THE EFFECT OF NEW BART STATIONS ON HOUSING PRICES

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ABSTRACT

This paper seeks to analyze the relationship between housing prices and the opening of new BART stations. Three new residential BART stations have opened in recent years: Warm Springs/South Fremont and the new eBART extension that includes Pittsburg Central and Antioch. In this paper, I use a Difference-in-Differences approach to look at the difference in housing prices between the zip codes containing to the new stations as a treatment group and the stations further out as the control. I use seven different metrics of housing prices. My results are mixed and vary between the two areas that received new stations.

INTRODUCTION

The original BART (Bay Area Rapid Transit) system opened its doors to passengers Sept. 11, 1972 ("A History of BART | bart.gov"). Since its opening, BART has added several new stations including the entire Dublin/Pleasanton line and the airport connection stations. However, in the last 20 years, the only non-airport station additions have been the extension to the Warm Springs/South Fremont station on the Fremont line and the Pittsburg Central and Antioch stations extension on the Pittsburg/Bay Point line. The Warm Springs/South Fremont station opened on March 25, 2017, marking the first step in a planned expansion down to San Jose ("BART Historical Timeline"). The Pittsburg Central and Antioch stations both opened on May 25, 2018, as part of a new eBART system that connects to the existing BART system ("East Contra Costa BART Extension FAQ | bart.gov").

The original BART system was built to address a growing Bay Area population and increased congestion in travel between San Francisco and the East Bay (Healy, 2016). After WWII the Bay Area saw population growth of approximately fifty percent, but it still took many years before construction began on the new rapid transit system (Healy, 2016).

With the current tech boom, the SF Bay Area faces many of the same problems it did 50 years ago. Traffic congestion is getting worse. A 2017 report found that traffic congestion in the SF Bay increased by 80% from 2010 (Goodwin, 2017). Bay Area housing costs are skyrocketing with San Francisco and San Jose being ranked among the most expensive cities in the country. As it becomes more expensive to live near the big employment centers in the Bay and traffic conditions worsen, BART is looking more appealing as a cheap and fast way to get into San Francisco or close to San Jose. For example, to get to the SF Financial District from Downtown Berkeley during the morning rush hour can take as long as 80 minutes by car while it only takes about 45 minutes by BART (google.com/maps). Although the round-trip BART fare comes to $8.20, this can easily represent a substantial saving over the cost of daily parking alone (bart.gov/tickets/calculator).

My interest is in how the expansion of public transport affects the desirability of living areas. “Desirability” is an abstract and difficult measure, so I am going to assume that the desirability of neighborhoods is reflected in the prices of housing. Specifically, my research question and the focus of this paper is whether housing prices have responded to the opening of a nearby BART station and, if so, in what direction. My hypothesis is that demand for housing that has easy access to high employment density areas will be demonstrated by an increase in housing prices in nearby areas, around the time of opening of the new BART stops reflecting the increased demand for housing that has easy access to high employment density areas. I use a Diff-in-Diff approach to compare different housing price metrics from the zip codes next to the stations with zip codes farther away. My results are mixed and show a difference between the two areas that received new BART stations.

I will start with a review of other similar work and recent studies on the BART system. I will then describe my data, models, and methodology, and afterward discuss my results in detail. I will conclude with a summary and a discussion of potential areas for future research. The appendix contains visual representations of the data as well as maps of the regions in question.

LITERATURE REVIEW

The Bay Area Rapid Transit system was studied intensely soon after its opening in the 1970s. However, interest in its impact on housing prices has flagged in recent years. The most recent comprehensive analysis of the impact of BART on land use and development was from

1997, a 20-year update on an older paper that addressed the same issues soon after the BART system opened (Cervero & Landis, 1997). There have been a few more recent studies on topics related to BART (Cervero, Caldwell, & Cuellar, 2015; Dinno, Powell, & King, 2011; Rodier & Shaheen, 2010) but it has been a while since the relationship between housing prices and the BART system has been evaluated.

There are also several recent papers that are relevant in topic if not location. Zhong and Li (2016) investigated the effects of transit access on housing prices for the Los Angeles public transit system. They looked at the impact of opening new rail transit stations on housing prices across several variables including single vs. multi-family housing, station development stage, type of rail, and the presence of absence of Park-and-Ride facilities (Zhong & Li, 2016). Baum-Snow and Kahn (2000) used panel data to look at rail transit expansions in 5 cities from 1980 to 1990. The authors focused on the demographics of rail usage and the effect of rail system improvements on rental and home prices (Baum-Snow & Kahn, 2000). Bowes and Ihlanfeldt (2001) looked at Atlanta's public rail transit Metropolitan Atlanta Rapid Transit Authority (MARTA) and examined the effect of its rail stations on property values through the lens of four different competing forces: reducing commuting costs, increasing retail activity, various pollutions of the station, and attracting crime (Bowes & Ihlanfeldt, 1999).

Most of the analytical methodology in these papers are better suited to broader studies that are outside the scope of this paper. Zhong and Li compared regression models as part of their research, contrasting spatial models with a standard OLS model. Their most relevant conclusion was that proximity to a rail transit station increase multifamily property values but decreased single-family property values (Zhong & Li, 2016). Baum-Snow and Kahn used an event study since their main data sets are the 1980 and 1990 census tracts. Using census data to estimate public transit use and home prices in several different regressions, they used city fixed effects to control for city-specific changes (Baum-Snow & Kahn, 2000). They concluded that better access to public transit systems results in higher usage, housing price increases do not fully reflect cost savings from using public transit, and some commuters will change to using transit if it is expanded (Baum-Snow & Kahn, 2000). Bowes and Ihlanfeldt used a standard hedonic model with a few auxiliary models. They concluded that the total effects vary greatly based on the income level of the nearby residents, how far the station was from downtown, and how far away the station was from the housing (Bowes & Ihlanfeldt, 1999).

This paper is intended to be an update on some analyses of BART that other scholars have written in the past. There are more recent studies in other cities, but the effect of BART on development and housing has not been studied extensively in a while, and most research was conducted immediately after the system opened in the 1970s and 1980s. As one of the biggest industry growth hubs in the country, the San Francisco Bay Area has been understudied, particularly in regard to its public transportation infrastructure.

METHODS

MODELS

My basic approach for this analysis is using a Difference-in-Differences model, which measures trends in several variables through time. My main independent variables are time and the opening of a new BART station; despite significant economic and population growth, only three new BART stations (excluding airport connections) have opened since Cervero & Landis reported their 1997 update. My main dependent variable is housing prices, which I represent with seven different metrics. As the new stations opened in two geographically distinct areas, the Warm

Springs/South Fremont station represents one independent panel of data and the Pittsburg Center and Antioch stations together represent another panel of data.

