Do Costco Openings Increase Nearby Property Values?

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Abstract

This paper assesses the impact of Costco openings on nearby property values within a 20-mile radius. Using Costco openings from 2002 to 2020 across the U.S. and Zillow ZHVI data at the zip code level, I use spatial difference-in-differences and event study methodologies to find that Costco openings led to no significant changes in property values on average. Property values in above-average population density counties saw a 7.9% increase within 5 miles of Costco openings and property values in above-average household income counties saw a 5.2% increase within 5 miles of Costco 2.5 years after store openings. Conversely, properties in below-average population density, below-average household income, and below-average white population counties saw decreases in property values of 3 to 6% within 5 miles with weaker depreciating effects up to 15 to 20 miles from Costco openings. Lastly, I also find no significant dynamic effects of Costco openings on property values within 20 miles for 30 months following Costco openings. (*JEL* R30, R31)

1. Introduction

A standalone paper on the impact of Costco openings on property values finds no change in property values as a result of Costco openings within a 6-mile radius (Lethco, 2023). This result is surprising given other literature on the impact of retail store openings on property values generally finds appreciating effects of store openings in nearby property values which diminish with distance to the store in cases of other retailers such as Walmart, Whole Foods, and IKEA (Pope & Pope, 2015; Saengchote, 2020; Hoelzlein & Miller, 2023; Daunfeldt et al., 2021). Could this result be a consequence of the author's choice of empirical specification, or does this result hold even with changes in empirical choices? The purpose of my study is to investigate this question with data on 84 Costco openings across the U.S., compared with the author's data from 9 Costco openings in California. Further, this paper extends the discussion to understanding the dynamic effect of Costco openings on nearby property values. In summary, the questions I answer in this paper are firstly, how do Costco warehouse openings impact nearby property values, and how does this vary with distance from Costco? Is this effect non-linear? Then, connecting these results to the broader economic literature, what can one say about how the positive and negative externalities generated by Costco openings differ based on distance?

This paper will be organized as follows. Section 2 provides a detailed review of the previous literature on the impact of retail store openings on nearby property values. Section 3 introduces the economic framework of amenities and disamenities which informs my hypothesis. Section 4 describes the data source used for my analysis. Section 5 introduces the empirical strategy for my analysis. Section 6 provides a discussion of my main results and heterogeneity results, and provides robustness checks for my analysis. Lastly, section 7 concludes with a review of the contribution of this study and future directions for research.

2. Literature Review

The previous literature that investigates the causal impact of retail store openings on nearby property prices uses various empirical specifications such as pooled OLS regressions, fixed effects OLS regressions, spatial difference-in-difference models, and event studies. I choose to focus only on difference-in-difference studies and event studies related to this topic because they do the best job at producing accurate estimates by controlling for time-invariant omitted variables, given they sufficiently meet the parallel trends assumptions. I exclude studies on this topic that rely on pooled OLS regressions because they fail to allow for observation-specific or time-specific effects and are as a result likely to produce biased estimates of our causal parameters. Similarly, fixed effect OLS regressions would produce biased estimates in our research topic because they do not address the problem of unobserved time-variant heterogeneity, which would likely play a substantial role given our analysis of the impact of store openings on housing prices over time. Thus, while some studies fail to control for spatial and temporal heterogeneity and their estimates may be affected by potential omitted variable bias, others produce more accurate estimates by using some combination of controls, fixed effects, and nifty techniques such as matching. The careful choice of research design is thus an important area of attention and is imperative to making robust causal claims.

Underlying this discussion of empirical models is the highly important consideration of identification strategies that allow for the estimation of causal parameters. Ideally, identification is done so that the problem of endogeneity is effectively mitigated and causal estimates are accurate and unbiased. Difference-in-difference analyses rely on the parallel trends assumption, which in the context of our research question, is the idea that in the absence of the treatment or intervention, the treated and control land or property values would have followed parallel trends over time. Evidence for this is provided graphically by plotting data in the pre-treatment and post-treatment periods to show that changes in the outcome mostly occur after treatment. Notably, this assumption only relies on the slope of the pre-trends being close to parallel over time and does not require the levels of the outcome variable for the treated and control groups to be the same. If this condition is met and the research design is robust, any differential changes in outcomes observed between the treated and control groups after the introduction of the treatment can be attributed to the treatment itself, rather than pre-existing trends or differences in trends between the groups. For example, a landmark study of the impact of Walmart openings on property prices using a difference-in-differences specification requires that within a localized 4-mile zone, Walmarts were not built in areas where there was a preexisting trend in housing prices (Pope & Pope, 2015). Another, looking at the impact of Walmart openings on land values requires that land price trends within 3 miles would have been the same had the Walmart store not been built (Slade, 2018). A paper looking at the impact of Whole Foods Market openings on property values requires that land price trends be similar within 2 miles of Whole Foods Market openings (Saengchote, 2020). Conversely, a study of Costco openings requires that housing prices within an 8-mile radius of Costco openings would have followed a similar trend, had Costco not been built there (Lethco, 2023). Ultimately, any empirical analysis using a difference-in-differences specification requires that this condition be met so that estimates are not biased.

Implicit in our discussion of identification strategies is the discussion of the choice of a control group, which applies more broadly to both difference-in-differences and event study designs. Several unique control groups have been applied in previous studies, including an outer-ring radius of properties around store openings surrounding the treated groups, control groups formed by matching, and even a within-city analysis which makes no clear distinction between any treatment and control groups. Pope & Pope (2015) use a control group that consists of properties in the 2 to 4-mile radius range around each Walmart opening. They also restrict their sample to properties located within the city of entry to avoid any heterogeneity imposed by across-city varying economic conditions. Conversely, Slade (2018) uses a control group that includes land parcels 1 to 3 miles of a Walmart opening, since they look at land values as their outcome variable. Saengchote (2020) uses a control group within 1 to 2 miles from Whole Foods Market openings since they look at the highly localized effect of Whole Foods openings on property values. On the other hand, Lethco (2023) uses property values in the 6 to 8-mile range from store openings as their control group because of Costco warehouses' presumably wider range of impact on property prices relative to other retailers such as Walmart. Straying from the other studies, Hoelzlein & Miller (2023) construct a control group based on neighborhoods that receive a non-premium store by matching premium store openings with non-premium store openings that opened within the same year and state as the premium store, dropping all matches that are within 3 miles of each other to prevent capturing spillovers between control and treatment neighborhoods. They then perform their estimation on the 1-mile radius around their treatment and control group as a part of their event study to isolate a "premium store effect" relative to non-premium stores. Conversely, Daunfeldt et al. (2021) do not make a clear distinction between any treatment and control groups within the city and instead use a within-city analysis of the impact of IKEA entry on property values, estimating the effects of a new IKEA retail area on the prices of all properties located no more than 10 km (~6.2 miles) from the entry locations. They also restrict their analysis to within-city properties, following Pope & Pope

(2015). Ultimately, the choice of an appropriate control group is important for a credible and robust analysis and is relevant to the interpretation of our causal estimates.

Given our discussion of the empirical choices of these papers, it is appropriate to discuss the accompanying findings of each of these papers as well as the extended analysis and choices made within each of these papers including their choice of fixed effects. A crucial aspect to bear in mind in conducting this analysis pertains to the selection of the temporal window for each of the referenced papers. The decision to examine property values 2.5 years, 3 years, or 5 years post-store openings holds significant implications, as the magnitude of agglomeration effects—stemming from nearby stores establishing themselves after initial openings—becomes more pronounced with an extended temporal window. Consequently, the choice of timeframe can lead to markedly different estimates and interpretations. As the first notable paper using a difference-in-differences specification for this type of analysis, Pope & Pope (2015) find an appreciating effect of Walmart's entry on property values very near each opening, with weaker appreciating effects further from each opening across the US. More precisely, they find an appreciation of 2 to 3% within 0.5 of Walmart store openings 2.5 years after the opening date and an appreciation of 1 to 2% between 0.5 miles and 1 mile of Walmart openings. They use data at the property transaction level, control for property attributes, and include store-by-year-by-month fixed effects. They also extend their analysis by performing the same analysis on Target store openings, finding a similar effect on property values with a roughly similar magnitude. In an adjacent analysis, Slade (2018) found a strong appreciating effect of Walmart openings on nearby vacant land prices, with dissipating effects further from the store openings. They find that land prices rose by 26% within 0.25 miles of Walmart store openings and 18% between 0.25 to 0.5 miles of Walmart store openings 3 years after the opening date, suggesting that land values may experience stronger appreciating effects of store openings relative to property values. This analysis of land parcels includes controls for each land parcel's observable characteristics instead of property attributes like Pope & Pope (2015) because land parcel value is the primary outcome variable in this paper as opposed to property value. Concerning “premium” store openings, Saengchote (2020) finds a strong increase in property values very close to the Whole Foods Market openings, with increases of smaller magnitudes further from openings. They find that property values rose by 6.7% within 0.5 miles of Whole Foods Market openings, 5% between 0.5 to 1 miles, and 3.3% between 1 to 2 miles 2.5 years after the opening date, also exhibiting diminishing appreciating effects with distance. The magnitude of the effect very near store openings (within 0.5 miles) is twice that of the effect found in the same range for Walmart openings found in Pope & Pope (2015), providing some insight into the differential “premium” store opening effect. They choose to control for property attributes and include store-by-year-by-month fixed effects in their difference-in-differences specification following Pope & Pope (2015). Similarly, Hoelzlein & Miller (2023) find that home values increased by a substantial amount very close to these premium store openings relative to non-premium store openings. They track changes in home values within 0.5 miles of the store three years before entry and 5 years after the entry of Whole Foods Markets, finding that property values increased by 10 to 20 % within 0.5 miles of these “premium” store openings 5 years after the opening date.

Looking at a big-box retailer, Daunfeldt et al. (2021) found that IKEA openings had a non-linear, inverse U-shaped impact on property values: property values experience smaller increases close to the IKEA openings, the highest increases in a “sweet-spot” distance further away, and smaller property value increases furthest from IKEA store openings. Specifically, they find that property values increase by 6.87% at 1.5km (0.93 miles) away from IKEA openings, 6.95% at 2km (1.2 miles) away from IKEA openings, and 2% at 10km (6.21 miles) away from IKEA openings 2.5 years after the opening date. They rely on a quadratic difference-in-differences specification which allows them to capture this effect, and have a coefficient of interest that captures the impact of the interaction of a "post" opening variable and the inverse of distance to the opening. They also include year, city, and city-year fixed effects to control for city-specific heterogeneity, city-specific shocks that could affect property values, and year-specific shocks to the real estate market. They also use property attribute controls in their analysis. Lastly, Lethco (2023) finds Costco openings had no statistically significant effect on property values using a specification similar to Pope & Pope (2015), except that they used observations 6 to 8-mile from store openings as their control group, and included zip code-fixed effects in their model as opposed to store-by-year-by-month fixed effects. This null effect result leaves much to be investigated in terms of whether this is a characteristic of Costco openings in California, if it is generalizable to Costco openings in general, or if this result is a consequence of the author's data and choice of empirical strategy. Overall, the previous literature seems to suggest the impact of various store openings on property values is positive with weaker effects further from openings in most cases, while "premium stores" like Whole Foods and Trader Joe's as well as big-box stores like IKEA experience these effects with a greater magnitude than a retailer like Walmart. The study on Costco openings stands as an outlier in finding no significant effect on property values. These key findings and characteristics of the relevant studies can be found in Table 1.

3. Economic Framework

The introduction of a large retailer in a community can affect home prices through two primary channels: on one hand, disamenities such as automobile congestion depress property values (Tang, 2021), while on the other hand, increased access to retail nearby is an amenity associated with higher property values and place attractiveness (Sirpal, 1994). As discussed in the previous section, the literature on the opening of retailers finds that property values either have no change or increase near big-box store openings, implying that the positive externalities from a big-box store opening typically outweigh the costs imposed by any negative externalities that it imposes on the local community where a store is built. Thus, a price increase near a Costco opening would indicate the stronger presence of amenities than disamenties and a price decrease would indicate the opposite. The size of the price increases or decreases would represent the extent to which positive externalities outweigh the negative externalities, or vice versa. The use of property values is also supported by the fact that the variation in residential property prices across cities and over time is mostly explained by amenities (Roback, 1982), and disamenities such as noise and pollution are also factored into housing prices (Pope, 2008; Chay & Greenstone, 2005).

