Empirical Evidence for Community Perceptions: Assessing the Impact of Below Market Rate Housing on Reported Crime in the City of Los Angeles[1]

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Undergraduate Honors Thesis

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Abstract: Affordable housing entitlements face significant opposition from neighbors in the surrounding area. These sentiments are known to stop or even delay the production of below-market-rate housing. One well-cited reason for this opposition is that affordable housing could increase crime in the surrounding area. I study the impact of affordable housing on reported crime in Los Angeles using data from the Los Angeles Police Department (LAPD), a public records request from Los Angeles Housing Department, and the U.S. Census. Using both a staggered difference-in-differences model and an event study model, I find that the introduction of an affordable housing covenant has no impact on block crime when introduced in Los Angeles. I also that find an affordable housing covenant can be approved in areas of both low-density and high-density zoning without increasing reported crime. My results even suggest that the affordable housing introduction of affordable housing covenants in single-family areas could decrease reported crime. Finally, I find that the spatial concentration of affordable housing has no extraneous impacts on crime, which contradicts existing scholarship.

Keywords: affordable housing, crime, single-family zoning, spatial analysis

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[1] Data and replication code available here.

I. Introduction

Affordable housing entitlements in cities are sometimes opposed by constituents living in the surrounding area. One common reason for opposition is the fear that affordable housing would increase crime in their neighborhoods. Current scholarship shows that the fear of crime is one of the strongest perceived consequences of affordable housing (Homer, 2009; Agnew, 2010). These perceptions have an impact. David Glick, Katherine Einstein, and Maxwell Palmer, faculty fellows at the Initiative on Cities at Boston University, study how participatory politics impacts the future of cities. They find that concerned community members, coined as "neighborhood defenders," have the power to delay or even stop development in their neighborhoods by using "every regulatory tool at their disposal" (Glick et al., 2). Acting under the guise of community protection, these neighborhood defenders use public hearings for proposed developments, environmental review litigation, and administrative appeals through local regulatory processes to stop development from keeping course (O'Neill et al., 2022; Glick et al., 2020). While these perceptions are often rooted in deep-seated racial antagonisms, they are incredibly powerful in planning spaces.

There are also positive perceptions of affordable housing. These perceptions are reflective of current legislation in California. One example is S.B. 35, which allows for local jurisdictions to streamline affordable housing entitlements through a ministerial process (as opposed to a discretionary process) if the jurisdiction has not met their Regional Housing Need Allocation (RHNA) requirements (S.B. 35, 2017–2018 Reg., Leg. Sess). This bill encourages the production of new, below-market-rate housing by alleviating the impact of participatory local politics on the approvals process for residential development. Bills such as S.B. 35 operate under the pretext that affordable housing can be used as a tool for community and economic advancement, which would lead to lower levels of reported crime.

Using the City of Los Angeles as my study jurisdiction, I am interested in understanding what perceptions of below-market-rate housing are supported in empirical analysis. Is there a significant, causal change in crime in the geographic area for which an affordable housing covenant was approved in Los Angeles? How has the introduction of an affordable housing covenant on a U.S. Census Block in Los Angeles impact crime on and immediately around the block?

I plan to use a differences-in-differences design to assess the causal impact of affordable housing. I also plan to estimate a secondary event study model to detect any patterns in crime before receiving an affordable housing covenant. Using a dataset of crime incidents in Los Angeles from the Los Angeles Police Department (LAPD), I aggregated crime data by blocks to find the number of crimes committed every year from 2010 to 2019 on each block. Using data retrieved by Public Records Request from the Los Angeles Housing Department, I identified blocks that have received an affordable housing covenant, which will be used to assign treatment. An affordable housing covenant refers to the ensured restriction that below-market-rate units will exist or continue to exist on a parcel of land (LawInsider, 2022).

