Transit-Oriented Development or Transit-Oriented Displacement? Evaluating the Sorting Effect of Public Transportation in Los Angeles County

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Abstract

The intent of this paper is to determine causal effects of transit-oriented developments, or TOD's, on the neighborhoods they are implemented in. By exploiting delays in construction of LA Metro lines due to Proposition A, a difference-in-differences approach is used to compare areas that received a station with areas that were promised a station but did not receive one. Neighborhood changes are characterized by population, race, household income, and rent using census data. Treatment areas experienced higher increases in Hispanic and overall population, and comparatively lower black population, average household income and median rent compared to control areas. These findings point to TOD's being attractive for low-income communities and not a catalyst for gentrification, but due to data limitations, further study is necessary.

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1 Introduction

Public transportation has long been a defining feature of urbanism, and cities with well-developed public transit systems have been deemed progressive and innovative. Public transit fits the Triple Bottom Line that city planners refer to in their work: it is environmental, economical, and equitable. Higher transit ridership means lower vehicular usage, which reduces emissions significantly. Public transit is shown to have a high return on investment for cities—the American Public Transportation Association found that a $1 billion investment in public transportation would lead to a $3.7 billion increase in GDP growth that would be sustained for at least 20 years.[1] Public transportation is also equitable. Low income populations who may not be able to afford a car rely heavily on public transportation for mobility purposes, such as having access to healthcare and retail services. Higher mobility also increases job opportunities for low income demographics outside of their local area, which is why implementation of public transit has been proven to reduce social and wealth inequalities.[2] Public transit reduces transportation costs as well—a study done in 2000 by the Surface Transportation Policy found that for Americans of the bottom 20% percentile in wealth, transportation accounted for 36% of their overall spending, 98% of which was spent on cars.[3]

While public transit has been regarded as a socially beneficial good

[1] Glen Weisbrod and Arlee Reno. *Economic impact of public transportation investment.* Citeseer, 2009.

[2] Madelaine Criden. "The stranded poor: Recognizing the importance of public transportation for low-income households". In: *National Association for* (2008).

[3] *Transportation and Housing.* `http://transact.org/library/factsheets/housing.asp`.

for decades, transit-oriented developments are a fairly recent phenomenon. Transit-oriented developments, abbreviated as TOD's, are a growing trend in urban planning that are essentially communities with transit as their central feature. TOD's are mixed-use developments, meaning they include residential, retail, and office spaces. Not only are they be centered around a transit station, they are generally transit-oriented: multiple bus lines, bicycle lanes and rental stations, and wide sidewalks are common features of TOD's. Although there has not been a consensus as of yet for what specifically constitutes a TOD, the most commonly used metric are areas that are no further than 0.5 miles away from a transit station.

The majority of city planners and experts have converged on the opinion that TOD's fit the Triple Bottom Line. From an environmental lens, TOD's have the potential of boosting ridership and reducing emissions since it solves the 'first mile last mile' issue of public transit, in which people opt against using existing public transit because they have no way to get to the transit station without using a car. TOD's are pedestrian-focused and are sustainable—ideally, residents in these communities should not need to own a car. Economically, TOD's are meant to serve as a tool for community development and urban revival. Cervero (2004) found that TOD's had not only direct financial benefits with increased ridership and transit agency revenue, but also indirect long-term benefits such as reduced roadwork expenditures. Robert Cervero. *Transit-oriented development in the United States: Experiences, challenges, and prospects.* Vol. 102. Transportation Research Board, 2004

From an equitable lens, however, conclusions have not been as straightforward. Some posit that TOD's can increase inter-generational mobility for its residents by providing access to better opportunities, career or otherwise. However, it is possible that TOD's can have segregation effects that can exacerbate socioeconomic inequalities. There has not been much research exploring the potential negative effects of TOD's, especially on lower income populations, but experts warn that TOD's can be a catalyst for gentrification, as certain amenities of these developments, such as its proximity to retail, may be alluring to more affluent people. The subsequent rising property prices can lead to lower-income populations, who depend on transit the most, to become displaced to faraway areas and ultimately experience significantly less mobility.