The Warm Springs/South Fremont station opened on March 25, 2017, and the Antioch and Pittsburg Center stations opened simultaneously on May 25, 2018 (www.bart.gov/stations). For the initial Diff-in-Diff model, I labeled the observations on or after those months as the post-treatment variables for each panel of data. *Post* is a binary variable which takes a 1 if the metric is after the opening of the new BART station and a 0 otherwise. *Treat* is another binary variable that takes a 1 if the area is a zip code containing a new BART station and a 0 otherwise. Since we want to know what happened to the housing prices near the new BART stations after the stations opened, the variable of interest is the *post x treat* variable, measuring the effect of the interaction of time and treatment on housing prices. Since the data is for several areas over time, I used area and time fixed effects to control for differences not caused by the addition of a new BART station.

$$Housing\ Price_{it} = \beta_0 + \beta_1\ post_t + \beta_2\ treat_i + \beta_3\ post\ x\ treat_{it} + zip\ FE_t + month\ FE_i + e \qquad (1)$$

The usual Diff-in-Diff approach assumes that there is a shock to one of the variables that happens very quickly at one specific point. Since the BART stations were known about in advance and the opening was not a surprise, I've constructed a modified Diff-in-Diff model to account for the lead-up to the actual opening. In this model, there are the same *post*, *treat*, and *post x treat* variables, but I've added a *during* and a *during x treat* variable. *During* is defined as an observation from the year leading up to the opening of the new BART station, but not past its opening, since that would be a *post* observation.

$$\textit{Housing Price}_{it} = \beta_0 + \beta_1\, during_t + \beta_2\, post_t + \beta_3\, treat_i + \beta_4\, during\ x\ treat_{it} + \beta_5\, post\ x\ treat_{it} + zip\ FE_t + month\ FE_i + e \quad (2)$$

DATA

To evaluate housing prices, I used data collected by Zillow and provided by Data Planet. Zillow is a website that lists homes available for sale and rent and also collects data on other rents and sale prices. Although Zillow collects data in some areas on the neighborhood level, the smallest area available near the BART stations in question is at the zip code level.

I chose seven metrics representing housing prices: median rent per square foot, median rent, median home value per square foot, the price-to-rent ratio, and bottom, middle, and top tier home values. These metrics were chosen partly based on the availability of data, as not all of Zillow's metrics go back long enough for a time series analysis and not all metrics are available for every zip code. All the metrics, besides the price-to-rent ratio, are classified by Zillow as "All Homes". This category includes: "single-family, condominium and co-operative homes with a county record" ("Data - Zillow Research,"). Since owner-occupied and rental housing attract different types of occupants, I want to look at both aspects of the housing market. The price-to-rent ratio is calculated by taking the estimated market value of homes and dividing by the rental price per year (the monthly rent multiplied by 12) (Zillow). Housing "tiers" are calculated by Zillow by dividing the distribution of home prices as determined by their value and rent metrics into thirds.

For median rent and median home value per square foot, I used monthly data from Nov. 2010 to Aug. 2018. This full range was not available for median rent per square foot, so for the Antioch and Pittsburg Central stations the data is only from Jan. 2011 to Aug. and 2018, and for

Warm Springs/South Fremont, the start of the range varies from May 2015 to Jun 2017, but all have data through Aug. 2018 (See Table 2).

For my analysis, I am using the zip codes that are nearest the stations as the treatment groups and the bordering zip codes as the control group for each analysis. The Antioch station is on the border straddling zip codes 94509 and 94531 and the Pittsburg Center station is in 94565 so I have used all three of these zip codes as the treatment group. These treatment group zip codes are bordered by 94513, 94517, 94520, 94521, 94561, and 94571. Zip code 94517 was excluded as a control because it had some of the characteristics of an outlier. Median rent per square foot for the Antioch and Pittsburg stations did not have complete data for all of the zip codes, so the controls for that regression are 94513 and 94521.

The Warm Springs/South Fremont station is on the border between the zip codes 94538 and 94539, so these codes have been used as the treatment group. These zip codes are bordered by 94536, 94560, 94586, 95035, and 95143. Data was not available for 94586, so it was excluded. Median rent per square foot was not available for 95134, so the controls for that metric are 94536, 94560, 94586, and 95035 (See Table 1 and Appendix).

To verify the quality of my control groups I compared the median incomes for the treatment zip codes and the control zip codes. Median incomes are taken from the 2013-2017 American Community Survey 5-Year Estimates (U.S. Census Bureau). For the Antioch stations the treatment zip codes 94509, 94531, and 94565 had 2013-2017 5-year median incomes of $58,823, $93,466, and $62,255 respectively. The control zip codes 94513, 94520, 94521, 94561, and 94571 had median incomes of $96,827, $52,082, $94,637, $88,795, and $64,694 respectively. Bordering zip code 94517 was excluded because the median income was $140,361, which is significantly higher than the control zip codes (See Table 2).

For the Warm Springs/South Fremont treatment zip codes 94538 and 94539 the median incomes are $101,065 and $160,542 respectively. The control zip codes 94536, 94560, 95035, and 95134 have median incomes of $112,587, $96,817, $110,659, and $132,891 respectively (U.S. Census Bureau) (See Table 2). Unfortunately, near both stations, the treatment zip codes have widely divergent median incomes. However, generally, the surrounding zip codes are of similar magnitude. So, although the bordering zip codes are not an exact match, all the zip codes are from the same main area with similar demographics and should be comparable.

ASSUMPTIONS AND STRATEGY

When constructing my model, I had to make assumptions about the way BART interacts with the surrounding landscape and people. For instance, it's hard to know how large the radius of effect is around the opening of a new BART station. The new stations have parking structures specifically so people can drive in to the station and take BART for the rest of their commute. Since the smallest area I had reliable data for was the zip code, I assumed that the two or three zip codes nearest the stations experienced the greatest effect of the new station. This accounts for a 4 to 5 mile radius around the stations. Choosing control variables is difficult because of the unknown zone of influence and how quickly the demography and geography changes as you move further away from the metropolitan hubs of the Bay Area. Thus, I erred on the side of demographic similarity and chose the surrounding zip codes as my controls, however, it is possible that the control zip codes were also affected by the new BART stations.

A standard Diff-in-Diff model assumes that the data is homoskedastic, not multicollinear, and that its residuals are normally distributed. The data points are assumed to be independent and identically distributed random variables. Because of the nature of the data, several of these assumptions are not necessarily met, so I used various strategies to compensate. Homoskedasticity is almost never a reasonable assumption with real-world data so I will be using robust calculations for the standard errors in my first regressions.