I speculate that Costco openings will cause a weak increase in property values very near each Costco with stronger appreciating effects further from each Costco opening which dissipate with more distance from Costco openings. This hypothesis follows from the reasoning that the value of retail accessibility declines less rapidly across space than the costs of localized negative externalities such as traffic congestion and noise (Li & Brown, 1980). I expect that this would especially be true of Costco, which typically opens in the suburbs of major cities, where income levels are somewhat higher than the national average (Testa, 2015). The primarily suburban locations of Costco warehouses would be associated with greater automobile usage (Brownstone & Golob, 2009); thus, the opening of a Costco would likely be associated with increases in highly localized negative externalities such as congestion and noise from automobile traffic concentrated very near Costcos, while these negative externalities have a weaker effect further from each Costco opening. Conversely, the retail accessibility benefits generated from Costco warehouse openings should persist a fair distance away from the stores since the higher use of automobiles allows the retail accessibility benefits to be experienced further away from each Costco warehouse's local area. Overall, the intended main contribution of the paper is to understand whether or not the benefits of retail accessibility outweigh the costs of negative externalities on average, and the extent to which these effects vary with distance from Costco openings through the analysis of housing prices before and after a Costco is built in a given community.

4. Data Source and Description

The data used in this project consists of data on Costco openings from 2000 to 2023 and data from the Zillow Home Value Index (ZHVI) Single-Family Homes Time Series data for the zip codes surrounding these openings. Specifically, I use data within a 25-mile radius of each Costco opening 2.5 years before and after each Costco opening. This proposed paper differentiates itself from the paper on Costco openings in California by using data from Costco openings across the U.S. and single-family home price data aggregated by zip code, which serves as the unit of observation. There are 593 Costco store openings in the U.S., with the earliest opening date being July 1st, 1976 and the latest being November 16th, 2023. I restrict the sample to stores that opened between January 1st, 2000, and September 30th, 2023, since the ZHVI values only include data within that time range. Further, I remove the store openings that are both within 50 miles of one another and open within 5 years of each other since property values that are impacted by store openings multiple times within a short period would likely bias the results of the estimation. This results in a sample of 84 Costco stores that opened between 2002 and 2020, which are shown in Figure 1 with a 25-mile radius around each opening with the ZHVI observations accompanying each opening. Figure 2 shows information on the distribution of Costco opening years from 2002 to 2020 to show the temporal distribution of Costco openings in the sample.

For my dependent variable, I use the Zillow Home Value Index (ZHVI) Single-Family Homes Time Series data, which is panel data that represents the smoothed and seasonally adjusted typical value of single-family residential homes in the 35th and 65th percentile range for a given zip code for every month over the timeframe of January 1st, 2000 to September 30th, 2023 (Olsen, 2023). Several key variables in this dataset include the zip code number and the state, city, and county of that zip code. I merge this dataset with the U.S. ZIP Codes Database which contains the latitude and longitude values for the centroid of each given zip code. This gives us a dataset with the Zillow data over time for each zip code with associated latitude and longitude values, which are used to plot the data points in Figure 1. I also calculate the distance of each ZHVI observation to their nearest Costco and generate bins for the distance to the nearest Costco (0-5 miles, 5 to 10 miles, 10 to 15 miles, 15 to 20 miles, and 20 to 25 miles) corresponding with the treated groups and the control group.

Table 2 shows the means of the dependent variable for each distance range category which encompasses the means from aggregating ZHVI values every month for 2.5 years before and after store openings, which is displayed below in Table 2. I also performed a t-test on the difference in means between each distance category and the control group, the p-values of which are displayed in the table below. The t-test results suggest that there are significant differences between the change in the log ZHVI value for each of the treated groups and the change in the control group over time. Table 2 also includes the means of the American Community Survey (ACS) data on household income and population density for each distance category which are provided at the county level. Notably, the mean household income and population density for the control 20-25 mile range before and after Costco opening is lower than the treated groups, which shows the relevance of controlling for these variables in my analysis.

In Figure 4, I display a plot of the normalized means of the log ZHVI values for the treated groups and control group for each quarter 2.5 years before and after Costco openings. In this plot, the trends of the normalized mean log ZHVI values for the treated groups and control group follow a nearly identical slope from -10 quarters from opening to -4 quarters from opening, then only slightly change in slope from -4 quarters from opening to the store opening date. The near-parallel trajectories followed by the treated groups and control group before the store opening provide evidence that there are no significant pre-trends in my data, supporting a causal interpretation of my results. There is also some weak evidence of an anticipation effect since the slopes of the lines only start to deviate from one another at around -4 quarters or 1 year before opening (around the time when Costco typically announces its new locations) up until store opening time. Lastly, this plot of simple means shows lines that diverge more clearly after store opening up until 10 quarters (2.5 years) after Costco store openings.

5. Estimation Strategy

The estimation strategy I use is the spatial difference-in-difference specification, a quasi-experimental method that exploits the timing of the Costco openings to estimate the local effect on treated spatial zones. The key advantage of the spatial difference-in-differences specification is that by including spatial and time-fixed effects and comparing aggregate housing prices before and after the opening of Costcos, I control the impact of time-invariant omitted variables that could bias our estimates. The key identifying assumption is that housing price trends for areas near Costco and those slightly farther away from Costco would have been the same had the Costco store not been built. Specifically, my specifications require that housing price trends are the same in the 25-mile radius surrounding each Costco. I choose to split the treatment groups into 4 groups (0-5 miles, 5-10 miles, 10-15 miles, and 15-20 miles) to provide a clearer idea of the treatment effect heterogeneity with distance to Costco openings and ideally capture the non-linearity of the treatment effect. This would lend itself more to the analysis of Costco given the wider range of positive externality benefits in the car-dependent suburbs where Costcos typically open. While Lethco (2023) uses 6-8 miles as the control group for their analysis of Costco openings, I use a control group of ZHVI values 20-25 miles from Costco openings. This choice is based on research on Costco which suggests that a 27-minute drive is the average high for a Costco customer to travel (Testa, 2015). At 45 mph on average, a 27-minute drive is equivalent to ~20 miles, which motivates the choice of 20 miles as the boundary of Costco's impact on property values. Crucially, this choice implies that I believe the treatment effect of Costco openings on property values past 20 miles is zero and works better with the data I use at the zip code level. Further, smaller control rings would not be suitable for my data because of the average area of zip code regions. A visualization of the character of my estimation strategy and data can be found in Figure 3, which shows the size of the concentric rings and the density of the ZHVI observation centroids for a sample of my data. As such, my specification would at best capture the presence of negative externalities in 5-mile intervals of a store opening and likely only in the 0-5-mile radius, assuming negative externalities such as traffic congestion and noise are strongest nearest to Costco openings following the discussion in the economic framework section. Unfortunately, this data limitation and empirical choice also precludes the capture of hyper-localized negative externalities which could be observed with smaller concentric rings. Regardless, this research design effectively compares the changes in each of these treated groups against the changes in the control group over time.

I run the following spatial difference-in-difference specification:

$$[1] \quad log(P_{ijym}) = \beta_0 {D_{ij}}^5 + \theta_0 {D_{ij}}^{10} + \phi_0 {D_{ij}}^{15} + \psi_0 {D_{ij}}^{20} + \\ (\beta_1 {D_{ij}}^5 + \theta_1 {D_{ij}}^{10} + \phi_1 {D_{ij}}^{15} + \psi_1 {D_{ij}}^{20}) * Post_{iym} + \\ \mu_y + \delta_m + \sigma_c + \gamma_{yc} + \mu_y * \gamma_{yc} + \varepsilon_{ijym}$$

where the outcome variable $log(P_{ijym})$ is the log Zillow Home Value Index (ZHVI), which represents a smoothed and seasonally adjusted typical value of a single-family home in the 35th and 65th percentile range for a given ZIP code. ${D_{ij}}^5, {D_{ij}}^{10}, {D_{ij}}^{15}, {D_{ij}}^{20}$ are dummy variables that switch on if the ZIP code is 0-5 miles, 5-10 miles, 10-15 miles, or 15-20 miles from a Costco opening, and a dummy variable $Post_{iym}$ switches on if a zip code is within 25 miles of a newly opened Costco. This specification also relies on the use of year, month, and location fixed effects, represented as μ_y, δ_m, and σ_c respectively. While the month and year fixed effects are included to control for seasonal trends and yearly shocks in property values, the location fixed effect controls for heterogeneity in property values between geographical regions at the state, county, or city level. I also use a vector of control variables γ_{yc} for household income and population density. Since these values vary for each year for each county, I also interact these control variables with the year variable to control for the effect of these variables over time. I choose to include both household income and population density since they are related to property values through the ability of households to purchase property and the competition for single-family residential homes respectively. The model also includes standard errors clustered at the store level since observations geographically close to each other are likely to be similar and thus correlated to each other.

To assess the dynamic, monthly effect of Costco openings up to two and a half years after the store opening, I run the following event study specification:

$$[2]\ \ log(P_{it}) = \alpha + \sum_{j=2}^{30} \beta_j (\text{Lead } j)_{it} + \sum_{k=1}^{30} \lambda_k (\text{Lag } k)_{it} + \mu_t + \sigma_c + \gamma_{tc} + \varepsilon_{it}$$

where the outcome variable is also the log Zillow Home Value Index (ZHVI), μ_t is the time-fixed effect for each year-month combination, and σ_c is the county-fixed effect. Here, the control variables γ_{tc} serve a similar function in controlling for time-varying household income and population density for each time period. Similar to the previous model, the county fixed effect handles heterogeneity in housing prices by county, and time-fixed effects control for trends in property values over time. This event study specification allows us to understand the dynamic effects of Costco openings on nearby property values over time while controlling for fixed factors by area and time (Clarke & Tapia-Schythe, 2021).

6. Main Results

The spatial difference-in-differences results from using specification 1 are in Table 3, where the columns of the table are organized in the order of increasing geographic granularity:

the first column shows the coefficients for the specification with the state fixed effect, the second column shows the results for the specification with the county fixed effect, and the third column shows the results with the city fixed effect. I find that Costco does not affect property values within 20 miles on average after controlling for county-level household income and population density, as shown through the coefficients on the distances interacted with the POST variable. This is a surprising result considering Costco is typically seen as an amenity but supports the findings of Lethco (2023) where null coefficients are estimated for the 0-6 mile range from Costco openings in California. A visualization of these key coefficients from columns 2 and 3 of Table 3 is shown in Figures 5 and 6. To check the robustness of my results, I rerun the specification without the time-varying controls. However, even after rerunning the empirical specification without the controls, I find null coefficients that are not significant, which indicates that these null estimates are not a product of the controls capturing all the variation in the data.

I provide additional robustness by producing estimates for placebo Costco openings. Table 4 shows the results of these falsification tests where I shifted the opening date back 3 years, 2.5 years, and 2 years before the opening date, corresponding with columns 1, 2, and 3 in the table. The point estimates on the key interaction variables for the falsification tests are also non-significant null values, providing evidence that the results in Table 3 are robust. Conversely, if I found significant coefficients in my falsification tests, it would be problematic for the interpretation of the main results, since I expect to see no significant effect on these placebo Costco openings. In Table 5, I adjust the temporal window to produce estimates with ZHVI values 3 years before and after Costco openings and 2 years before and after, shown in columns 1 and 2 respectively, as another robustness test. Here, I also find null results, showing the results are not a result of the choice of temporal window for producing these estimates. In columns 3 and 4, I show the results of running the specification using the approximate announcement date one year before the store opening date as a treatment instead of the store opening date. While there are significant negative point estimates in column 3 on the key coefficients “0-5 miles * POST” and “5-10 miles * POST”, these effects disappear when I increase the geographic granularity by including city-fixed effects instead of the preferred county-level fixed effects. The lack of consistent significant coefficients across specifications suggests there is no significant impact of Costco announcements one year before Costco openings on property values.