On the contrary, there are fears that public transit will lead to a decrease in quality of the surrounding neighborhood. This opinion has popularized into the characterization of NIMBY (Not in My Backyard). NIMBY's reject proposals like public transit, high density housing, and walkability out of fear that these amenities will bring lower-income communities or minority populations into the area and lower housing values.[4] In this scenario, TOD's can effectively become concentrated with low-income populations. This may be a good thing considering that these populations benefit most and have access to more opportunities through public transit. However, several studies have linked low-income concentrated areas to having high crime rate and lower education quality. Considering that TOD's have become so popular in urbanism, it is important to understand how they effect

[4] Rose Weitz. "Who s afraid of the big bad bus? NIMBYism and popular images of public transit". In: *Journal of Urbanism* 1.2 (2008), pp. 157–172.

their neighborhoods. This paper aims to understand the spatial sorting effect brought on by transit-oriented developments by exploiting the delays in transit construction in Los Angeles County.

2 Literature Review

Most of the current research done on transit-oriented developments mostly include best practices and procedures on building these developments, and they seem to take the benefits of TOD's as given rather than challenging its effects and influence. However, there are studies that do research economic consequences of building public transportation infrastructure with varying results.

A large number of studies show that proximity to transit has gentrifying effects. Craig Jones and David Ley (2016) analyze a corridor populated by low-income demographics with proximity to a rapid transit route of the SkyTrain, Vancouver's public transit service. The transit-oriented development initiative in Vancouver allowed the construction of high-density apartments near the stations, which resulted in displacement of over half of the low-income residents in the corridor. Daniel Baldwin Hess and Tangerine Maria Almeida (2007) use a hedonic approach to assess the impact of proximity to light rail rapid transit stations on property values in Buffalo, New York. Variables in this model cover property characteristics, neighborhood characteristics, and locational distance. It was found that for homes located within half a mile of 14 transit stations, every foot closer to the station increased property values by $2.31 using a straight-line distance (aka Euclidean distance) and \$0.99 using network distance (aka distance using roads)—however, number of bathrooms, size, and location were heavier indicators than station proximity. Debrezion et al. (2007) conducted a meta-analysis of 57 cities and found that for every 250 meters closer to a transit station, the property value increases by 2.3%. Heblich et al. (2018) modeled London from 1801-1921 to find that removing the city's railway network results in property values decreasing by over 20%.

On the other hand, research done by Dena Belzer and Gerald Autler (2002) show that transit-oriented developments boost lower socioeconomic classes by offering more transportation options. Gatzlaff and Smith (1993) studied property values near the Miami Metrorail and found that they were only weakly impacted by the announcement of the new rail system. Landis et al. (1995) used a hedonic approach to study California rail systems, including BART and CalTrain, and found that property value changes vary based on quality of service—while areas close to BART experienced increased property values, areas close to CalTrain, which has poorer service, did not. A study by Duncan Michael (2010) that does try to model the effect of TOD's specifically, also with a hedonic approach, uses San Diego, California as a case study to determine the influence of TOD's in the area. Specifically, it aims to measure the influence of TOD's on the San Diego condominium and apartment market. The study estimates a hedonic price model to be able to extract and isolate purely the statistical effects of the transit-oriented development. The results of the study show that the presence of TOD's raise housing prices in the area, but also lower housing prices in other regions that are more auto-oriented but still near a transit station.

The majority of these studies use a hedonic approach, which raises issues about endogeneity. Rising property values can be attributed to a multitude of factors that are not able to be separated from transit proximity or the presence of TOD's. It is likely that transit stations and TOD's were selected in areas that were already undergoing initial growth, meaning that the effect of transit and TOD's on property values may suffer from an upward bias. Diao et al. (2017) circumvents this by using a difference-in-differences model with state fixed effects to estimate the impact of Singapore's Circle Line on property values and found significant results. However, while Diao does apply a difference-in-differences to assess impacts of transit proximity, its scales for proximity are all over 1 mile, which does not meet the standards for TOD's, which are 0.5 mile.

