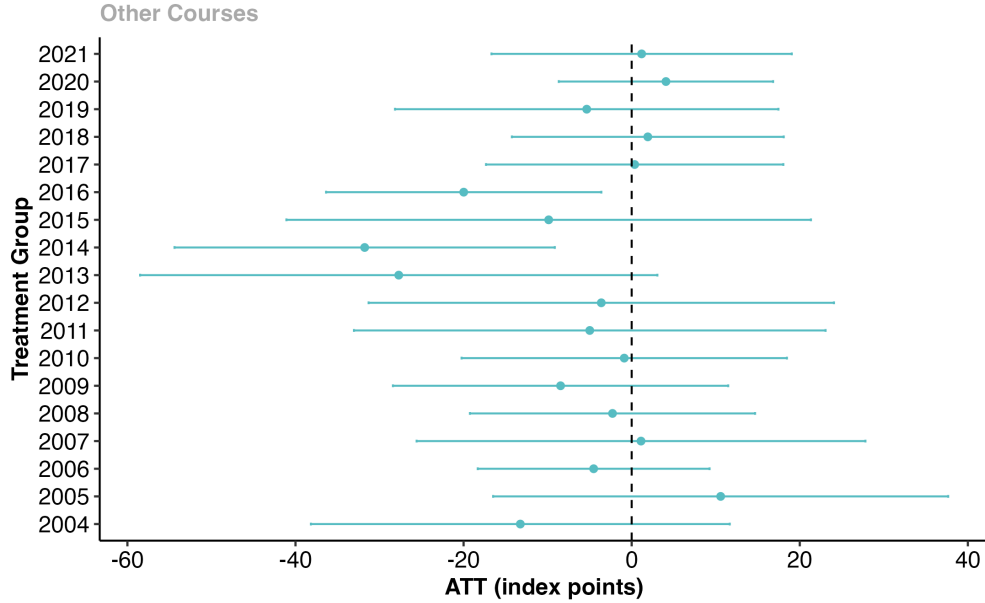


Figure 9: Group Aggregations across Different Types of Courses (cont.)

(c) Group Aggregation of $ATT(g,t)$'s for Municipal Courses



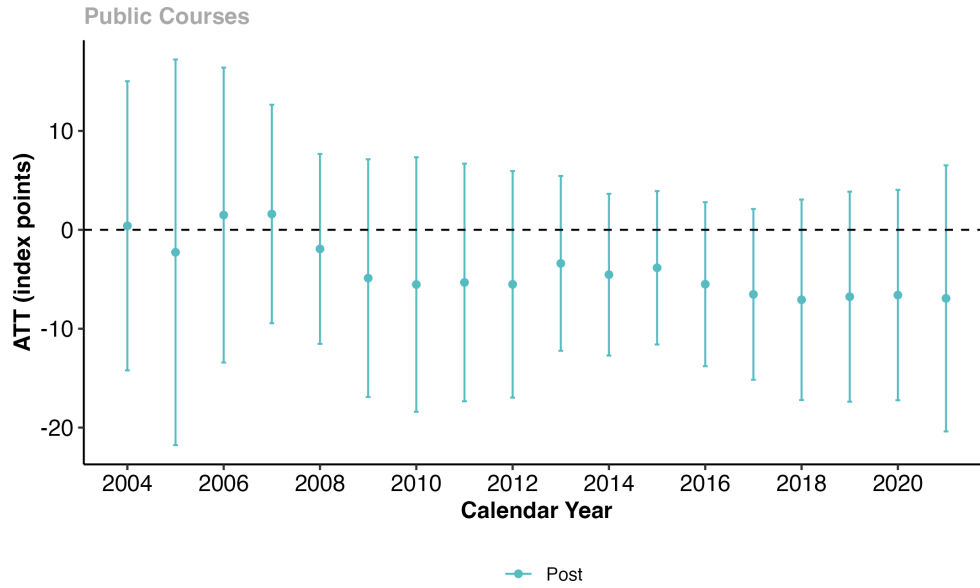
(d) Group Aggregation of $ATT(g,t)$'s for Other Course Types



Notes: This figure shows the group aggregations of ATTs produced by grouped difference-in-differences regression per Callaway and Sant'Anna, stratified by course type. Each data point in the graphs represents the average treatment effect across all post-treatment periods experienced by tracts that received a golf course in a given year. The outcome variable is House Price Index (*hpi*). Panel (a) shows results for public courses. Panel (b) shows results for private courses. Panel (c) shows results for municipal courses. Panel (d) shows results for other course types. The y-axis displays the treatment group by calendar year. The x-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with horizontal bars.