I proceed to further my analysis with different subsets of property values based on demographic characteristics using the empirical specification with county fixed effects. Table 6 shows the results of this heterogeneity analysis and Figures 10 to 12 show how the data is split visually. The demographic information from the ACS is used to determine zip codes that are in counties that have above-average population density, above-average household income, and an above-average white population. Specifically, I used the data from 2010 in the ACS to generate the sample splits since it is close to the temporal midpoint of the Costco openings in our sample. Crucially, I find that for the subset of zip codes with above-average population density, there is a 7.9% increase in property values within 5 miles of a Costco opening after controlling for county-level household income and population density, significant at the 10% level. I also find a 5.2% increase within 5 miles for areas with above-average household income with the same controls, significant at the 10% level. These results can be found by looking at the statistically significant coefficients on the “0-5 miles * POST” interaction term in column 1 and 2 of Table 5. It is important to note that the key coefficients showing the effect of Costco openings on nearby property values diminish with distance for the above-average population density and above-average household income groups even if the coefficients of interest are statistically insignificant. The result that Costco has an impact on property values when they enter a wealthier area makes sense since Costco primarily chooses to locate in the suburbs where incomes are somewhat higher than average (Testa, 2015). This choice of Costco location combined with their reliance on mandatory membership fees for a large portion of their revenues and their preference for an auto-mobile friendly storefront supports the notion that Costco customers are somewhat wealthier than average and explains why we find a significant effect with this subset. Conversely, the appreciation in property values within 5 miles of a Costco opening for zip codes in above-average population density counties can be understood by the idea that a greater density of people leads to property values being more responsive to changes in nearby amenities. However, more concrete investigation must be done to understand the economic forces behind this result.

I supplement this heterogeneity analysis with falsification tests of Costco openings for these sample-type splits. Table 8 shows the results of the falsification tests for the above-average population density split. While there are significant coefficients when the opening date is shifted back 3 years to simulate fake opening dates, this coefficient is not consistent when the opening date is shifted back 2.5 years and 2 years. This suggests that the significant results for the zip codes within 5 miles of Costco openings in above-average population density counties are robust. Similarly, Table 9 shows the results of the falsification tests for the above-average household income split where I find no significant coefficients, suggesting that the significant result within 5 miles for the above-average household income sample split is robust.

I also ran tests for the complementing sample splits of below-average population density, below-average household income, and below-average white population zip codes to get a clearer picture of the data. The significant negative results in Table 7 are as expected given the positive coefficients in Table 6. There are depreciating effects for zip codes in counties with below-average population density, below-average household income, and below-average white population, with the magnitudes decreasing with distance from Costco openings. The coefficients in column 1 of Table 7 show that for zip codes in counties with below-average population density, Costco openings cause a 6.2% decrease in property values within 5 miles of a Costco, a 3.2% decrease from 5-10 miles, a 2.3% decrease from 10-15 miles, and a 1.2% decrease 15-20 miles from a Costco opening, mostly significant at the 1% level except for the 15-20 mile coefficient which is significant at the 10% level. These results suggest that areas with below-average population density see Costco as more of a disamenity than an amenity, which is a fairly interesting result. Column 2 of Table 7 shows us that for zip codes in counties with below-average household income, Costco openings cause a 3.5% decrease in property values within 5 miles of a Costco, a 2.6% decrease from 5-10 miles, a 1.6% decrease from 10-15 miles from a Costco opening, mostly significant at the 10% level except for the 5-10 mile coefficient which is significant at the 5% level. The magnitude of these coefficients is about half as much as the magnitudes for the below-average population density group we see in column 1 and suggests being in the below-average population density group is a more critical factor in determining the depreciating effects of Costco openings relative to being in the below-average household income group. These negative coefficients, which decrease in magnitude with distance, are expected given the positive coefficients produced in the above-average population density split and above-average household income split (although not all of those coefficients are significant). In column 3 of Table 7, we find negative coefficients mostly significant at the 5% level for the below-average white population zip codes, with a 3.7% decrease within 5 miles of a store opening, a 2.7% decrease 5-10 miles from a Costco opening, a 2.1% decrease from 10-15 miles, and a 1.6% decrease from 15-20 miles. These significant results in Column 3 of Table 7 stand in contrast to the non-significant results in Column 3 of Table 6 for the above-average white population split, although we see a similar pattern of treatment effect magnitude decreasing with distance from store openings. Ultimately, this heterogeneity analysis is highly informative and shows the importance of population density, household income, and white population on the impact Costco openings have on nearby property values. These results suggest that while areas with above-average population density and household income see Costcos as more of an amenity than a disamenity, areas with below-average population density, below-average household income, and below-average white population see Costco as more of a disamenity than an amenity.

Lastly, the event study results produced with empirical specification 2 are displayed in Figures 13 to 16. In all 30 months post-Costco opening, I find that after controlling for household income and population density, property values decrease, though not significantly, within 20 miles of Costco after it opens. The lack of significant estimates provides further evidence of the robustness of the spatial difference-in-differences estimates through the null dynamic effects of Costco openings on nearby ZHVI values. Further, the lack of significant estimates 30 months before Costco openings for each treated group also bolsters the claim of no significant pre-trends in the data conditional on covariates, supporting a causal interpretation of my results.

7. Conclusion

This study uses a spatial difference-in-differences model and an event study model to estimate the impact of Costco openings on nearby property values, finding that on average, property values within 20 miles do not significantly change as a result of Costco openings.

However, I find that with zip codes in counties with above-average population density or above-average household income, there are appreciating effects within 5 miles of a Costco opening. Conversely, for zip codes in counties with below-average population density, below-average household income, or below-average white population, Costco openings had a depreciating effect on nearby property values with the strongest negative effects within 5 miles of the stores which weaken and extend up to 15 to 20 miles from stores. While I had hypothesized that Costco openings would cause a weak increase in property values very near each Costco with stronger appreciating effects further from each Costco opening which dissipate with more distance, I find that this hypothesis is not supported by the data. Due to my empirical specification and choice of concentric rings in 5-mile intervals, my results were also unable to capture any non-linearity in changes in property values, which would have likely shown up with smaller rings.

The unique contribution of my paper to the literature is that this paper is part of the emerging literature that extends the spatial difference-in-differences model to an event study, improving the understanding of the dynamic effects of store openings on property values, following Hoelzlein & Miller (2023). Ideally, this would also allow for the identification of anticipation effects or agglomeration effects, providing a richer understanding of the impact of store openings on nearby property values. My study is also the first of its kind to incorporate controls for population density and household income into the analysis, which provides a more nuanced analysis by factoring in the role of these variables in determining property values. Ultimately, my main findings support the previous literature on the impact of Costco openings on property values in finding null results (Lethco, 2023), and extends this analysis by finding significant effects for subsets of the population. Namely, I find increases in property values within 5 miles of Costco openings for zip codes in counties with above-average population density or above-average household income and decreases in property values within 15 to 20 miles for zip codes in below-average population density, below-average household income, and below-average white population counties. It is important to note that the results for the above-average population density and above-average household income split are significant at the 10% level, meaning they can be subject to further tests for robustness. Conversely, the strong statistical significance of the below-average population density, below-average household income, and below-average white population splits is indicative of clearer treatment effects. The appreciating effects for the above-average population density and above-average household income follow the previous literature on other retail store openings, which typically find increases in property values as a result of store openings (see Table 1). Connecting to the economic framework, my findings suggest that the amenity value of Costco openings within 5 miles of the warehouse outweighs the negative externalities generated by the Costco opening within that distance for neighborhoods with above-average population density or above-average household income. On the other hand, the disamenities generated by Costco openings outweigh the amenities generated by the introduction of Costco in below-average population density, below-average household income, and below-average white population neighborhoods.

It is important to note the limitations of my study. Firstly, it is possible the controls do not capture the disamenities of neighborhoods where Costco chooses to enter, explaining the null result. If Costco enters neighborhoods that have not done well over the last 20 years in a way that is not captured by my controls, this could lead to biased estimates. Secondly, since I used ZHVI data which was aggregated at the zip code level, I was unable to control for changes in property characteristics over time since these could be related to changes in housing prices over the estimation period. This could lead to potentially biased estimates if the types of houses being built near a Costco after a Costco opens are significantly different than the ones being built before openings, and this choice deviates from most of the previous literature which controlled for property characteristics at the individual property transaction level. Lastly, since my outcome variable is a housing index produced by Zillow which has been seasonally adjusted and smoothed and represents a "typical" value within a zip code (Olsen, 2023), the drawbacks to using this data are that the identifying variation may have been massaged or aggregated away through the transformation of housing values into an index. Using this data to investigate the causal effect of other store openings on property values would be advisable, which would allow us to understand if the null results of my analysis in Table 3 come from using this measure of housing values.

Concerning the endogeneity of my results, it is well understood that Costco's opening locations are the result of careful planning (Testa, 2015). Critical to my research design, it is sensible to believe that Costco's opening locations are quasi-random with respect to housing prices conditional on some observables since it is more likely that Costco bases its choice of location on other factors such as distance to highways, lot size for which it can build its parking spaces, favorable local policies such as tax breaks offered by local governments, or local labor market conditions. Thus, there is sufficient reason to believe in the validity of my results because the assignment of treatment is quasi-random. Concerning the choice of the control group, it is also difficult to know the optimal control group radius. This is an ongoing point of discussion in the literature with no obvious solution and has non-trivial consequences; a choice of a treated group too narrow or too wide could result in the treatment effect being overestimated or underestimated. Further, there is no concrete way to tell if the treatment effect is zero past 20 miles or a distance much further, meaning control groups are somewhat arbitrarily chosen at the researcher's discretion.

In terms of future directions for research, investigating the impact of having nearby competitors on changes in property values would provide some insight into the extent to which changes in property values are driven by the availability of retail substitutes. Another extension would be to understand the role of neighbourhood structure by comparing suburban and urban Costcos, which would deepen our understanding of how neighborhood structure is related to store openings and changes in property values. Further, the incorporation of variables such as household income and population density necessarily brings up the relevance of gentrification effects of store openings. It would be interesting to investigate the role of Costco store openings and other similar businesses on the demographic compositions of neighborhoods in which they open and factor in the role of migration and demographics on property values. One possible extension to the spatial difference-in-differences estimation method would be to use a non-parametric approach that determines the number and location of the concentric rings in a data-driven way (Butts, 2023), fixing any problems of using control and treated radii which are either too narrow or too wide. Excitingly, novel machine-learning techniques that involve the use of convolutional neural networks have also been used to identify counterfactual Costco opening locations. An implementation of this technique would provide the ideal control group since these counterfactual store opening locations would act as the "next-best" Costco opening locations (Pollman, 2020; Qian et al., 2023). In conclusion, novel methods are improving the identification of causal parameters and there is much that can be done to improve our assessment of the impact of Costco and other retailers on nearby property values.