However, robust standard errors still assume that data points are independent and identically distributed. The data points are not independent because they are serially correlated through time in each zip code. For example, rent one month is closely related to what the rent was last month. The value of a group of properties tends not to change dramatically over time unless there is a catastrophic event. People also tend to live in the same place periods of at least several years, so rents and values can be even stickier since they usually change most between occupants. Thus, in my second set of regressions, I use clustered standard errors which allows for the data to violate the independence assumption within the specified variable—in this case is zip code. The robust standard errors are likely too small and the cluster standard errors are likely too large, and so a good estimate is that the true standard error is somewhere in between these two.

RESULTS

The results of my analysis are mixed. Since these are Diff-in-Diff regressions, the coefficients of interest are the ones on the interaction terms *during x treat* and *post x* $treat_i$ highlighted in the tables. These interaction coefficients show what happens after a new BART stop has opened in an area.

The results for the different categories of housing can lend subtlety to the interpretation of the results. Home value and rent are essentially measures of the same thing—cost of housing—but there is an important difference between the two. When someone is buying a home, the goal is usually to own the home for a long period of time, and thus the price of the house reflects the predicted value of the home over the foreseeable future. When someone is renting a home, they are usually on no more than a few years lease, so the rent reflects the monthly cost of the living space over a much shorter time horizon. It is also important to consider the types of housing that are included in this analysis since only single-family homes are included and multi-family housing might show different trends.

ANTIOCH AND PITTSBURG CENTER RESULTS

In the first set of regressions without the *during* variable, we see two statistically significant results for the *post x treat* variable (See Tables 4 and 5). The change in Price-to-Rent ratio shows a value of 0.377 which is statistically significant at the 1% level with robust standard errors and at the 5% level with cluster standard errors. This is strong evidence to suggest that after the stations opened, rents rose more than home values. The change in home value per square foot metric shows a value of -10.46 which is statistically significant at the 10% level with robust standard errors and not statistically significant with cluster standard error. This suggests that the opening of the Antioch and Pittsburg Center stations may have reduced home values in the area by $10.46 per square foot, which is a substantial decrease given the average home value per square foot in the wider area is $202.27. However, we should not consider this a firm conclusion since it was not significant with cluster errors and only marginally significant with robust errors.

When we look at the regression that includes the *during* and *during x treat* variables, we see two statistically significant results for the Price-to-Rent ratio for both *during x treat* and *post x treat* with values of 0.517 and 0.434 respectively (see Tables 6 and 7). These coefficients are statistically significant at the 1% level with robust errors and at the 5% level with cluster errors. This can be interpreted this as very strong evidence for the idea that both in the year leading up to the stations opening and after the opening, rents were relatively higher and home value was relatively lower compared to each other.

This matches a change of -$7250 for top tier home value and of -$10.74 for home value per square foot, both of which are statistically significant at the 5% level with robust standard errors but not significant with cluster standard errors. This can be interpreted as further evidence to support the theme of decreasing home values associated with the opening of the Antioch and Pittsburg Center stations.

WARM SPRINGS/SOUTH FREMONT RESULTS

In the initial regressions without the *during* variable, almost all of the results besides rent per square foot are statistically significant by at least the 10% level with the robust standard errors, however with the cluster standard errors, none of the results are statistically significant (see Tables 8 and 9). That said, they show different trends across the metrics than for the Antioch and Pittsburg Center stations. The Warm Springs/South Fremont results show increases in home values, likely pushing the Price-to-Rent ratio to its negative value of -1.014. Interestingly, the home value per square foot metric is actually slightly negative with a value of -6.127. However, this does not represent a significant change from the mean value of $475.88 per square foot and is likely a result of natural variability in the data collected.

When the *during* terms are added in, the pattern doesn't change much. All of the results for both *during x treat* and *post x* treat except home value per square foot with *post x treat* (which was insignificant) and rent per square foot (which had insufficient data), have very statistically significant results for robust errors—all at the 1% level (see Tables 10 and 11). However, once we use cluster standard errors, only one remains statistically significant: bottom tier home value during the lead up to the station opening. This result of $48,100 indicates that the bottom third of homes increased significantly in value in the year before the station opened. The average value for bottom tier homes is $565,925.20 so this is a relatively large and meaningful increase.

DISCUSSION

From the Antioch and Pittsburg Center stations results, we can see that home values in the area appear to be trending down, and in particular, the ratio between home values and rental prices is increasing. This suggests that adding new BART stations does not affect all types of housing the same way. Rental prices trend higher and home values trend a little lower, perhaps speaking to the demographics of the populations that live in each type of housing and how they make use of BART.

From the Warm Springs/South Fremont station results, we can see the opposite trend where home values are going up, and particularly significantly in the bottom tier of homes. This discrepancy between the stations may have something to do with their function. Antioch and Pittsburg Center are an extension into the suburbs of the East Bay while Warm Springs/South Fremont is a stepping stone on the way down to San Jose. There could also be factors in the residual that are affecting both housing prices and the choice of where to expand the BART system with new stations. All three new stations were built on extensions, bringing service to new neighborhoods by expanding the reach of the BART system, while none were added within existing lines or between existing stations.

CONCLUSION

Residents of the Bay Area are acutely aware of the region's rapidly increasing housing prices and frustrating traffic congestion. BART is one of the few ways to avoid highway traffic, especially during commute hours. Commuting by BART allows people to live in an area that is more affordable than San Francisco while still being able to commute there easily.

To assess the effect the opening of a new BART station has on housing prices in the nearby area, I looked at the opening of the Antioch and Pittsburg Central and Warm Springs/South Fremont stations. Using a Diff-in-Diff approach, I compared the zip codes containing the new stations with the bordering zip codes as a control group. The results were mixed and depended on the area. For Antioch and Pittsburg Center, the new stations decreased home value, but for Warm Springs/South Fremont, the new station increased home value.

These results are likely particular to the SF Bay Area and more specifically the East Bay. Public transit systems vary greatly between cities and the SF Bay Area has unique characteristics in its geography and nearby industries that make any conclusions about the area unlikely to transfer to other situations.

For potential further research analysis on the same dataset, the regressions could include more control variables besides just using fixed effects. Zip codes cover relatively large and non-cohesive areas, which may obscure the effects of transit facilities opening if their radius is small or if adjacent neighborhoods are sufficiently different in cost, demographics, or transit access. Since Zillow publishes data down to the neighborhood level for some locations, it would be possible to better analyze the areas affected by the opening of a new BART station if they publish this more granular data for the SF Bay Area. When new BART stations are opened in the future, those can be added to the analysis. Additional public transit options, such as CalTrain, ferries, and commuter bus routes, could also be compared. Any research that helps us understand the problems in housing costs and traffic congestion in the SF Bay Area will benefit the region and inform both policy-makers and current and future residents.