Figure 10: Calendar Aggregations across Different Types of Courses

(a) Calendar Aggregation of ATT(g,t)'s for Public Courses



(b) Calendar Aggregation of ATT(g,t)'s for Private Courses

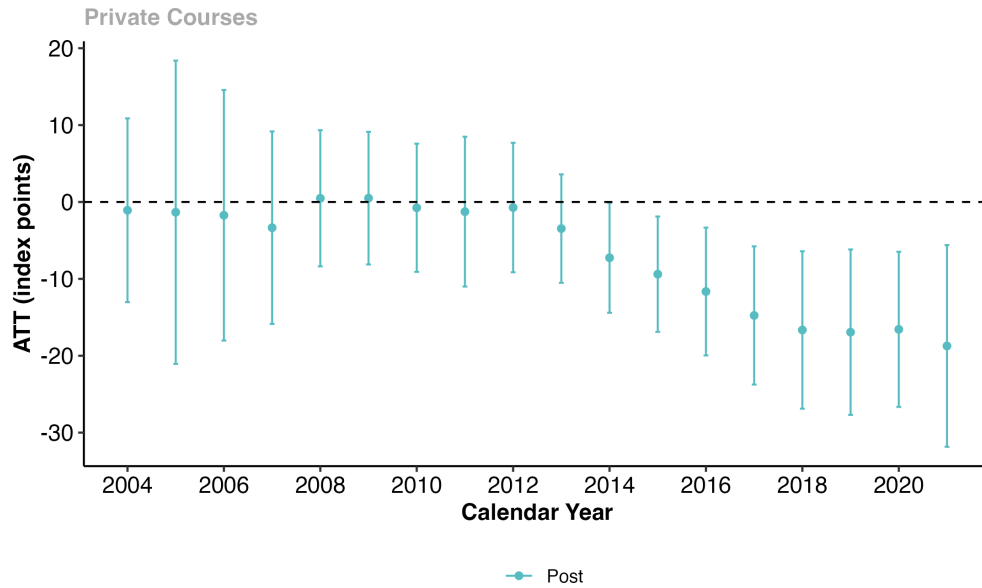
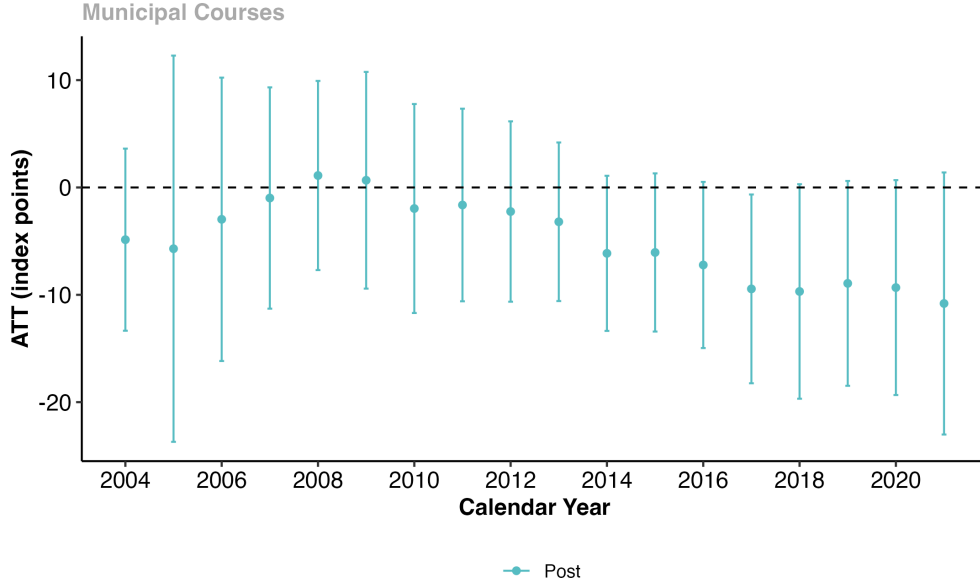
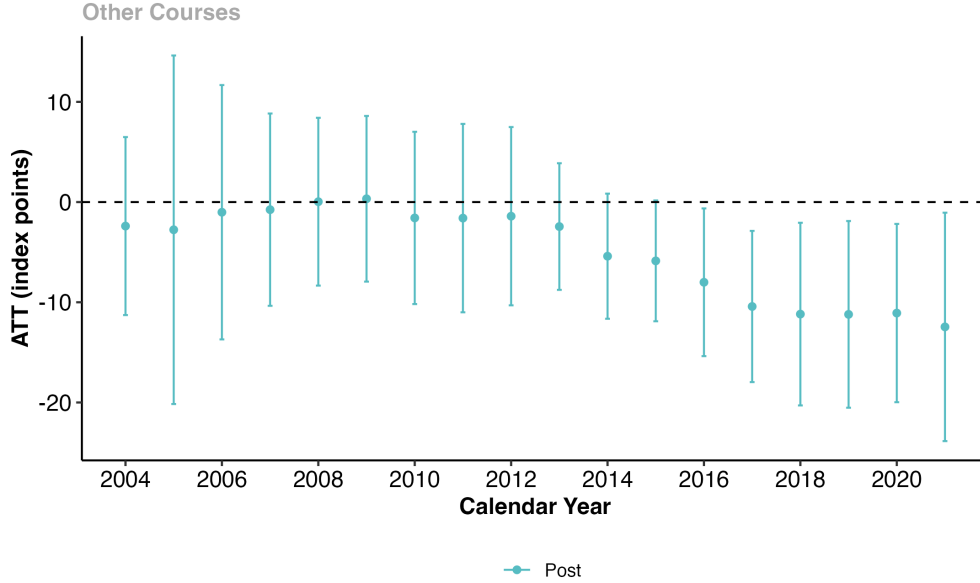