Diverging from existing literature, I am using the City of Los Angeles as my study jurisdiction. As the largest city in California and the second largest in the country, Los Angeles will possibly allow findings from existing research to extend beyond the Northeastern region. Further, using innovative geoprocessing techniques, I plan to construct time-varying controls that will allow me to constrain the impact of the spatial concentration of affordable housing in my analysis. Another difference I would like to highlight between my research methodology and current research is the use of affordable housing covenants as my assignment of treatment. Using all affordable housing covenants in Los Angeles will allow me to make broader conclusions about

the true impact of below-market-rate development. Finally, I also plan to assess whether affordable housing impacts reported crime differently in areas of lower density versus areas of higher density with the use of zoning data from the Othering and Belonging Institute. The use of zoning data in my analysis is unique from existing literature. Areas that permit only single-family developments are areas that tend to have more opposition to affordable housing. It is an important finding to see how these perceptions of affordable housing are realized in areas where these notions are voiced heavily and exploited to the advantage of individuals who oppose affordable development.

II. Literature Review

The research regarding the impact of affordable housing on crime is not substantial. Often, existing research evaluates the impact of affordable housing on property values, which is an amalgamation of existing neighborhood-quality variables, like the level of reported crime (Angew, 2010). In his white paper on the impact of affordable housing on communities, Spencer Agnew finds that "affordable housing typically has no effect on neighborhood crime," but "three studies which considered the role of scale found that large projects or large concentrations of affordable units can lead to an increase in crime" (Angew, 2010, p. 10). Therefore, the concentration of affordable housing seems to be an important determinant of the impact of affordable housing on crime.

In 2013, Albright et al. uses mixed-method research techniques to assess the impact of affordable housing on suburban communities. Using time-series regression analysis, they find affordable housing was not associated with any increasing trends in crime, property values, or taxes in Mount Laurel, New Jersey. Albright et al. also draws on qualitative interviews with residents, planners, and local government officials to understand why their zero-treatment effect occurred. From this qualitative work, they find that this zero-treatment effect was a result of

planning practices by local municipalities and developers "mitigat[ing] potential negative externalities and . . . promot[ing] social cohesion and security among project residents," such as ensuring "articular consistency with surrounding neighborhoods" and "careful attention to landscaping and aesthetics." (Albright et al., 2013, p. 16). This analysis highlights the importance of planning processes on the extraneous impacts of development.

Moving away from suburbia and to cities, Woo et al. in 2015 estimated the impact of the Low-Income Housing Tax Credit (LIHTC) Program on neighborhood crime in Austin, Texas. Like other metropolitan areas, Austin has a growing concern of a lack of affordable housing, so the development of below-market-rate is of top priority to planners in this area (Woo et al., 2015). Using an Adjusted Interrupted Time Series-Differences in Differences approach, they find that LIHTC developments may even ameliorate crime in areas where crime is already prevalent. Their results indicate that LIHTC developments can be used as a tool for community and neighborhood advancement, all while decreasing neighborhood crime.

While Agnew, Albright et al., and Woo et al., come to similar conclusions, their research is focused on geographic areas not in California. Existing research on the extraneous impacts of affordable development has been largely focused on Northeastern cities, such as New York, Baltimore, and Philadelphia (Woo et al, 2015; Nguyen, 2005). Such research may not generalize to Los Angeles or other cities in California due to state-wide differences in planning processes, crime rates, and community opposition to housing. Existing scholarship also has focused on investigating the negative externalities of specific types of affordable housing, such as non-profit assisted living or public housing (Agnew, 2010). However, increases in crime is a perceived consequence of affordable housing developments more generally.

III. Data

The original crime data from LAPD contains 2,060,948 observations. However, I dropped incidents of crime that were not geolocated, which is less than .1% of the data. I also dropped projects that fell outside the City of Los Angeles. After these two edits, 1,820,212 incidents of crime will be used in the calculation of block crime rates. Similarly, the original affordable housing covenant data contains 1,302 covenants. However, after dropping projects that fell outside of the Los Angeles city boundaries, there are now 1,283 covenants to be used in analysis. Some blocks may have received more than one covenant. Therefore, out of the 30,691 blocks in Los Angeles, 1,041 blocks received a covenant from 2010 to 2021.