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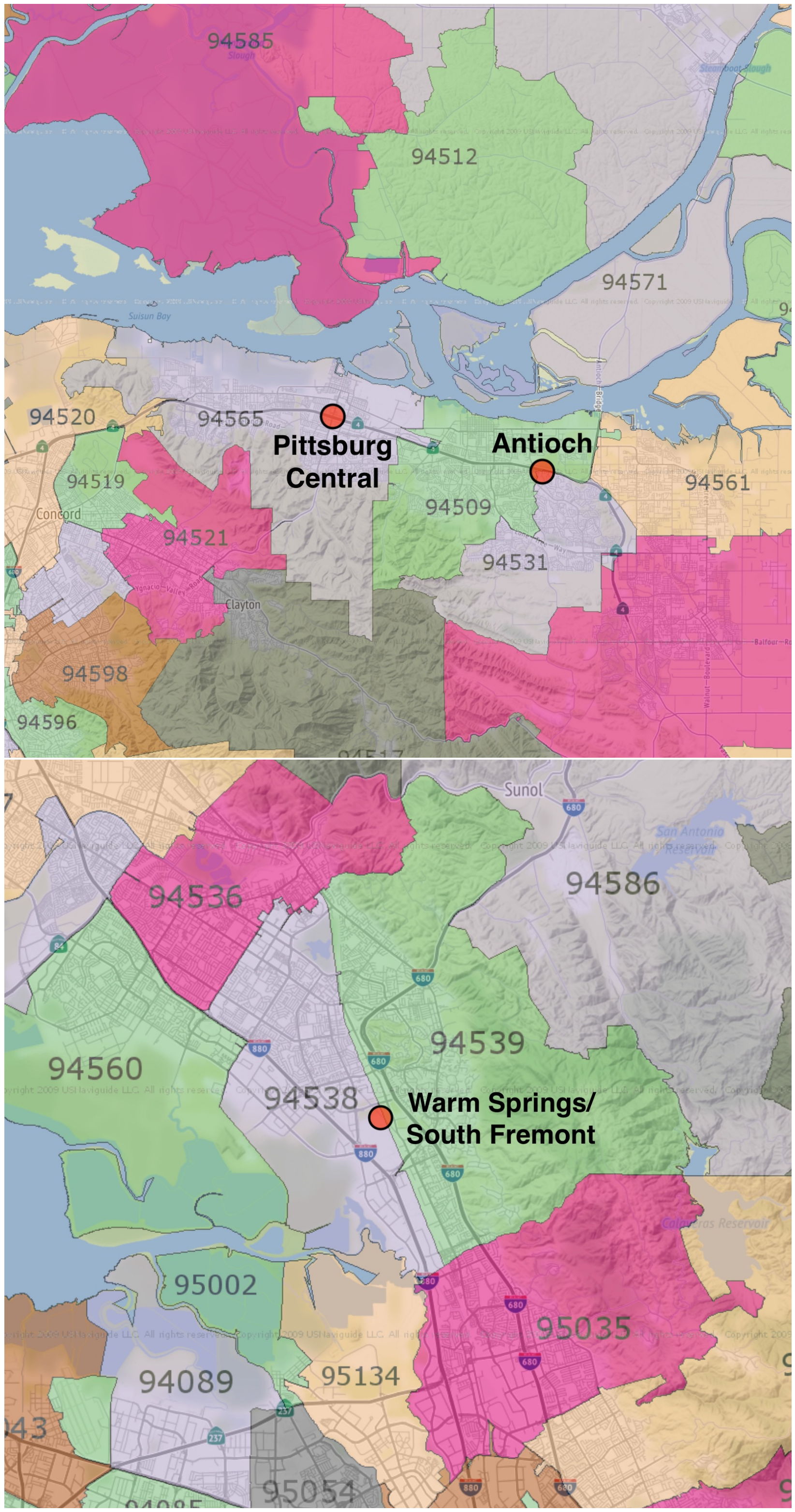
APPENDIX



Source: www.zipmap.net

Table 1: Treatment and Control Groups

Station	Treatment	Control
Antioch and Pittsburg Center	94509 (Antioch)	94513
	94531 (Antioch)	94520
	94565 (Pittsburg Center)	94521
		94561
		94571
Warm Springs/South Fremont	94538	94536
	94539	94560
		95035
		95134

Table 2: Incomes and Data Availability

Zip code Antioch Pittsburg	Income	Price to Rent Ratio	Rent Per Square Foot	Median Rent	Home Value per Square Foot	Bottom Tier Home Value	Middle Tier Home Value	Top Tier Home Value
94509	$ 58,823	11/10 - 08/18	1/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94531	$ 93,466	11/10 - 08/18	1/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94565	$ 62,255	11/10 - 08/18	1/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94513	$ 57,652	11/10 - 08/18	1/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94520	$ 52,082	11/10 - 08/18	N/A	11/10 - 08/18	11/10 - 08/18	1/14 - 08/18	11/10 - 08/18	11/10 - 08/18
94521	$ 94,637	11/10 - 08/18	2/10 - 08/18	11/10 - 08/18	11/10 - 08/18	1/13 - 08/18	11/10 - 08/18	11/10 - 08/18
94561	$ 88,795	11/10 - 08/18	N/A	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94571	$ 64,694	11/10 - 08/18	N/A	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
Zip code Warm Springs/South Fremont								
94538	$ 101,065	11/10 - 08/18	07/16 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94539	$ 160,542	11/10 - 08/18	07/16 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94536	$ 112,587	11/10 - 08/18	05/15 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
94560	$ 96,817	11/10 - 08/18	01/16 - 08/`8	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
95035	$ 110,659	11/10 - 08/18	09/13-08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18
95134	$ 132,891	11/10 - 08/18	N/A	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18	11/10 - 08/18

Table 3: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
PtoR_ap	752	13.96326	2.839843	8.03	19.49
rentsf_ap	459	1.219083	0.2403341	0.872703	2
medrent_ap	752	1978.211	335.0295	1404	2823
valuesf_ap	752	202.2726	72.33598	98	390
bottomtier_ap	688	261781.3	93603.01	97200	475500
midtier_ap	752	337928.6	119237.9	148500	656100
toptier_ap	752	423314.1	133279.7	208700	772400
PtoR_wssf	564	21.20078	3.383969	15.25	31.55
rentsf_wssf	172	2.167631	0.1563664	1.73358	2.45394
medrent_wssf	564	2861.135	662.6313	1911	4791
valuesf_wssf	564	475.8848	136.6902	254	805
bottomtier_wssf	564	565925.2	217624.3	250000	1237600
midtier_wssf	564	754302.7	286350	378500	1675100
toptier_wssf	564	954826.1	399567.7	456700	2243300