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Table 1: Effect of Retail Store Opening on Property Prices Literature Review

Citation	Method + Duration	Field	Controls + Additional FE	# of Store Openings	Main Results	Temporal Window
Pope & Pope (2015)	DID (1998-2008)	Single-family residential property prices	**Controls:** Property Attributes **FE:** store-level	159 Walmart openings in the US	+2-+3% within 0.5 miles +1-+2% between 0.5-1 mile	2.5 years after opening date
Slade (2018)	DID (1990-2015)	Residential, commercial and industrial property prices	**Controls:** Land location characteristics **FE:** store-by-year by-quarter	3,180 Walmart openings in the US	+26% within 0.25 miles +18% between 0.25 to 0.5 mile	3 years after the opening date
Saengchote (2020)	DID (2002-2012)	Single-family residential property prices	**Controls:** Property Attributes **FE:** store-by-year-by month	100 Whole Foods openings in the US	+6.7% within 0.5 miles +5% for between 0.5 to 1 mile +3.3% for between 1-2 miles	2.5 years (10 quarters) after opening date
Hoelzein & Miller (2023)	Event Study	Home values by Census block groups	Matching used **FE:** year, store, match-post	117 Whole Foods Market openings	+10-20% within 0.5 miles	5 years after opening date
Daunfeldt et al. (2021)	DID (2005-2014)	Single-family residential property prices	**Controls:** Property Attributes **FE:** city, year, and city-year	5 IKEA openings in Sweden	+4.4% in the entry cities Non-linear effect: +6.87% 1.5km away +6.95% 2km away +2% 10km away	2.5 years after opening date (?)
Lethco (2023)	DID (1988-2012)	Single-family detached residential property prices	**Controls:** Property Attributes **FE:** Zipcode	9 Costco openings in California	No change in single-family property values	2.5 years after opening date

Table 2: Means of Key Variables Pre & Post Costco Openings

Distance Category	Mean ZHVI		Mean Log ZHVI			Mean Household Income		Mean Pop. Density		Observations
	Pre-Open	Post-Open	Pre-Open	Post-Open	P-value for t-test	Pre-Open	Post-Open	Pre-Open	Post-Open	
0 to 5 miles	208,931	269,163	12.08	12.30	0.04	225,506	233,821	0.04	0.04	320
	(132,443)	(192,522)	(0.58)	(0.63)		(158,577)	(164,847)	(0.05)	(0.06)	
5 to 10 miles	192,367	243,631	11.97	12.18	0.00	226,816	234,334	0.04	0.04	618
	(138,485)	(190,198)	(0.65)	(0.67)		(166,368)	(173,156)	(0.05)	(0.05)	
10 to 15 miles	195,568	249,276	12.00	12.22	0.02	230,364	240,477	0.03	0.04	633
	(123,183)	(172,994)	(0.64)	(0.67)		(194,482)	(206,174)	(0.04)	(0.04)	
15 to 20 miles	203,424	257,514	12.05	12.27	0.01	182,828	190,081	0.02	0.03	604
	(151,049)	(199,717)	(0.56)	(0.60)		(185,574)	(195,174)	(0.03)	(0.03)	
20 to 25 miles	201,501	262,246	12.03	12.29	—	161,817	166,976	0.02	0.02	683
(Control)	(173,115)	(233,038)	(0.55)	(0.58)		(180,385)	(187,113)	(0.02)	(0.02)	

Source: Zillow Home Value Index (ZHVI) data from 2000 to 2022 for 2.5 years before (Pre-Open) and after opening (Post-Open). Household income and population density data are from the American Community Survey. P-values are from t-tests of difference-in-differences between pre and post values vs. the control group.

Table 3: Impact of Costco Openings on ZHVI values

VARIABLES	(1) ln(ZHVI)	(2) ln(ZHVI)	(3) ln(ZHVI)
0 to 5 miles	0.106*	0.115*	0.0379
	(0.0564)	(0.0683)	(0.0925)
5 to 10 miles	-0.0249	0.00418	-0.105
	(0.0493)	(0.0619)	(0.0816)
10 to 15 miles	-0.0232	0.00355	-0.100
	(0.0613)	(0.0622)	(0.0958)
15 to 20 miles	0.0238	0.0303	0.0138
	(0.0375)	(0.0406)	(0.0715)
0 to 5 miles * POST	0.0129	-0.00260	0.00308
	(0.0182)	(0.0172)	(0.0208)
5 to 10 miles * POST	0.000311	-0.00977	-0.00646
	(0.0129)	(0.0134)	(0.0152)
10 to 15 miles * POST	0.00897	-0.00226	0.000547
	(0.0142)	(0.0153)	(0.0176)
15 to 20 miles * POST	-0.00383	-0.0169*	-0.0125
	(0.01000)	(0.00985)	(0.0114)
Constant	11.20***	12.50***	10.55***
	(0.320)	(3.009)	(0.434)
Year FE	✓	✓	✓
Month FE	✓	✓	✓
State FE	✓		
County FE		✓	
City FE			✓
Controls	✓	✓	✓
Observations	5,698	5,698	5,698
R-squared	0.465	0.606	0.756

Standard Errors are clustered at the store level.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Falsification Tests of Costco openings on ZHVI values

Analysis Type	Opening Date Falsification Tests		
# of years open date shifted	3 Years earlier	2.5 Years earlier	2 Years earlier
	(1)	(2)	(3)
VARIABLES	ln(ZHVI)	ln(ZHVI)	ln(ZHVI)
0 to 5 miles	0.0375	0.0284	0.0699
	(0.0641)	(0.0603)	(0.0621)
5 to 10 miles	-0.0943*	-0.0937*	-0.0612
	(0.0547)	(0.0526)	(0.0528)
10 to 15 miles	-0.0900	-0.0805	-0.0639
	(0.0590)	(0.0576)	(0.0571)
15 to 20 miles	-0.0291	-0.0241	-0.0125
	(0.0371)	(0.0359)	(0.0348)
0 to 5 miles * POST	-0.00853	-0.00610	-0.0211
	(0.0183)	(0.0183)	(0.0177)
5 to 10 miles * POST	0.0100	0.00563	-0.0105
	(0.0150)	(0.0144)	(0.0135)
10 to 15 miles * POST	0.0169	0.00758	0.00494
	(0.0128)	(0.0122)	(0.0137)
15 to 20 miles * POST	0.00454	0.00344	-0.00157
	(0.00993)	(0.00888)	(0.00909)
Constant	11.39***	11.69***	11.57***
	(0.393)	(0.380)	(0.436)
Year FE	✓	✓	✓
Month FE	✓	✓	✓
County FE	✓	✓	✓
Controls	✓	✓	✓
Observations	5,700	5,881	5,891
R-squared	0.553	0.567	0.575

Standard Errors are clustered at the store level.

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Temporal Robustness Check

Temporal Adjustment	3 Year Window	2 Year Window	Announcement Date as Treatment	
	(1)	(2)	(3)	(4)
VARIABLES	ln(ZHVI)	ln(ZHVI)	ln(ZHVI)	ln(ZHVI)
0 to 5 miles	0.108	0.134**	0.0956	0.0628
	(0.0683)	(0.0652)	(0.0658)	(0.0727)
5 to 10 miles	-0.0131	0.0116	-0.0275	-0.0881
	(0.0530)	(0.0575)	(0.0526)	(0.0591)
10 to 15 miles	-0.0126	0.00309	-0.0252	-0.0979
	(0.0552)	(0.0575)	(0.0537)	(0.0906)
15 to 20 miles	0.0237	0.0302	0.00790	0.0228
	(0.0350)	(0.0387)	(0.0347)	(0.0730)
0 to 5 miles * POST	-0.0237	-0.00646	-0.0317*	-0.0243
	(0.0190)	(0.0146)	(0.0165)	(0.0205)
5 to 10 miles * POST	-0.0262	-0.00596	-0.0219*	-0.0175
	(0.0168)	(0.0117)	(0.0126)	(0.0154)
10 to 15 miles * POST	-0.0113	-0.00193	-0.00349	0.000528
	(0.0192)	(0.0133)	(0.0161)	(0.0197)
15 to 20 miles * POST	-0.0153	-0.0102	-0.0108	-0.00709
	(0.00969)	(0.00838)	(0.00888)	(0.0108)
Constant	5.958**	11.50***	15.81***	9.801***
	(2.690)	(2.573)	(3.216)	(1.206)
Year FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
County FE	✓	✓	✓	
City FE				✓
Controls	✓	✓	✓	✓
Observations	5,123	5,945	5,493	5,493
R-squared	0.594	0.608	0.589	0.736

Standard Errors are clustered at the store level.
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Costco Heterogeneity Analysis

Sample Split Type			
	(1)	(2)	(3)
VARIABLES	> Avg. Pop. Density	> Avg. Income	> Avg. White
0 to 5 miles	0.0665	0.0911	0.0739
	(0.157)	(0.130)	(0.134)
5 to 10 miles	-0.102	-0.0134	0.00842
	(0.160)	(0.116)	(0.122)
10 to 15 miles	-0.177	-0.108	-0.0775
	(0.161)	(0.131)	(0.136)
15 to 20 miles	-0.0566	0.00990	-0.00598
	(0.116)	(0.0933)	(0.102)
0 to 5 miles * POST	0.0790*	0.0523*	0.0373
	(0.0410)	(0.0293)	(0.0278)
5 to 10 miles * POST	0.0463	0.0350	0.0260
	(0.0386)	(0.0234)	(0.0216)
10 to 15 miles * POST	0.0434	0.0204	0.0271
	(0.0412)	(0.0235)	(0.0241)
15 to 20 miles * POST	0.000251	-0.0221	-0.00950
	(0.0262)	(0.0164)	(0.0176)
Constant	9.544***	5.857***	15.48***
	(1.361)	(1.585)	(0.918)
Year FE	✓	✓	✓
Month FE	✓	✓	✓
County FE	✓	✓	✓
Controls	✓	✓	✓
Observations	2,208	2,218	2,132
R-squared	0.600	0.583	0.608

Standard Errors are clustered at the store level.

*** p<0.01, ** p<0.05, * p<0.1

Sample Split Type	Table 7. Costco Heterogeneity Analysis		
	(1)	(2)	(3)
VARIABLES	< Avg. Pop. Density	< Avg. Income	< Avg. White
0 to 5 miles	0.118**	0.117*	0.137**
	(0.0581)	(0.0630)	(0.0614)
5 to 10 miles	0.0685	-0.000635	-0.00955
	(0.0478)	(0.0529)	(0.0497)
10 to 15 miles	0.116***	0.0875**	0.0533
	(0.0376)	(0.0386)	(0.0451)
15 to 20 miles	0.0595**	0.0332	0.0434*
	(0.0279)	(0.0284)	(0.0255)
0 to 5 miles * POST	-0.0618***	-0.0347*	-0.0365**
	(0.0143)	(0.0185)	(0.0174)
5 to 10 miles * POST	-0.0316***	-0.0261**	-0.0270**
	(0.0118)	(0.0126)	(0.0115)
10 to 15 miles * POST	-0.0230***	-0.0162*	-0.0213**
	(0.00829)	(0.00937)	(0.00893)
15 to 20 miles * POST	-0.0123*	-0.00975	-0.0165*
	(0.00698)	(0.00787)	(0.00947)
Constant	9.009***	8.381***	8.716***
	(2.475)	(0.401)	(2.734)
Year FE	✓	✓	✓
Month FE	✓	✓	✓
County FE	✓	✓	✓
Controls	✓	✓	✓
Observations	3,350	3,340	3,426
R-squared	0.624	0.609	0.583

Standard Errors are clustered at the store level.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Falsification Tests of Costco openings on ZHVI values for >Avg. Population Density			
Analysis Type	Opening Date Falsification Tests		
# of years open date shifted	3 Years earlier	2.5 Years earlier	2 Years earlier
	(1)	(2)	(3)
VARIABLES	ln(ZHVI)	ln(ZHVI)	ln(ZHVI)
0 to 5 miles	-0.0702	-0.0241	-0.0313
	(0.149)	(0.147)	(0.151)
5 to 10 miles	-0.282**	-0.238*	-0.224
	(0.139)	(0.138)	(0.140)
10 to 15 miles	-0.321***	-0.294**	-0.288**
	(0.124)	(0.127)	(0.123)
15 to 20 miles	-0.152*	-0.136	-0.124
	(0.0851)	(0.0857)	(0.0850)
0 to 5 miles * POST	0.0510**	-0.00720	0.0492
	(0.0227)	(0.0308)	(0.0321)
5 to 10 miles * POST	0.0579**	0.00580	0.0371
	(0.0225)	(0.0291)	(0.0285)
10 to 15 miles * POST	0.0393**	-0.00391	0.0304
	(0.0193)	(0.0261)	(0.0289)
15 to 20 miles * POST	0.0123	-0.0148	-0.00492
	(0.0148)	(0.0167)	(0.0202)
Constant	20.90***	27.48***	-0.941
	(5.536)	(5.207)	(5.470)
Year FE	✓	✓	✓
Month FE	✓	✓	✓
County FE	✓	✓	✓
Controls	✓	✓	✓
Observations	1,889	1,974	1,953
R-squared	0.509	0.540	0.542