There are a very limited number of studies that address the sorting effects of public transit. Heilmann (2017) uses a difference-in-differences approach on the Dallas Area Rapid Transit (DART) and finds that richer areas benefited from the implementation of public transit more than poorer areas did. On average though, incomes and household values in treatment areas increased at a higher amount than those in control areas.

3 Methodology

3.1 Identification

The unusual circumstances of the LA Metro make it possible to infer causal effects of transit infrastructure due to its delayed implementation. In the 1980s, the transit system was planned and given funding to the Los Angeles

County Metropolitan Transportation Authority (MTA) to be constructed. However, the completion of the first three lines in 1996 went significantly over budget, leaving the MTA in debt and giving support to Proposition A, a 1998 ballot measure that blocked future spending of sales tax revenue on subway construction.[5] This situation allows meaningful comparison between areas that were able to receive a transit station prior to the passing of Proposition A and areas that were due to receive a transit station but did not. Similar to the identification strategies used in Diao et al. (2017) and Heilmann (2017), I assign areas that received a station as the treatment group and areas that did not receive a station as the control group.

3.2 Data

The Center for Transit-Oriented Development provides longitude and latitude coordinates for transit-oriented developments as well as their corresponding transit stations through their National TOD database. Longitude and latitude coordinates for each TOD were pulled using the TOD database and then inputted in the Neighborhood Change Database (NCDB) to acquire decennial census data by census tract. For population, race, and family income statistics, data from 1970-2010 was used; for household income and median rent statistics, only data from 1980-2010 was available. To maintain consistency, the NCDB re-weights all data to 2010 census tract boundaries.

For both the control and treatment groups, a buffer zone of 0.5 miles was drawn around each coordinate provided by the TOD database—this

[5] Ethan N Elkind. *Railtown: The fight for the Los Angeles metro rail and the future of the city.* University of California Press, 2014.

distance is in accordance to official TOD designations. Census tracts whose centroids were within the 0.5 mile distance for TOD's that got a station before Proposition A were assigned to the treatment group. Census tracts whose centroids were within the 0.5 mile distance for stations that were promised but delayed due to Proposition A were assigned to the control group.

3.3 Model Setup

The objective is to determine how and whether the implementation of transit-oriented developments can shift neighborhood demographics and displace certain slices of communities. Several indicators are used in the model—population, race (% white, % black, and % Hispanic), household income, and median rent. Zuk and Chapple (2015) use similar population and race indicators in their Urban Displacement Project. Guerrieri et al. (2010) show that rising rent prices and rising incomes are correlated with gentrification, and Jeffrey Lin (2002) uses household income as an indicator of gentrification to assess the relationship between gentrification and transit in northwest Chicago. On the other hand, changing demographics can be the sign of a poverty magnet, defined by high concentrations of low-income and usually minority communities.

Similar to Diao et al. (2017), a difference-in-differences approach is used for each instrument. A visual assessment of time series for each instrument passes the parallel trends check (Figure 1). To prepare the data for the model, features were added. 'Treat' is a dummy variable, in which areas that received a station are classified with a 1, whereas areas that have not are classified with a 0. To account for time, the dummy variable 'Time' is used, which is a binary classifier for whether the time is pre- or post- the implementation of Proposition A. Time post-enactment is classified with a 1, whereas time pre-enactment is classified with a 0. The intention of this is to isolate pre-existing differences in areas from the differences in the areas post-treatment. Finally, following the difference-in-differences specification, an interaction term is used to determine the effects caused by the treatment for areas with a TOD transformation. The full model is specified below:

$$y = \beta_0 + \beta_1(Treat) + \beta_2(Time) + \beta_3(Treat \times Time) + \gamma(Controls) + \epsilon$$

where y represents each indicator (population, race, income, rent), β_0, β_1, and β_2 are coefficient estimators, γ is the coefficient for controls, and ϵ is the error term. The coefficient of interest is β_3, which measures the impact of constructing the transit station on the indicator of interest. A larger increase in population of whites as well as higher incomes and rents would be a sign that gentrification is occurring as a product of the treatment. An increase in minority populations as well as lower incomes and rents would be a sign that displacement is occurring in the other direction, and that the treatment drives away affluent demographics.