Using 2010 population data from the census, all blocks with a population of fewer than 50 persons were discarded from all analyses. After this final adjustment, there are 18,437 blocks used in all future analyses. Blocks are the smallest aggregation level of the U.S. census; they are delineated by geography and not population. If a reported crime incident is in an area with a small population, then the incidents are then magnified once I normalize by 2010 block populations. Blocks with a population of more than 50 persons are more dense and likely to be built upon, which is important for this analysis. In this same vein, blocks with less than 50 persons are blocks where people tend to not live and have a low likelihood of receiving development in my period of study. Therefore, I discarded these blocks before any modeling.

Using Python and the geopandas library, I first found the number of crime incidents that fall into each census block for each year. Thereafter, I normalize these crime counts by 2010 block populations to calculate block crime rates per 100 persons from 2010 to 2019. Also using geopandas and data from the Los Angeles Housing Department, I found blocks that received an affordable housing covenant from 2010 to 2019. Out of the 18,437 relevant blocks in Los Angeles,

651 blocks received an affordable housing covenant from 2010 to 2019, which are the treated blocks in my analysis. Note that 191 relevant blocks received an affordable housing covenant in 2020 or 2021, but these blocks are considered to have never been treated.

Table 1 shows the trend in (calculated) block crime rates in Los Angeles from 2010 to 2019. My calculations in Table 1 show that crime rates have not been on a particular trend. What is interesting, however, is an incredibly steep drop in crime rates from 2011 and 2012 and from 2015 to 2016. Such a dramatic decrease in crime calls into question whether there is a data issue in these years. However, crime incidents were also reported in each month of each year from 2010 to 2019, so crime reporting and documentation did occur in these years. Therefore, any differences in crime are not a result of data construction or crime incident aggregation at the block level.[2]

Table 1: Mean block crime rates per 100 persons, by year

2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
5.025	4.792	1.430	4.536	4.578	5.222	1.711	5.540	5.461	5.123

Note: An aggregate of the 2010 Census Block populations from the U.S. Census Bureau was used for block normalization for all years. Blocks with a population smaller than 50 were discarded from the calculations.

Similarly, Table 2 shows the number of blocks that received an affordable housing covenant in the years of my analysis. These counts in Table 2 display the increasing trend in the number of blocks that receive an affordable housing covenant. This is reflective of both state and local policies[3] that is incentivizing the entitlement and production of affordable housing in high-cost areas in California.

[2] See Table 13 in Appendix for further information. This table shows the breakdown of crime incidents in the City of Los Angeles by month and year. Observe that crime incidents in 2016 and 2016 are relatively low for all months, indicating that there are no systemic period gaps (i.e., underreporting in the month of November or December) in crime incidents date in 2012 or 2016. While this table rules out any period gaps, it is still possible that underreporting could have occurred during the whole year.

[3] Several bills in the California legislative are incenting affordable housing in rent burdened areas (i.e., SB 35; Housing Crisis Act of 2019). Similarly, there is also Los Angeles Planning Policy that is also impacting the rise in affordable housing. One initiative in Los Angeles is the Transit Oriented Communities (TOC) Incentives Program,