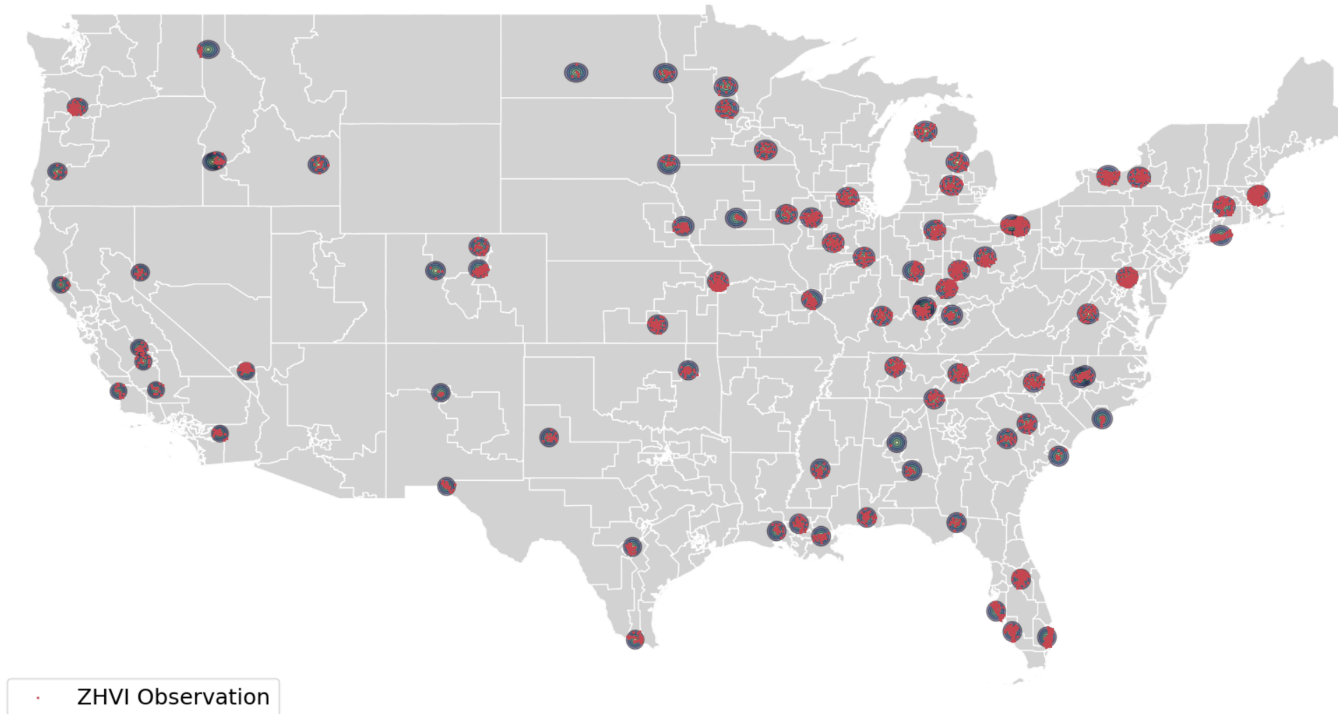
Standard Errors are clustered at the store level.
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Falsification Tests of Costco openings on ZHVI values for >Avg. Household Income			
Analysis Type	Opening Date Falsification Tests		
# of years open date shifted	3 Years earlier	2.5 Years earlier	2 Years earlier
	(1)	(2)	(3)
VARIABLES	ln(ZHVI)	ln(ZHVI)	ln(ZHVI)
0 to 5 miles	0.0735	0.0946	0.0916
	(0.120)	(0.118)	(0.121)
5 to 10 miles	-0.0852	-0.0754	-0.0696
	(0.0922)	(0.0916)	(0.0940)
10 to 15 miles	-0.163	-0.157	-0.167
	(0.105)	(0.105)	(0.107)
15 to 20 miles	-0.0330	-0.0263	-0.0244
	(0.0736)	(0.0720)	(0.0749)
0 to 5 miles * POST	0.00265	-0.0255	-0.00627
	(0.0192)	(0.0209)	(0.0204)
5 to 10 miles * POST	0.00799	-0.0140	0.00159
	(0.0149)	(0.0183)	(0.0166)
10 to 15 miles * POST	0.0114	-0.00382	0.0112
	(0.0163)	(0.0197)	(0.0203)
15 to 20 miles * POST	-0.00358	-0.0212	-0.0185
	(0.0148)	(0.0162)	(0.0165)
Constant	10.48***	22.26	9.519***
	(0.682)	(17.20)	(2.161)
Year FE	✓	✓	✓
Month FE	✓	✓	✓
County FE	✓	✓	✓
Controls	✓	✓	✓
Observations	2,135	2,214	2,121
R-squared	0.579	0.579	0.590

Standard Errors are clustered at the store level.