4 Results

4.1 Population

Table 1 shows the results of running the difference-in-differences regression for population. Column (1) is the most basic specification—the *treatment* coefficient is -350 and the *time* coefficient is 600, meaning that the treatment group started with 350 less people on average compared to the control prior to Proposition A, and that the control group experienced a population increase of 600 people on average between 2000-2010. The interaction term is 337, indicating that areas that received stations underwent higher population increase than those that were promised but did not receive stations by 337. With a p-value of 0.03, this is a statistically significant increase, which aligns with the hypothesis that the addition of public transit sparks growth in the area. The second specification in Column (2) shows that this phenomenon is not driven by race, considering that the interaction coefficient increases just slightly to 370 and remains statistically significant with a p-value of 0.02 after regressing with race controls. The interaction term is about half of the *time* term, meaning that census tracts that were treated experienced 50% more growth compared to those that were not treated. This indicates that the treatment of building a transit station made the areas impacted more attractive, which can indicate either the presence of gentrification or the presence of a poverty magnet perpetuated by the implementation of a low-income mobility option.

4.2 Race

Table 2 shows the regression results for race. Column (1) regresses for the share of white population—the interaction term is -0.437, meaning that treatment areas experienced a smaller increase in white populations than control areas by 0.437%. This is contrary to the hypothesis that treatment areas are more susceptible to minority displacement, which is an indicator of gentrification. However, this result is not statistically significant and is rather small when compared to the natural decrease of whites in control areas post-treatment, seen in the *time* term of -15.916. On the other hand, the share of black population in treatment areas dropped -4.125% more compared to that of control areas (Table 3). This is a statistically significant decrease with a p-value of 0.09. The drop in black population usually implies a gentrification effect, as gentrified communities lose minority populations that are correlated with having lower-incomes. However, the *time* coefficient is slightly negative as well at -0.19, meaning that was no migration of blacks from the treatment areas to the control areas with no stations. Meanwhile, the share of Hispanic population experienced a very statistically significant 5.546% difference between treatment and control areas as seen in Table 4. Hispanics have on average a lower-income compared in Los Angeles, meaning that treatment areas may be attractive for low-income populations. Column (2) shows that this interaction term combined with *Average Household Income* is statistically significant (p=0.055) and negative, which indicates that the share of Hispanic population increased more in areas that were poorer. This points to a possible income segregation effect within the treatment census tracts, where lower-income populations may be more drawn to areas that are already low-income.

4.3 Income

Table 5 shows the regression results for household income. The interaction term is -6496, meaning that treatment areas experienced less growth in income than control areas by $6,496. Although race characteristics do play a factor, changing the gap to $5,438, the interaction is still statistically significant and negative. This is opposite to what would be expected if gentrification had occurred in the treatment areas. A caveat in the raw data is that only average household income was provided, rather than median household income, meaning that the data is susceptible to outliers. To adjust for this, Column (2) regresses on income and removes tracts whose household income lies outside of the inner quartile range. With this specification, the interaction term is much smaller but still negative. This points to the treatment as having poverty magnet effects rather than gentrification effects.

However, it is possible for some tracts in the treatment group to experience the poverty magnet effect and others to experience a gentrification effect. To check for this, Figure 2 shows a density plot of control and treatment areas over the years in order to capture changing income heterogeneity. If there is an income segregation effect present in the treatment areas, there should be a bimodal distribution after the time of treatment. However the distribution is still unimodal after the time of treatment and similar to the distribution of the control areas, which indicates that there is not a sorting effect taking place in the treatment areas.