ANTIOCH AND PITTSBURG RESULTS

Table 4: Antioch and Pittsburg without During with Robust Standard Errors

VARIABLES	(1) PtoR_ap	(2) rentsf_ap	(3) medrent_ap	(4) valuesf_ap	(1) bottomtier_ap	(2) midtier_ap	(3) toptier_ap
post_ap	6.238***	0.396***	601.2***	151.6***	217,976***	252,879***	258,407***
	(0.383)	(0.0564)	(63.93)	(9.608)	(9,091)	(10,913)	(15,984)
treat_ap	-2.137***	0.170***	199.7***	3.828*	-103,417***	1,749	-16,088***
	(0.0565)	(0.00838)	(12.70)	(1.979)	(1,784)	(3,389)	(4,753)
posttreat_ap	0.377***	0.0698	-6.472	-10.46*	2,306	-5,066	-4,930
	(0.0710)	(0.0561)	(23.71)	(6.304)	(3,788)	(4,926)	(6,817)
Constant	11.23***	0.915***	1,347***	106.2***	212,064***	156,319***	237,270***
	(0.368)	(0.0261)	(56.10)	(5.999)	(7,396)	(8,103)	(12,981)
Observations	752	459	752	752	688	752	752
R-squared	0.982	0.934	0.957	0.968	0.985	0.982	0.972

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

Table 5: Antioch and Pittsburg without During with Cluster Standard Errors

VARIABLES	(1) PtoR_ap	(2) rentsf_ap	(3) medrent_ap	(4) valuesf_ap	(1) bottomtier_ap	(2) midtier_ap	(3) toptier_ap
post_ap	6.238***	0.396**	601.2***	151.6***	217,976***	252,879***	258,407***
	(0.500)	(0.0873)	(97.60)	(15.39)	(14,767)	(16,885)	(26,451)
treat_ap	-2.137***	0.170***	199.7***	3.828***	-103,417***	1,749***	-16,088***
	(0.00604)	(0.00553)	(2.210)	(0.591)	(2,911)	(456.4)	(632.1)
posttreat_ap	0.377**	0.0698	-6.472	-10.46	2,306	-5,066	-4,930
	(0.142)	(0.127)	(51.93)	(13.89)	(8,849)	(10,726)	(14,855)
Constant	11.23***	0.915***	1,347***	106.2***	212,064***	156,319***	237,270***
	(0.395)	(0.0279)	(58.82)	(6.068)	(10,412)	(7,950)	(12,775)
Observations	752	459	752	752	688	752	752
R-squared	0.982	0.934	0.957	0.968	0.985	0.982	0.972

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

Table 6: Antioch and Pittsburg with During and Robust Standard Errors

VARIABLES	(1) PtoR_ap	(2) rentsf_ap	(3) medrent_ap	(4) valuesf_ap	(1) bottomtier_ap	(2) midtier_ap	(3) toptier_ap
during_ap	5.192***	0.392***	558.9***	133.6***	211,240***	222,898***	234,856***
	(0.390)	(0.0647)	(64.84)	(7.914)	(8,688)	(10,412)	(14,940)
post_ap	5.825***	0.397***	600.9***	149.4***	217,787***	249,208***	256,271***
	(0.378)	(0.0564)	(63.96)	(9.301)	(9,127)	(10,562)	(15,825)
treat_ap	-2.205***	0.173***	200.1***	4.163**	-103,956***	2,004	-15,128***
	(0.0553)	(0.00852)	(12.62)	(2.008)	(1,891)	(3,358)	(4,765)
duringtreat_ap	0.517***	-0.0207	-2.807	-2.532	3,409	-1,928	-7,250*
	(0.0623)	(0.0251)	(16.15)	(3.248)	(2,556)	(3,322)	(4,276)
posttreat_ap	0.434***	0.0679	-6.784	-10.74*	2,724	-5,280	-5,736
	(0.0737)	(0.0561)	(23.72)	(6.301)	(3,811)	(4,928)	(6,824)
Constant	11.26***	0.913***	1,347***	106.1***	212,373***	156,224***	236,915***
	(0.364)	(0.0266)	(56.15)	(6.001)	(7,444)	(8,096)	(12,993)
Observations	752	459	752	752	688	752	752
R-squared	0.983	0.934	0.957	0.968	0.985	0.982	0.972

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

Table 5: Antioch and Pittsburg with During and Cluster Standard Errors

VARIABLES	(1) PtoR_ap	(2) rentsf_ap	(3) medrent_ap	(4) valuesf_ap	(1) bottomtier_ap	(2) midtier_ap	(3) toptier_ap
during_ap	5.192***	0.392**	558.9***	133.6***	211,240***	222,898***	234,856***
	(0.569)	(0.110)	(111.2)	(14.45)	(16,145)	(19,021)	(27,773)
post_ap	5.825***	0.397**	600.9***	149.4***	217,787***	249,208***	256,271***
	(0.492)	(0.0910)	(98.95)	(15.25)	(15,263)	(16,801)	(26,704)
treat_ap	-2.205***	0.173***	200.1***	4.163	-103,956***	2,004	-15,128***
	(0.0326)	(0.0180)	(10.64)	(2.285)	(4,405)	(2,241)	(2,892)
duringtreat_ap	0.517**	-0.0207	-2.807	-2.532	3,409	-1,928	-7,250
	(0.205)	(0.0946)	(65.09)	(13.50)	(10,965)	(13,534)	(17,223)
posttreat_ap	0.434**	0.0679	-6.784	-10.74	2,724	-5,280	-5,736
	(0.168)	(0.135)	(58.51)	(15.11)	(10,060)	(12,209)	(16,712)
Constant	11.26***	0.913***	1,347***	106.1***	212,373***	156,224***	236,915***
	(0.397)	(0.0305)	(61.21)	(6.403)	(11,169)	(8,447)	(13,566)
Observations	752	459	752	752	688	752	752
R-squared	0.983	0.934	0.957	0.968	0.985	0.982	0.972