*** p<0.01, ** p<0.05, * p<0.1

Figure 1: U.S. Costco Warehouse Openings from 2002 to 2020



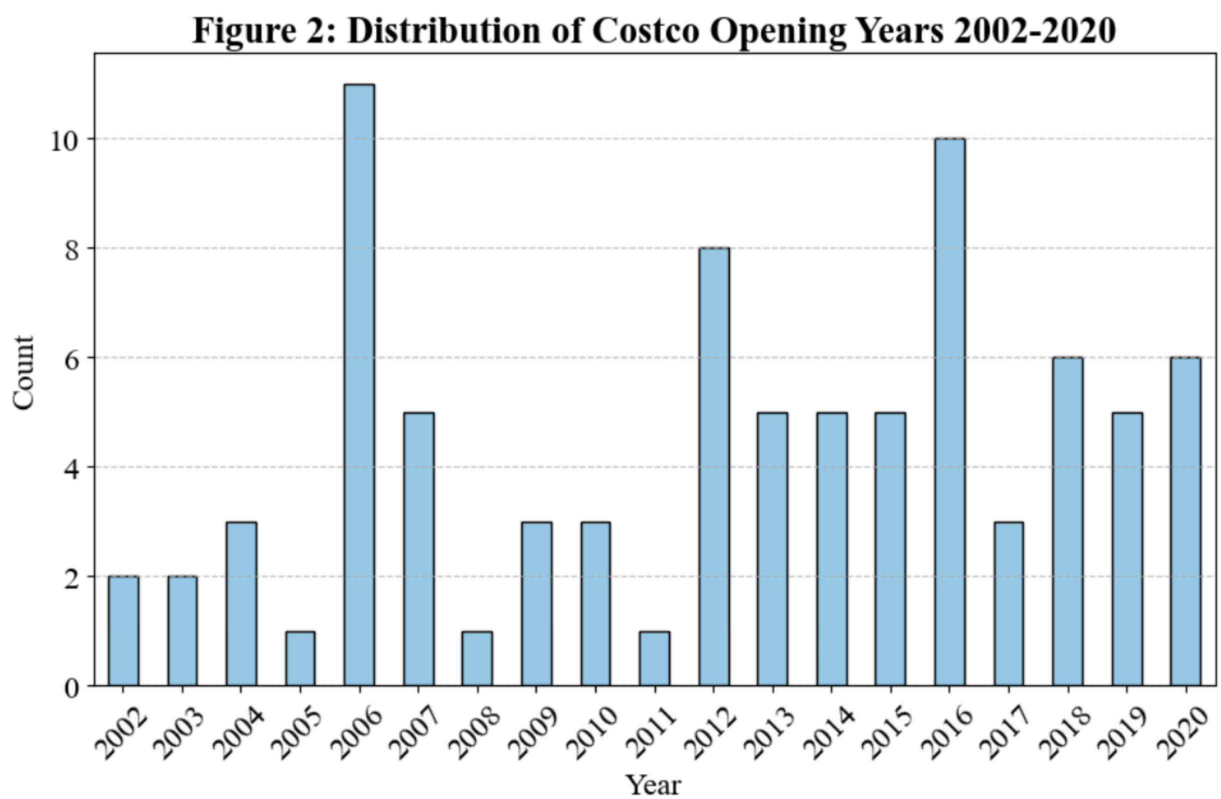


Figure 3: Concentric Ring Visualization

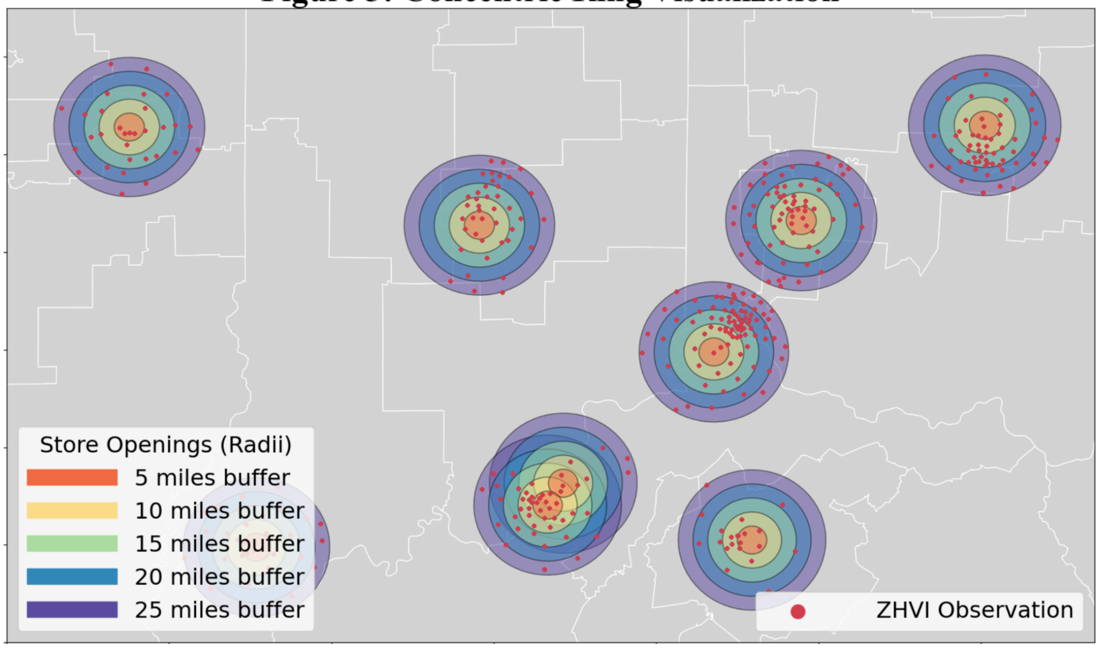


Figure 4:
Normalized Mean Log ZHVI Values over Quarters from Costco Opening

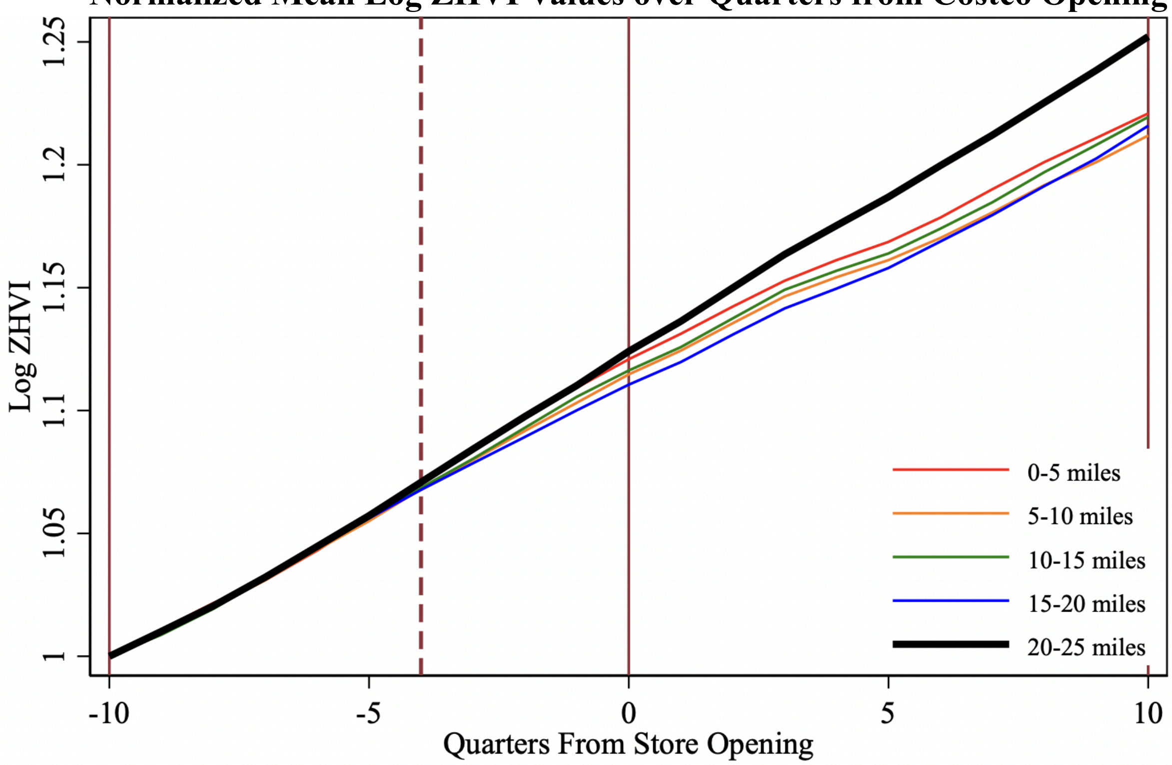


Figure 5: Specification 2 Coefficient Plot

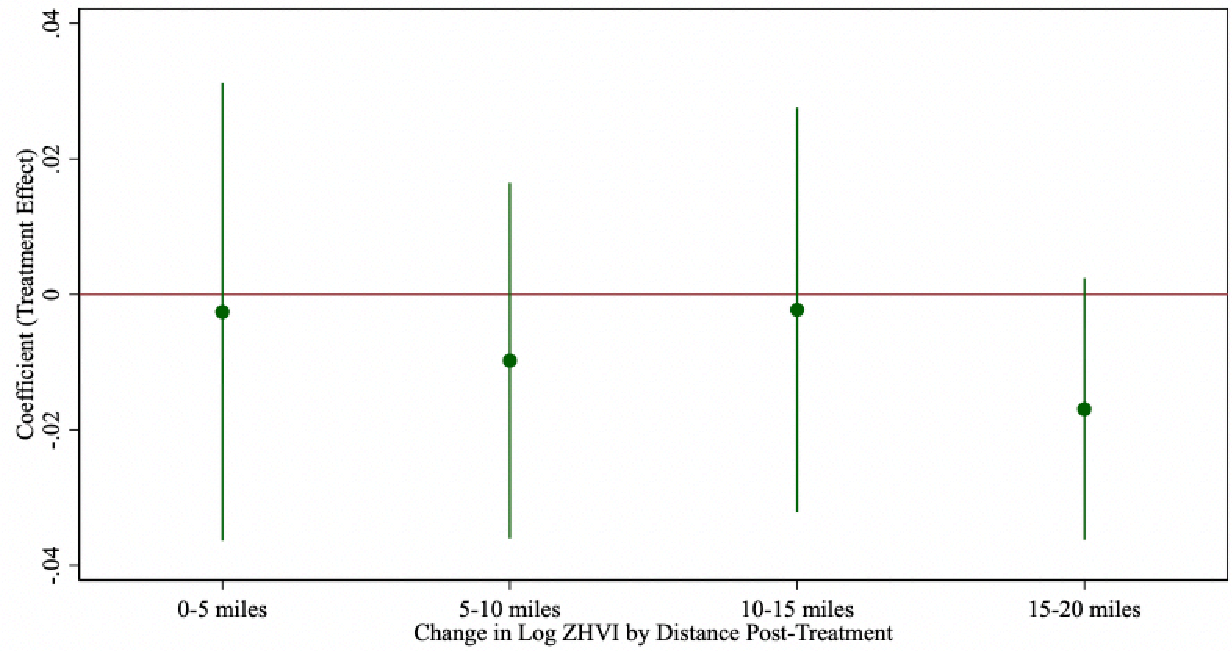
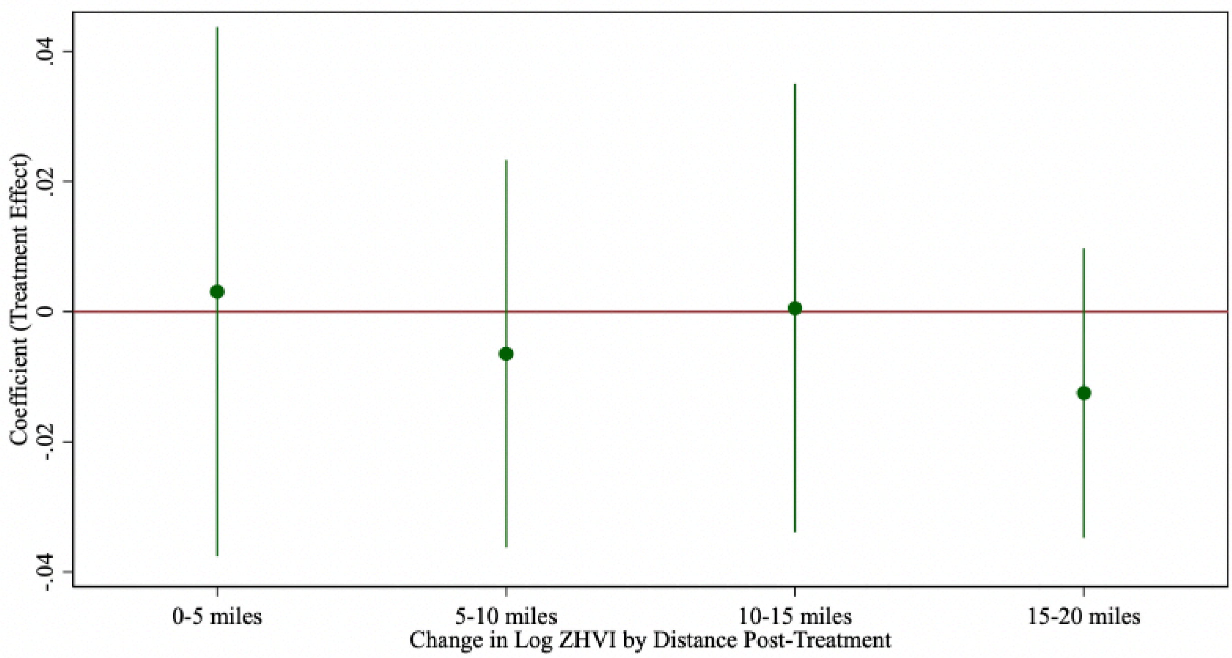


Figure 6: Specification 3 Coefficient Plot



I choose to include the coefficient plots for the more granular specifications 2 and 3, which control for county-fixed effects and city-fixed effects respectively.

Figure 7: Normalized Mean Log ZHVI Values over Quarters from Costco Opening for Above-Average Population Density

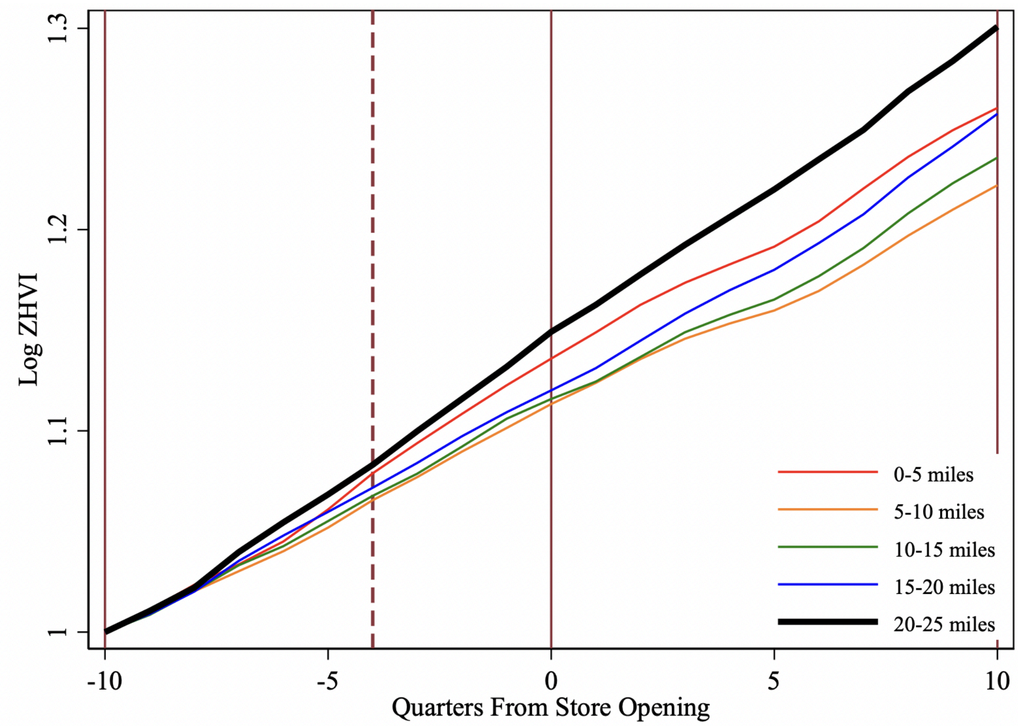


Figure 8: Normalized Mean Log ZHVI Values over Quarters from Costco Opening for Above-Average Household Income

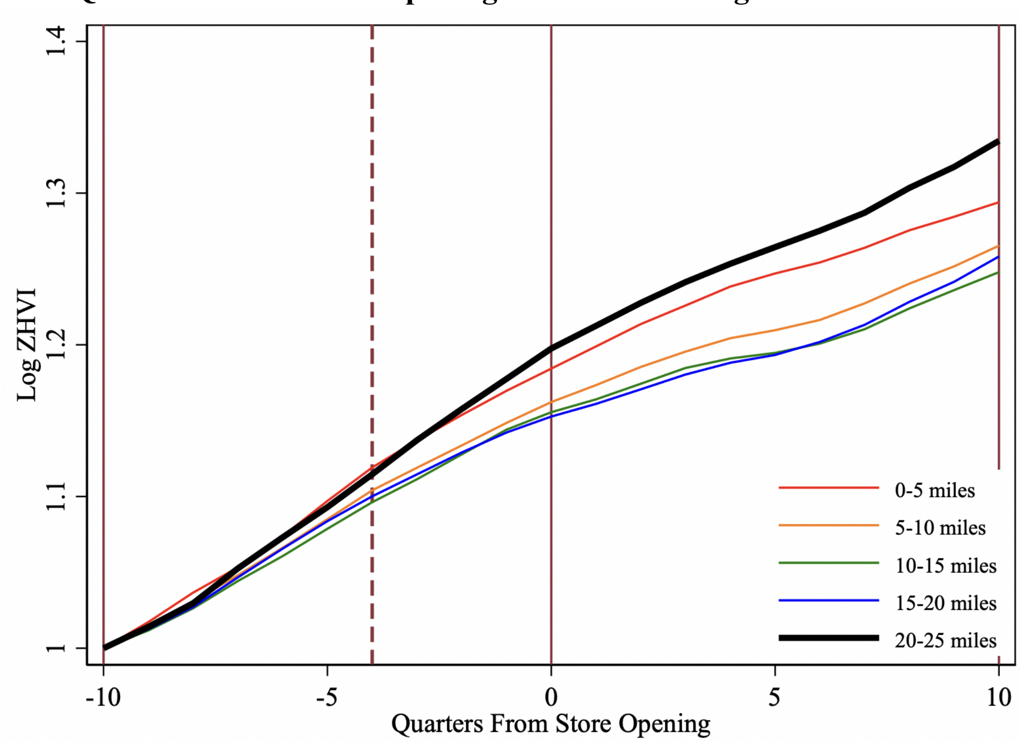


Figure 9: Normalized Mean Log ZHVI Values over Quarters from Costco Opening for Above-Average White Population