4.4 Rent

Table 6 shows regression results for median rent. The interaction term is slightly negative but not significant, at -\$37.961. When adding controls for race in Column (2), it changes slightly to -\$43.345 but is still not significant. Removing outliers in Columns (3) changes it slightly as well to -\$22.21, but is not significant either. The negative result aligns with the negative result seen when regressing for household income, implying that the treatment lures in low-income populations. However, the lack of statistical significance as well as the relatively small difference (in comparison, the *Time* term varies from \$400 to \$600) makes it difficult to surmise any inferences.

5 Conclusion

This paper uses a OLS-based difference-in-differences model in an attempt to infer causal effects of transit stations and transit-oriented developments on neighborhood changes, using population, race, income, and rent as indicators of neighborhood characteristics. Transit-oriented developments are seen as a progressive tool in the planning industry, but not much research has been done on the effects for people currently living in these communities. While many studies converge on positive long-term and high-level consequences of transit-oriented developments, existing literature has a mixed bag of results in terms of whether transit is helping residents in these communities or driving them away as a result of gentrification. The few studies that do research the effect on transit proximity on neighborhoods focus only on holistic effects and use a hedonic price approach that does not account for endogeneity. This study differs in that it focuses on sorting effects and individualized consequences for varying demographics, and is one of a few that utilizes difference-in-differences approach.

The indicators used to analyze neighborhood differences were population, race, household income, and median rent. Regressing for population showed a statistically significant uptick in treated areas compared to control areas, meaning that as a whole, public transit and TOD-characteristics are amenities that lure people into a neighborhood. Regressing for race shows exactly who is being lured in—results showed that treatment areas experienced a higher increase in the share of Hispanic populations and a higher decrease in the share of black populations when compared to control areas. As a whole though, Hispanic population in control areas has gone up by almost 30% and black population has gone down, indicating that treatment areas are experiencing the same migration and sorting effects as the general region but in a higher intensity. Changes in white share of population in treatment areas did not differ from control to treatment areas; however, findings were not statistically significant. Regressing for household income and median rent seems to point to the direction that TOD's are attracting lower-income communities, as treatment areas had comparatively lower household incomes and median rents compared to their control counterparts. Since minority populations are usually low-income in Los Angeles, this inference is backed by the higher Hispanic presence in treatment areas but not by the fact that blacks are moving out of the area.

Potential next steps for this study include more comprehensive data collection. The Neighborhood Change Database only provides decennial census data and a limited amount of neighborhood characteristics. Having other years would make the parallel trends assumption and the regressions more robust. The last year recorded is also 2010, which is ten years ago; since the effects of TOD's are meant to be long-term, it is possible that analysis on more recent years would provide different results. A wider selection of neighborhood characteristics would also strengthen this study. Indicators like poverty rate and education level that were not included in the NCDB would give more insight on the socioeconomic characteristics of the neighborhoods. Although this study focused on who was coming into these TOD's, it does not discuss the consequences of being a resident in these TOD's. By gathering census data on crime rates, education level, and unemployment rates, these questions can be explored.

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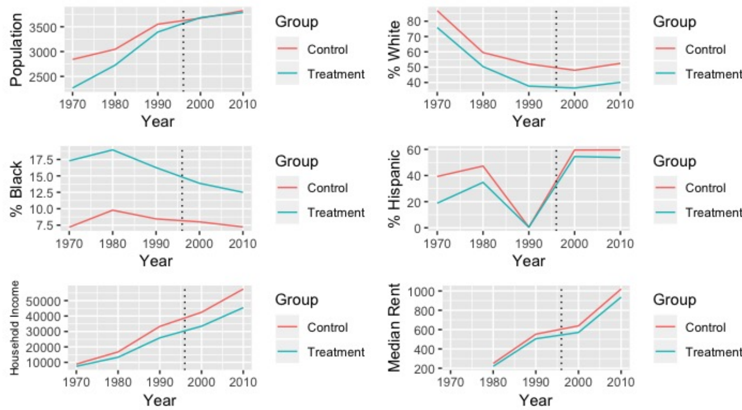