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

WARM SPRINGS/SOUTH FREMONT RESULTS

Table 6: Warm Springs/South Fremont without During with Robust Standard Errors

VARIABLES	(1) PtoR_wssf	(2) rentsf_wssf	(3) medrent_wssf	(4) valuesf_wssf	(1) bottomtier_wssf	(2) midtier_wssf	(3) toptier_wssf
post_wssf	5.108***	0.269***	1,022***	279.9***	357,315***	410,529***	504,048***
	(0.531)	(0.0359)	(84.09)	(9.548)	(15,790)	(27,395)	(54,220)
treat_wssf	-1.434***	-0.125***	-140.0***	16.25***	20,123***	-86,945***	-123,246***
	(0.0741)	(0.0293)	(8.926)	(1.255)	(2,054)	(3,666)	(5,568)
posttreat_wssf	-1.014***	0.0103	100.6***	-6.127*	36,755***	84,164***	80,507***
	(0.153)	(0.0299)	(23.51)	(3.450)	(5,870)	(13,631)	(19,994)
Constant	19.55***	2.014***	2,109***	302.1***	294,922***	500,206***	583,898***
	(0.504)	(0.0165)	(74.12)	(8.591)	(14,633)	(22,858)	(49,170)
Observations	564	172	564	564	564	564	564
R-squared	0.965	0.879	0.978	0.992	0.991	0.981	0.977

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

Table 9: Warm Springs/South Fremont without During with Cluster Standard Errors

VARIABLES	(1) PtoR_wssf	(2) rentsf_wssf	(3) medrent_wssf	(4) valuesf_wssf	(1) bottomtier_wssf	(2) midtier_wssf	(3) toptier_wssf
post_wssf	5.108***	0.269***	1,022***	279.9***	357,315***	410,529***	504,048***
	(0.598)	(0.0455)	(111.1)	(17.26)	(18,162)	(24,421)	(51,575)
treat_wssf	-1.434***	-0.125**	-140.0***	16.25***	20,123**	-86,945***	-123,246***
	(0.101)	(0.0291)	(12.26)	(2.782)	(5,137)	(13,473)	(19,570)
posttreat_wssf	-1.014	0.0103	100.6	-6.127	36,755	84,164	80,507
	(0.527)	(0.0580)	(64.03)	(14.53)	(26,826)	(70,359)	(102,198)
Constant	19.55***	2.014***	2,109***	302.1***	294,922***	500,206***	583,898***
	(0.532)	(2.89e-08)	(78.98)	(10.07)	(15,348)	(22,209)	(49,606)
Observations	564	172	564	564	564	564	564
R-squared	0.965	0.879	0.978	0.992	0.991	0.981	0.977

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

Table 10: Warm Springs/South Fremont with During and Robust Standard Errors

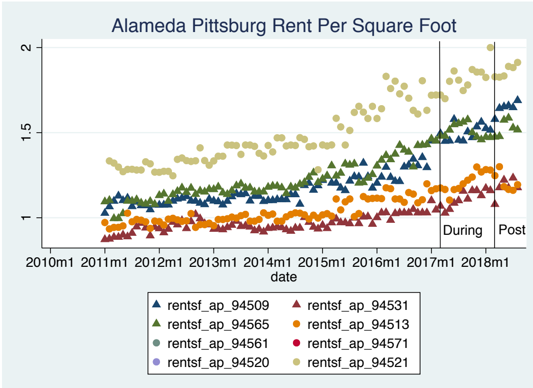
VARIABLES	(1) PtoR_wssf	(2) rentsf_wssf	(3) medrent_wssf	(4) valuesf_wssf	(1) bottomtier_wssf	(2) midtier_wssf	(3) toptier_wssf
during_wssf	3.270***	0.149***	968.8***	229.8***	280,517***	331,990***	396,743***
	(0.522)	(0.0522)	(78.56)	(9.402)	(13,961)	(25,167)	(49,849)
post_wssf	5.166***	0.232***	1,010***	279.3***	354,783***	405,914***	499,047***
	(0.518)	(0.0359)	(79.83)	(9.365)	(14,836)	(26,091)	(52,569)
treat_wssf	-1.260***	-0.114***	-175.9***	14.58***	12,529***	-100,789***	-138,249***
	(0.0837)	(0.0210)	(11.83)	(1.354)	(2,191)	(5,023)	(7,264)
duringtreat_wssf	-1.099***	-0.0103	227.1***	10.58***	48,100***	87,679***	95,021***
	(0.180)	(0.0299)	(38.23)	(2.387)	(3,777)	(13,902)	(17,688)
posttreat_wssf	-1.188***		136.5***	-4.457	44,350***	98,008***	95,510***
	(0.157)		(23.73)	(3.518)	(5,983)	(13,693)	(20,417)
Constant	19.50***	2.051***	2,120***	302.7***	297,454***	504,821***	588,899***
	(0.491)	(0.0165)	(69.20)	(8.384)	(13,587)	(21,283)	(47,340)
Observations	564	172	564	564	564	564	564
R-squared	0.967	0.879	0.981	0.992	0.992	0.983	0.979

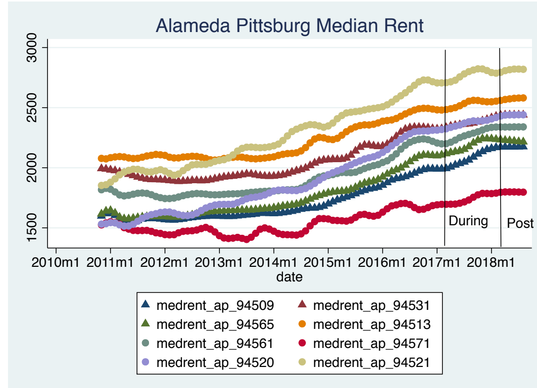
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

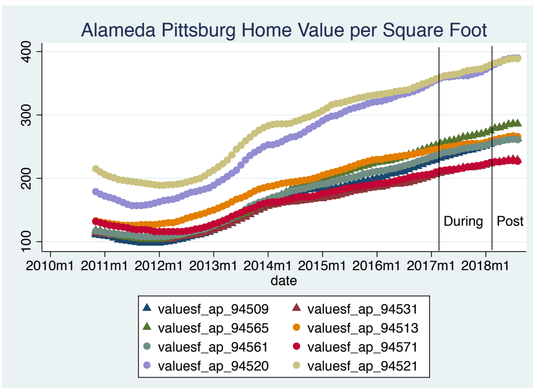
Table 7: Warm Springs/South Fremont with During and Cluster Standard Errors