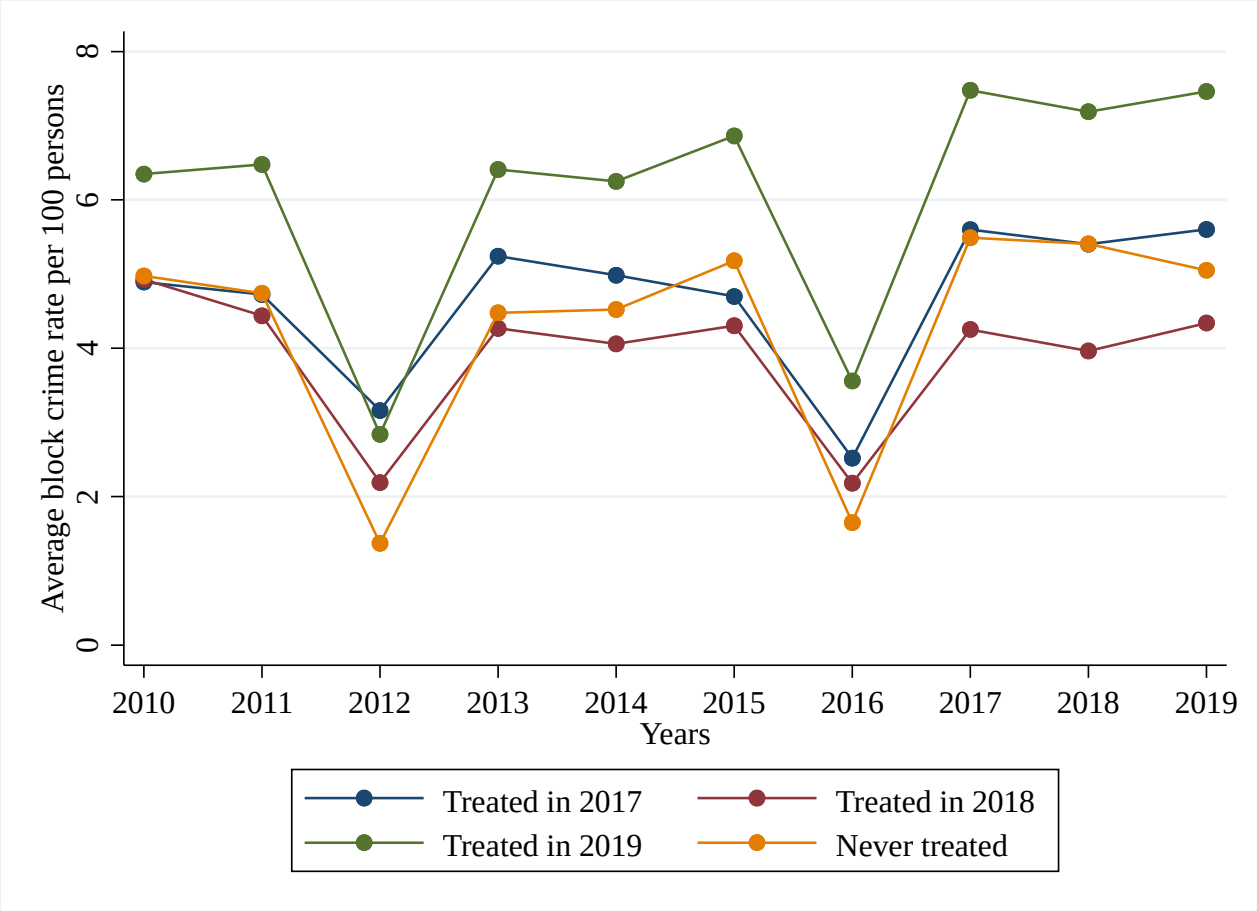
Table 2: Number of blocks that received an affordable housing covenant, by year

2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
52	31	48	49	49	66	72	105	107	143

Note: Housing covenants approved in a block that had a population of fewer than 50 persons were discarded from the calculations