Figure 1: Pre-trends

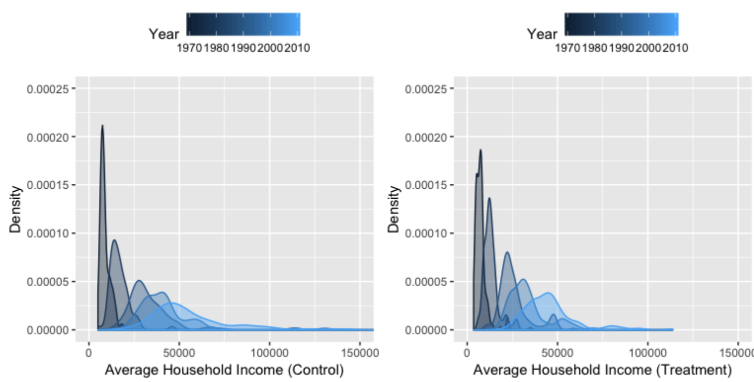

Figure 2: Density plot of household income

Table 1: Results: Population

	Dependent variable:	
	pop	
	(1)	(2)
Treatment	-350.576^{***}	-434.314^{***}
	(100.025)	(100.710)
Time	600.884^{***}	514.037^{***}
	(132.784)	(137.068)
Hispanic		2.917^{**}
		(1.366)
Black		11.943^{***}
		(1.841)
Treatment:Time	337.555^{**}	370.645^{**}
	(158.153)	(155.832)
Constant	$3,146.588^{***}$	$2,968.679^{***}$
	(83.980)	(93.581)
Observations	1,220	1,220
R^2	0.108	0.139
Adjusted R^2	0.106	0.136
Residual Std. Error	1,234.249 (df = 1216)	1,213.662 (df = 1214)
F Statistic	49.180^{***} (df = 3; 1216)	39.238^{***} (df = 5; 1214)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2: Results: Share of White Population

	Dependent variable:	
	White	
	(1)	(2)
Treatment	-11.532^{***}	-4.450
	(2.013)	(3.525)
Time	-15.916^{***}	-40.281^{***}
	(2.672)	(5.337)
Household Income		-0.0002
		(0.0001)
Treatment:Time	-0.437	0.081
	(3.183)	(6.890)
Treatment:Household Income		-0.001^{***}
		(0.0002)
Time:Household Income		0.001^{***}
		(0.0001)
Treatment:Time:Household Income		0.0004^{**}
		(0.0002)
Constant	66.144^{***}	69.879^{***}
	(1.690)	(2.908)
Observations	1,220	1,217
R^2	0.130	0.188
Adjusted R^2	0.128	0.184
Residual Std. Error	24.839 (df = 1216)	24.013 (df = 1209)
F Statistic	60.439^{***} (df = 3; 1216)	40.061^{***} (df = 7; 1209)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3: Results: Share of Black Population

	Dependent variable:	
	Black	
	(1)	(2)
Treatment	9.696***	11.467***
	(1.547)	(2.803)
Time	−0.194	−0.094
	(2.054)	(4.244)
Household Income		−0.0001
		(0.0001)
Treatment:Time	−4.125*	−9.234*
	(2.447)	(5.479)
Treatment:Household Income		−0.0001
		(0.0001)
Time:Household Income		0.00004
		(0.0001)
Treatment:Time:Household Income		0.0002
		(0.0002)
Constant	7.809***	9.069***
	(1.299)	(2.313)
Observations	1,220	1,217
R^2	0.044	0.049
Adjusted R^2	0.041	0.043
Residual Std. Error	19.094 (df = 1216)	19.095 (df = 1209)
F Statistic	18.545*** (df = 3; 1216)	8.830*** (df = 7; 1209)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: Results: Share of Hispanic Population