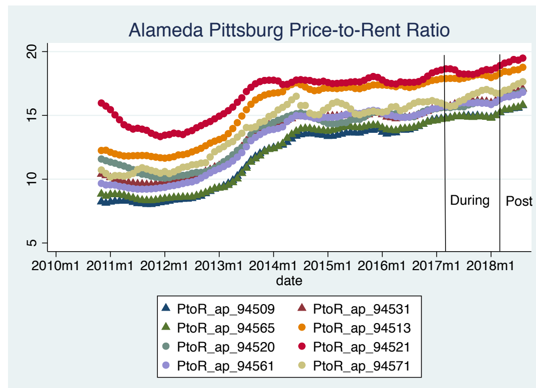
VARIABLES	(1) PtoR_wssf	(2) rentsf_wssf	(3) medrent_wssf	(4) valuesf_wssf	(1) bottomtier_wssf	(2) midtier_wssf	(3) toptier_wssf
during_wssf	3.270***	0.149*	968.8***	229.8***	280,517***	331,990***	396,743***
	(0.510)	(0.0574)	(65.13)	(14.32)	(16,105)	(18,457)	(43,602)
post_wssf	5.166***	0.232***	1,010***	279.3***	354,783***	405,914***	499,047***
	(0.550)	(0.0455)	(100.2)	(17.35)	(17,194)	(20,849)	(46,479)
treat_wssf	-1.260***	-0.114**	-175.9***	14.58**	12,529	-100,789***	-138,249***
	(0.188)	(0.0297)	(36.98)	(3.885)	(7,427)	(24,853)	(33,409)
duringtreat_wssf	-1.099	-0.0103	227.1	10.58	48,100**	87,679	95,021
	(0.706)	(0.0580)	(161.0)	(9.557)	(15,105)	(72,392)	(88,443)
posttreat_wssf	-1.188		136.5	-4.457	44,350	98,008	95,510
	(0.597)		(87.94)	(15.50)	(29,106)	(81,762)	(116,052)
Constant	19.50***	2.051	2,120***	302.7***	297,454***	504,821***	588,899***
	(0.486)		(67.24)	(10.06)	(13,943)	(17,773)	(44,064)
Observations	564	172	564	564	564	564	564
R-squared	0.967	0.879	0.981	0.992	0.992	0.983	0.979

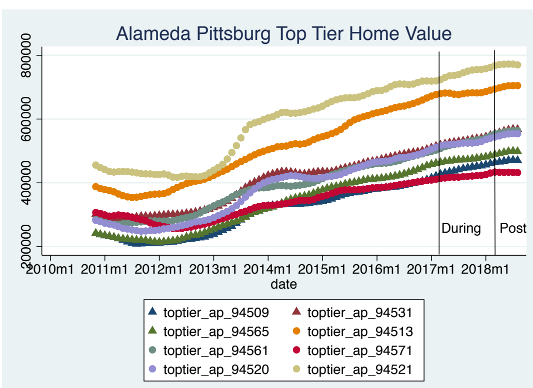
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

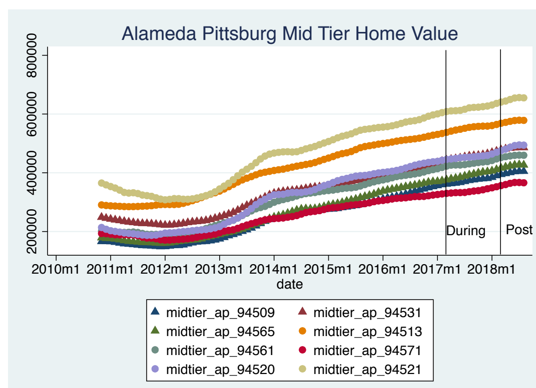

Alameda Pittsburg Rent Per Square Foot
1
1.5
2
During
Post
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
rentsf_ap_94509
rentsf_ap_94531
rentsf_ap_94565
rentsf_ap_94513
rentsf_ap_94561
rentsf_ap_94571
rentsf_ap_94520
rentsf_ap_94521

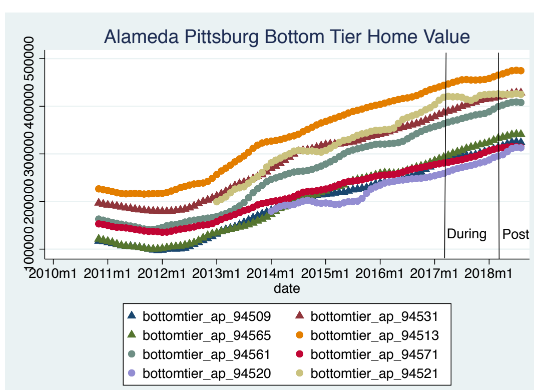

Alameda Pittsburg Median Rent
1500
2000
2500
3000
During
Post
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
medrent_ap_94509
medrent_ap_94531
medrent_ap_94565
medrent_ap_94513
medrent_ap_94561
medrent_ap_94571
medrent_ap_94520
medrent_ap_94521

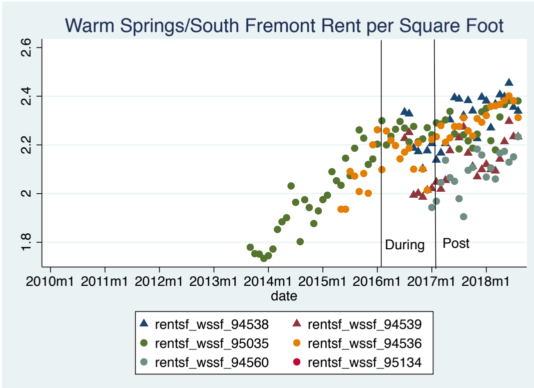

Alameda Pittsburg Home Value per Square Foot
100
200
300
400
During
Post
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
valuesf_ap_94509
valuesf_ap_94531
valuesf_ap_94565
valuesf_ap_94513
valuesf_ap_94561
valuesf_ap_94571
valuesf_ap_94520
valuesf_ap_94521

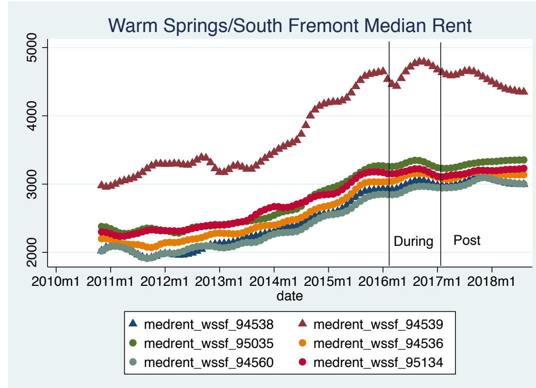

Alameda Pittsburg Price-to-Rent Ratio
5
10
15
20
During
Post
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
PtoR_ap_94509
PtoR_ap_94531
PtoR_ap_94565
PtoR_ap_94513
PtoR_ap_94520
PtoR_ap_94521
PtoR_ap_94561
PtoR_ap_94571