Figure 10: Calendar Aggregations across Different Types of Courses (cont.)

(c) Calendar Aggregation of $ATT(g,t)$'s for Municipal Courses

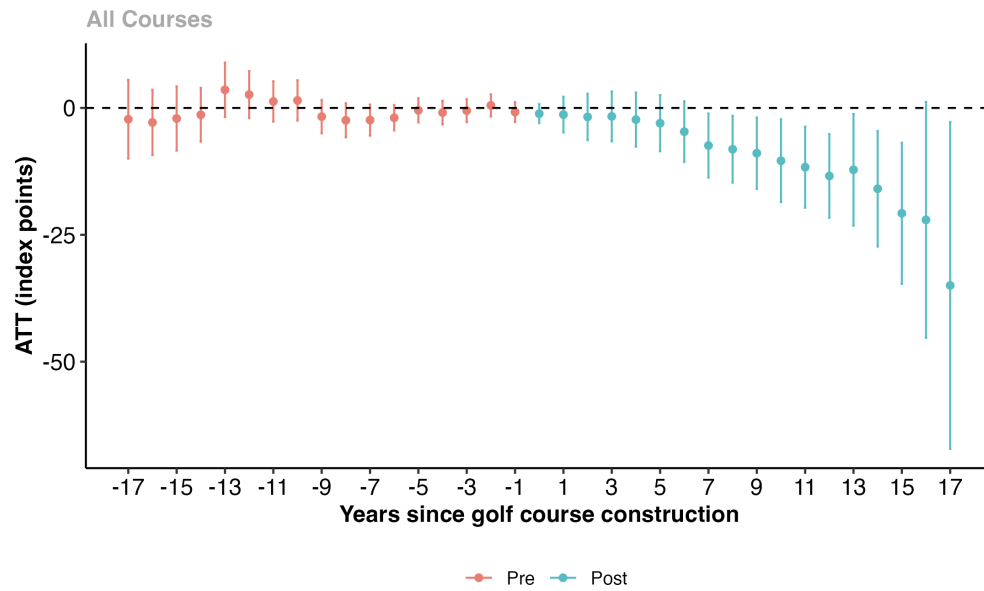


(d) Calendar Aggregation of $ATT(g,t)$'s for Other Courses



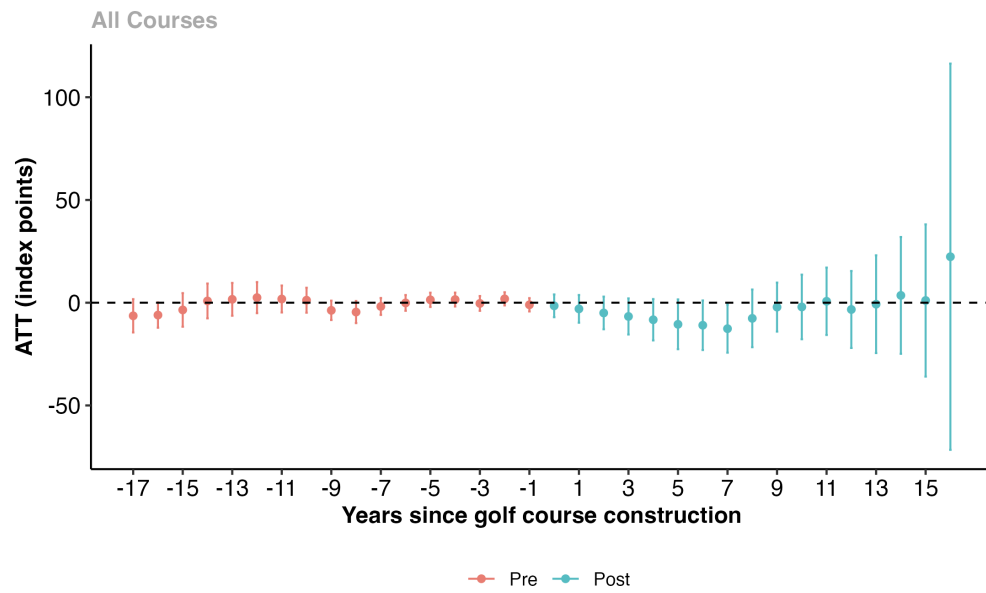
Notes: This figure shows the average treatment effect by calendar year produced by averaging $ATT(g,t)$'s across all treated groups in a given year, stratified by course type. Each data point represents the average treatment effect experienced by treated census tracts in that year. The outcome variable is House Price Index (*hpi*) and the independent variable is indicator for the presence of any type of golf course (*presence*). The outcome variable is House Price Index (*hpi*). Panel (a) shows results for public courses. Panel (b) shows results for private courses. Panel (c) shows results for municipal courses. Panel (d) shows results for other course types. The x-axis displays the calendar year. The y-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with vertical bars.

Figure 11: Event Study Aggregation of $ATT(g,t)$'s - All Courses - No Covariates



Notes: This figure shows the event-study aggregations of ATTs produced by grouped difference-in-differences regression per Callaway and Sant'Anna for the model of all courses without demographic covariates included. The outcome variable is House Price Index (*hpi*) and the independent variable is indicator for the presence of any type of golf course (*presence*). The x-axis displays the event-time in terms of years relative to golf course construction. The y-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with vertical bars.

Figure 12: Event Study Aggregation of $ATT(g,t)$'s - All Courses - Assumes 1 Period Anticipation Effects



Notes: This figure shows the event-study aggregations of ATTs produced by grouped difference-in-differences regression per Callaway and Sant'Anna for a model using all courses that assumes a 1 period of anticipation effects. The outcome variable is House Price Index (*hpi*) and the independent variable is indicator for the presence of any type of golf course (*presence*). The x-axis displays the event-time in terms of years relative to golf course construction. The y-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with vertical bars.

Figure 13: Event Study Aggregation of $ATT(g,t)$'s - All Courses - Assumes 2 Period Anticipation Effects



Notes: This figure shows the event-study aggregations of ATTs produced by grouped difference-in-differences regression per Callaway and Sant'Anna for a model using all courses that assumes a 2 period of anticipation effects. The outcome variable is House Price Index (*hpi*) and the independent variable is indicator for the presence of any type of golf course (*presence*). The x-axis displays the event-time in terms of years relative to golf course construction. The y-axis displays the ATT in terms of HPI index points. 95% confidence intervals are shown with vertical bars.