	Dependent variable:	
	Hispanic	
	(1)	(2)
Treatment	-10.993^{***}	-21.511^{***}
	(2.086)	(3.381)
Time	30.567^{***}	32.922^{***}
	(2.769)	(5.120)
Household Income		-0.001^{***}
		(0.0001)
Treatment:Time	5.546^{*}	11.673^{*}
	(3.298)	(6.609)
Treatment:Household Income		0.0003^{**}
		(0.0002)
Time:Household Income		0.001^{***}
		(0.0001)
Treatment:Time:Household Income		-0.0004^{*}
		(0.0002)
Constant	29.015^{***}	54.543^{***}
	(1.751)	(2.790)
Observations	1,220	1,217
R^2	0.314	0.452
Adjusted R^2	0.313	0.449
Residual Std. Error	25.737 (df = 1216)	23.034 (df = 1209)
F Statistic	185.924^{***} (df = 3; 1216)	142.515^{***} (df = 7; 1209)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5: Results: Household Income

	Dependent variable:			
	Household Income			
	(1)	(2)	(3)	(4)
Treatment	$-4,091.354^{***}$	$-6,053.294^{***}$	$-3,652.137^{***}$	$-5,300.863^{***}$
	(1,149.942)	(1,062.003)	(950.616)	(880.522)
Time	$30,334.960^{***}$	$37,674.510^{***}$	$24,951.680^{***}$	$31,689.450^{***}$
	(1,526.565)	(1,445.447)	(1,294.939)	(1,241.287)
Hispanic		-240.558^{***}		-198.292^{***}
		(14.414)		(12.115)
Black		-70.391^{***}		-57.646^{***}
		(19.418)		(16.079)
Treatment:Time	$-6,496.731^{***}$	$-5,483.645^{***}$	$-1,113.453$	-964.485
	(1,819.634)	(1,644.401)	(1,531.286)	(1,386.459)
Constant	$19,631.550^{***}$	$27,161.020^{***}$	$19,192.330^{***}$	$25,423.770^{***}$
	(965.485)	(986.892)	(798.678)	(821.588)
Observations	1,217	1,217	1,204	1,204
R^2	0.460	0.561	0.509	0.599
Adjusted R^2	0.458	0.559	0.508	0.598
Residual Std. Error	14,189.670 (df = 1213)	12,797.770 (df = 1211)	11,710.910 (df = 1200)	10,590.170 (df = 1198)
F Statistic	343.845^{***} (df = 3; 1213)	309.664^{***} (df = 5; 1211)	415.371^{***} (df = 3; 1200)	358.649^{***} (df = 5; 1198)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6: Results: Median Rent

	Dependent variable:			
	Median Rent			
	(1)	(2)	(3)	(4)
Treatment	−38.699*	−47.715**	−38.699**	−44.339**
	(22.619)	(20.333)	(19.673)	(17.845)
Time	426.856***	573.081***	388.203***	519.026***
	(26.904)	(25.356)	(23.655)	(22.679)
Hispanic		−4.083***		−3.458***
		(0.247)		(0.221)
Black		−1.748***		−1.691***
		(0.395)		(0.348)
Treatment:Time	−37.961	−43.345	−22.213	−32.304
	(32.049)	(28.332)	(28.138)	(25.103)
Constant	401.403***	513.150***	401.403***	497.744***
	(18.991)	(18.217)	(16.517)	(16.028)
Observations	972	972	958	958
R^2	0.441	0.565	0.473	0.583
Adjusted R^2	0.439	0.563	0.472	0.581
Residual Std. Error	227.893 (df = 968)	201.162 (df = 966)	198.207 (df = 954)	176.532 (df = 952)
F Statistic	254.469*** (df = 3; 968)	251.226*** (df = 5; 966)	285.951*** (df = 3; 954)	266.418*** (df = 5; 952)

Note: *p<0.1; **p<0.05; ***p<0.01