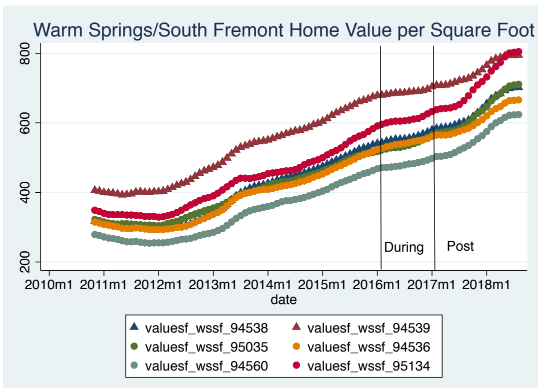

Alameda Pittsburg Top Tier Home Value
200000
400000
600000
800000
During
Post
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
toptier_ap_94509
toptier_ap_94531
toptier_ap_94565
toptier_ap_94513
toptier_ap_94561
toptier_ap_94571
toptier_ap_94520
toptier_ap_94521

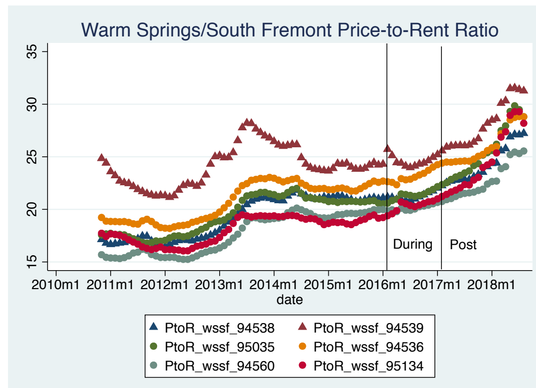

Alameda Pittsburg Mid Tier Home Value
200000
400000
600000
800000
During
Post
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
midtier_ap_94509
midtier_ap_94531
midtier_ap_94565
midtier_ap_94513
midtier_ap_94561
midtier_ap_94571
midtier_ap_94520
midtier_ap_94521

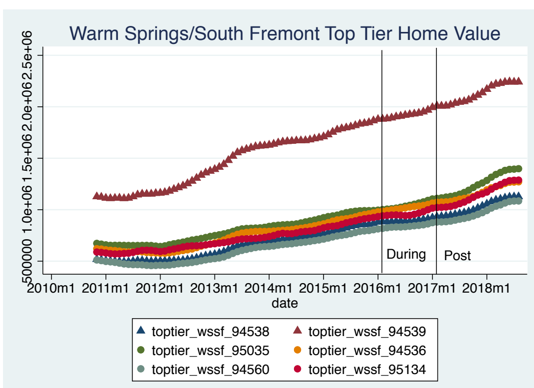

Alameda Pittsburg Bottom Tier Home Value
200000
300000
400000
500000
During
Post
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
bottomtier_ap_94509
bottomtier_ap_94531
bottomtier_ap_94565
bottomtier_ap_94513
bottomtier_ap_94561
bottomtier_ap_94571
bottomtier_ap_94520
bottomtier_ap_94521

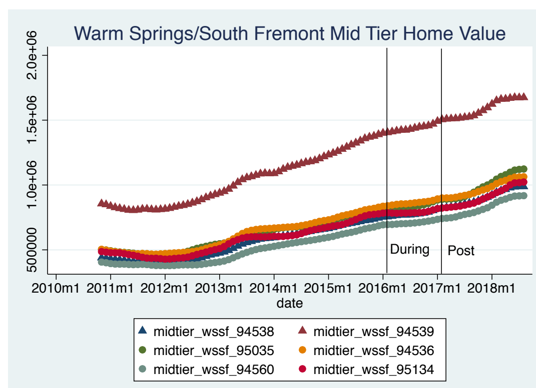

Warm Springs/South Fremont Rent per Square Foot
1.8
2
2.2
2.4
2.6
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
During
Post
rentsf_wssf_94538
rentsf_wssf_94539
rentsf_wssf_95035
rentsf_wssf_94536
rentsf_wssf_94560
rentsf_wssf_95134

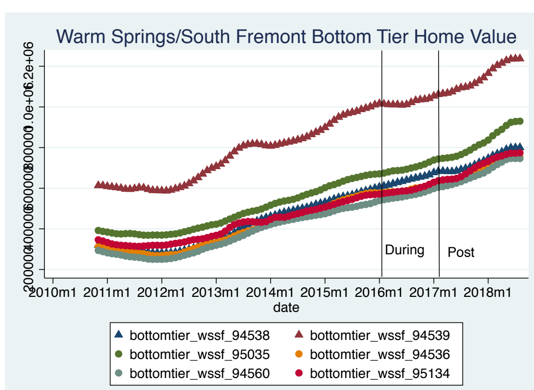

Warm Springs/South Fremont Median Rent
2000
3000
4000
5000
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
During
Post
medrent_wssf_94538
medrent_wssf_94539
medrent_wssf_95035
medrent_wssf_94536
medrent_wssf_94560
medrent_wssf_95134


Warm Springs/South Fremont Home Value per Square Foot
200
400
600
800
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
During
Post
valuesf_wssf_94538
valuesf_wssf_94539
valuesf_wssf_95035
valuesf_wssf_94536
valuesf_wssf_94560
valuesf_wssf_95134


Warm Springs/South Fremont Price-to-Rent Ratio
15
20
25
30
35
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
During
Post
PtoR_wssf_94538
PtoR_wssf_94539
PtoR_wssf_95035
PtoR_wssf_94536
PtoR_wssf_94560
PtoR_wssf_95134


Warm Springs/South Fremont Top Tier Home Value
500000 1.0e+06 1.5e+06 2.0e+06 2.5e+06
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
During
Post
toptier_wssf_94538
toptier_wssf_94539
toptier_wssf_95035
toptier_wssf_94536
toptier_wssf_94560
toptier_wssf_95134


Warm Springs/South Fremont Mid Tier Home Value
500000
1.0e+06
1.5e+06
2.0e+06
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
During
Post
midtier_wssf_94538
midtier_wssf_94539
midtier_wssf_95035
midtier_wssf_94536
midtier_wssf_94560
midtier_wssf_95134


Warm Springs/South Fremont Bottom Tier Home Value
2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1
date
During
Post
bottomtier_wssf_94538
bottomtier_wssf_94539
bottomtier_wssf_95035
bottomtier_wssf_94536
bottomtier_wssf_94560
bottomtier_wssf_95134