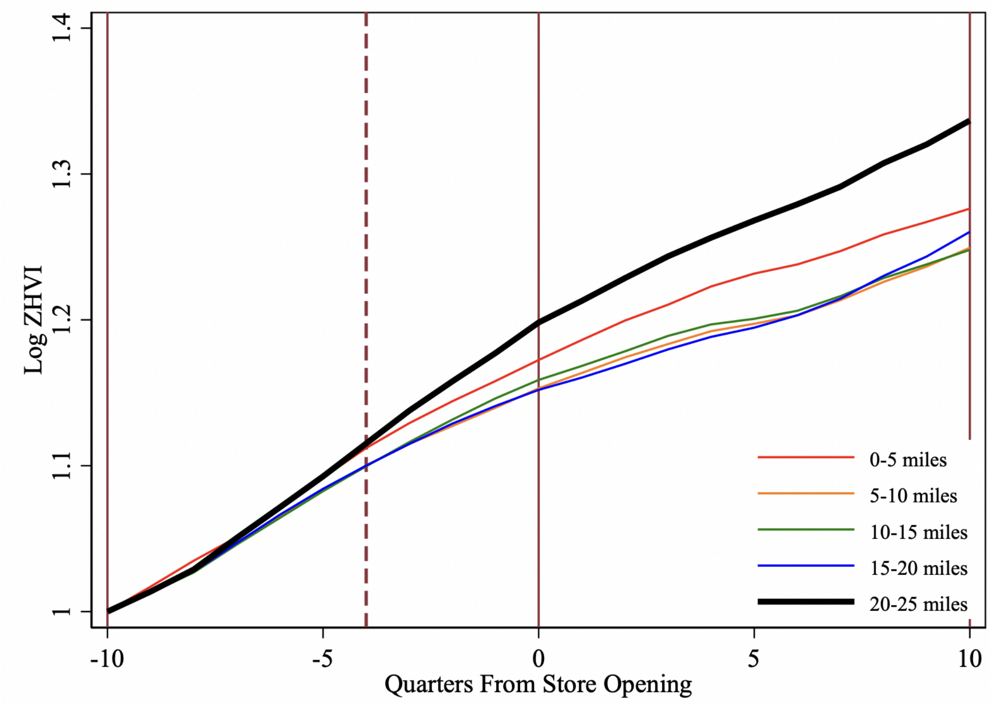


Figure 10: U.S. ZHVI Observations Highlighting Avg. Pop. Density Split

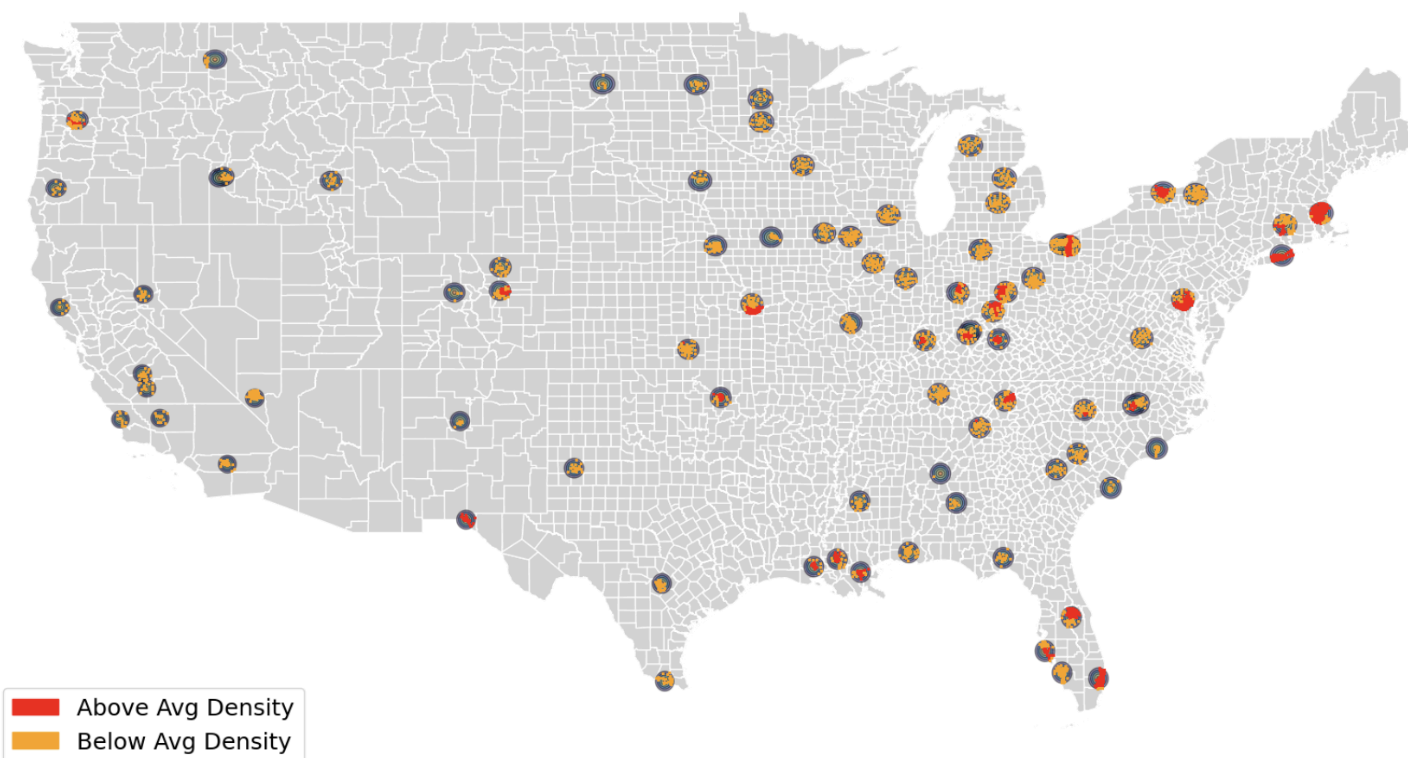


Figure 11: U.S. ZHVI Observations Highlighting Avg. Household Income Split

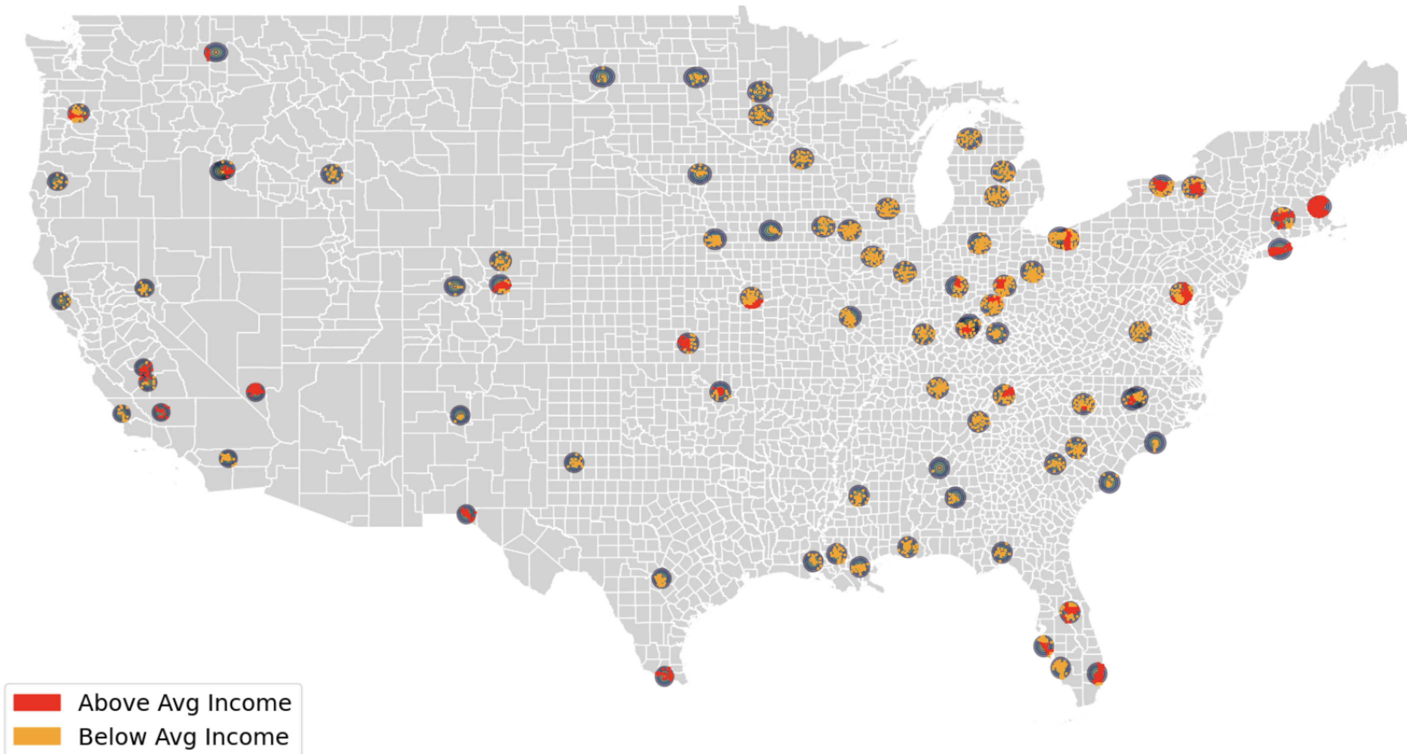


Figure 12: U.S. ZHVI Observations Highlighting Avg. White Pop. Split

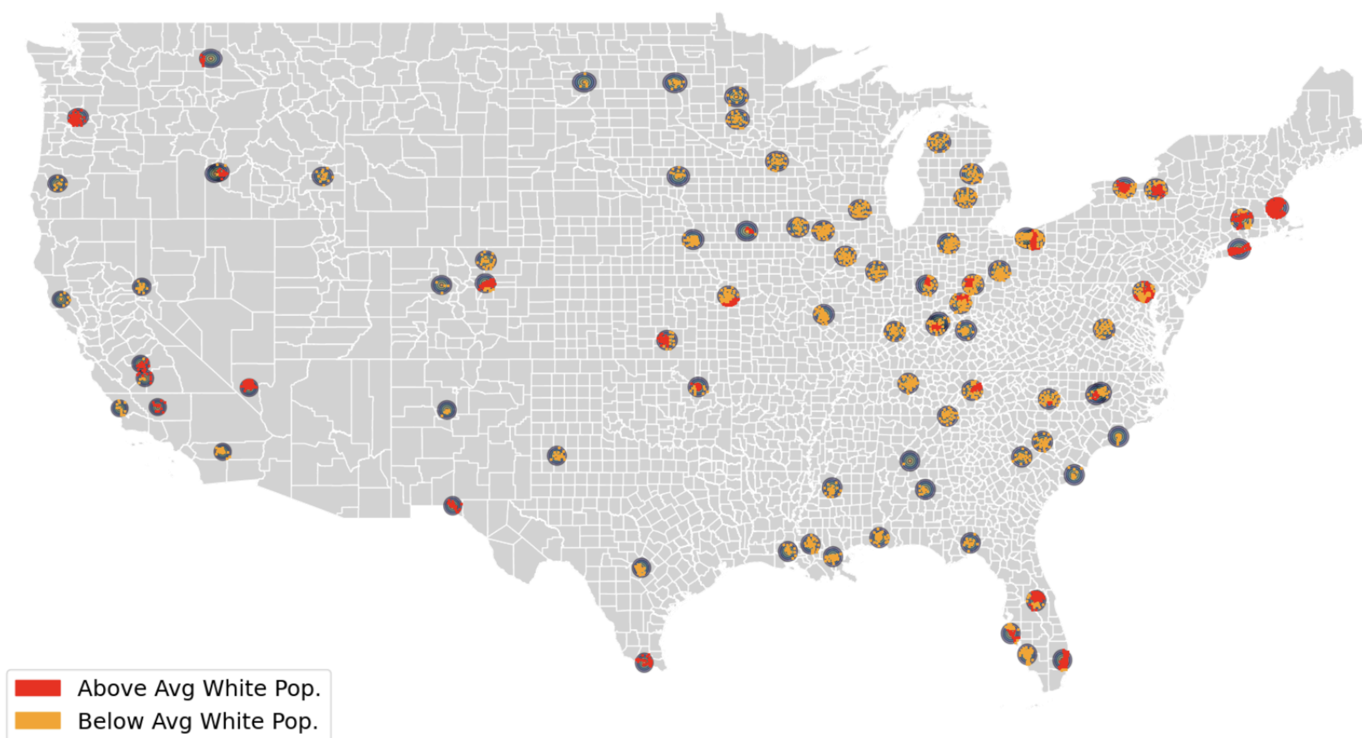


Figure 13: Dynamic Effect of Costco Openings on Property Values: 0-5 Miles

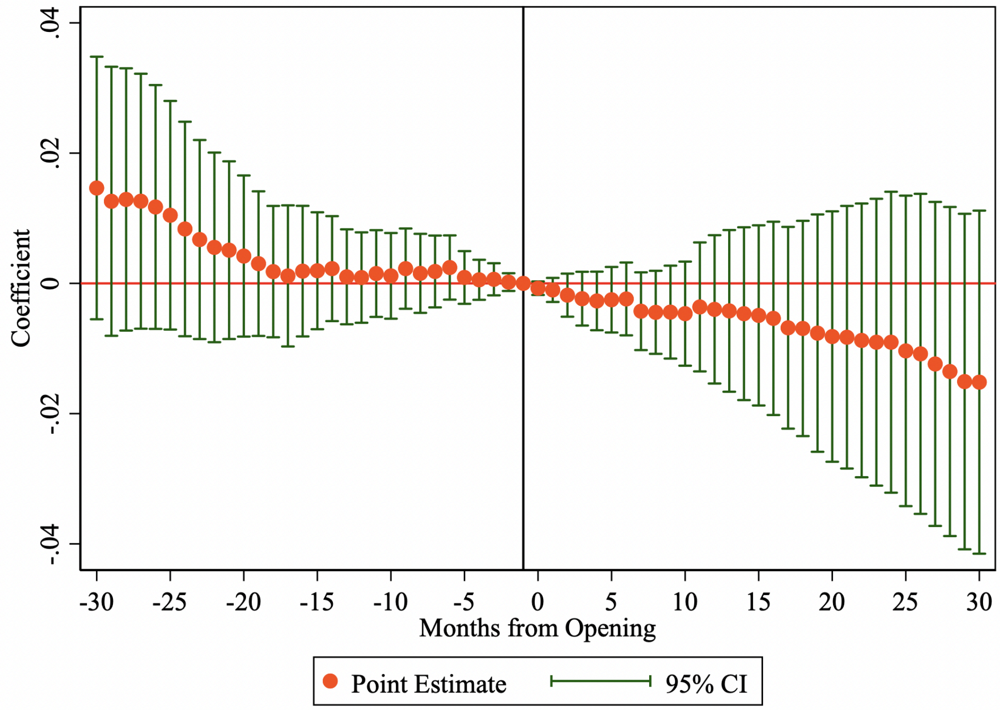
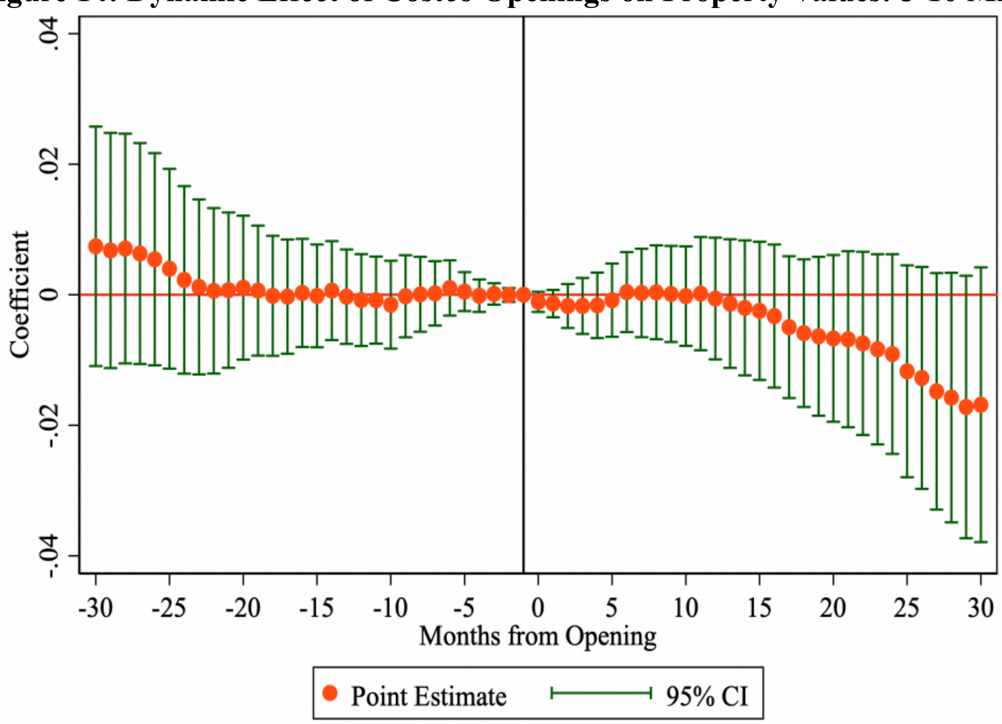


Figure 14: Dynamic Effect of Costco Openings on Property Values: 5-10 Miles



These event study graphs show the effect of Costco openings on nearby property values 30 months after the store opening date for each of the treated groups relative to the control group.

Figure 15: Dynamic Effect of Costco Openings on Property Values: 10-15 Miles

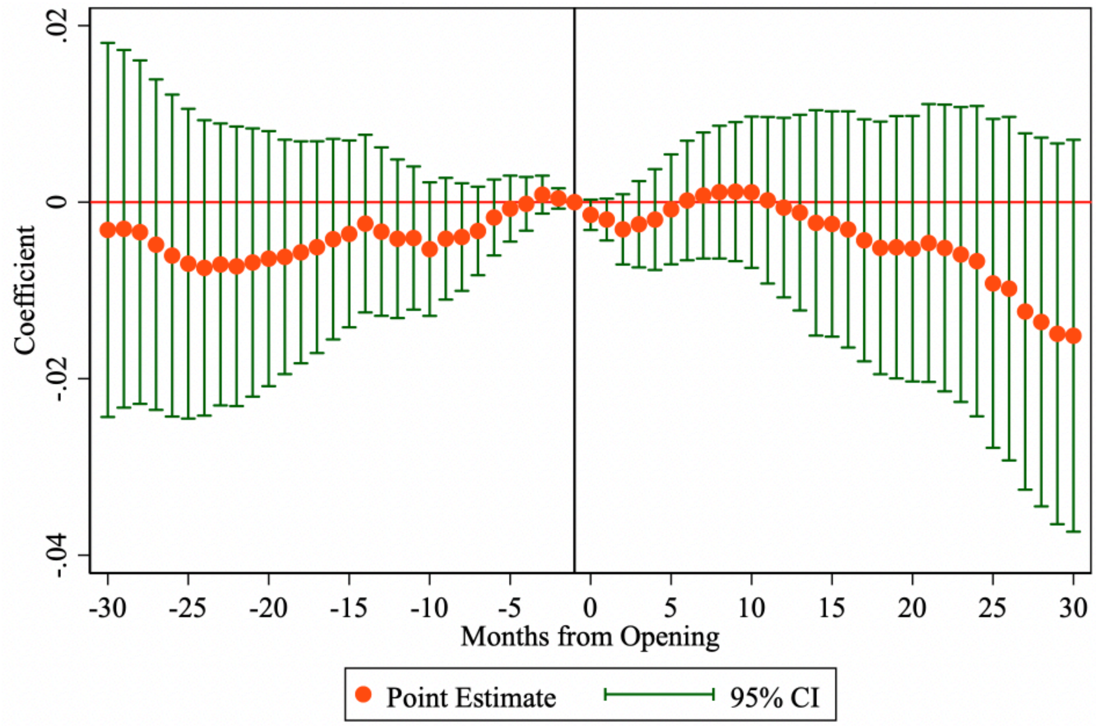
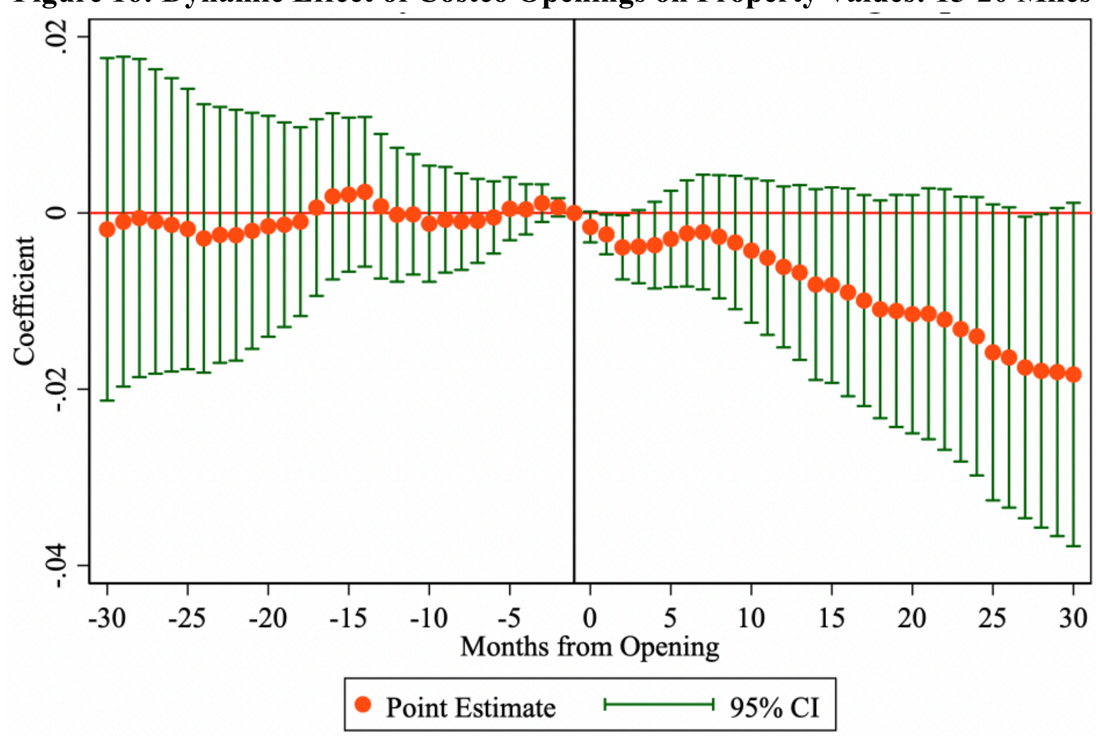


Figure 16: Dynamic Effect of Costco Openings on Property Values: 15-20 Miles



9. Appendix

For the Costco opening date data, several key variables already included are each store's identifying characteristics, including the store name, street address, city, state, zip code, phone, hours, website link, latitude, longitude, and opening date (which can be scraped directly from the store's website).

I use the U.S. Census Bureau API in Python to extract variables 'B01003_001E':' total population', 'B19001_001E': 'household income in the past 12 months (in 2019 inflation-adjusted dollars)', and 'B02001_002E': 'white alone', which are used as controls and heterogeneity analysis. The population density variable is constructed by taking the 'B01003_001E': 'total population' variable at the county level and the land area values based on the shape U.S. county shape file and dividing each population estimate by the land area. In terms of data construction, since the ACS 5-Year Estimates cover 2009 to 2021 and the ACS 1-Year Estimates from 2005-2008, I use the 2005 county-level estimates for these variables for our zip codes from the years 2000 to 2005, and the 2021 estimates for these variables for our observations from the years 2022 to 2023. Additionally, since some values were missing for specific counties for 2008 during the estimation process, the 2007 values from these counties were imputed for 2008.