Evolution of Block Crime Rate

Figure 3: Evolution of average block crime rate by treatment status



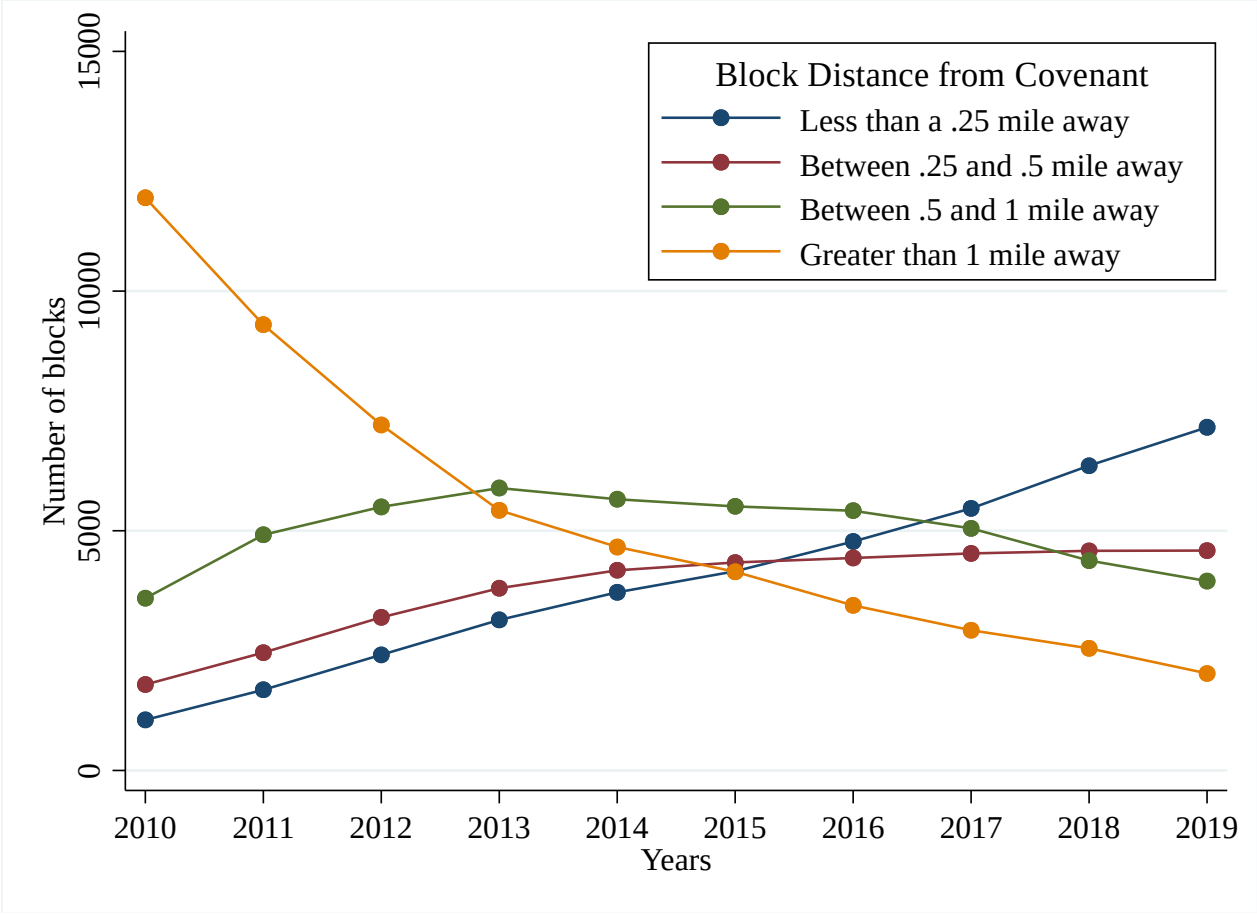
Showing the evolution of average block crime rates by block treatment status, Figure 3 visualizes the trend in crime rates for blocks that are treated in 2017, 2018, and 2019 as well as

which drives affordable housing production through development incentives and setbacks in areas near public transit ("Transit Oriented Communities Incentive Program").

blocks that have never been treated. Note that this figure does not include the trend of average block crime rates for blocks that were treated in the years 2010-2016. These trends are just as important and are included in the appendix. Visually, the trend in block crime rates from 2010 to 2019 for these four treatment statuses is very similar. This suggests that the census blocks were following similar trends in crime before any designation of an affordable housing covenant.

Spatial Distance Between Treated Blocks

Figure 4: Number of blocks that are some distance away (in miles) from an affordable housing covenant, by year



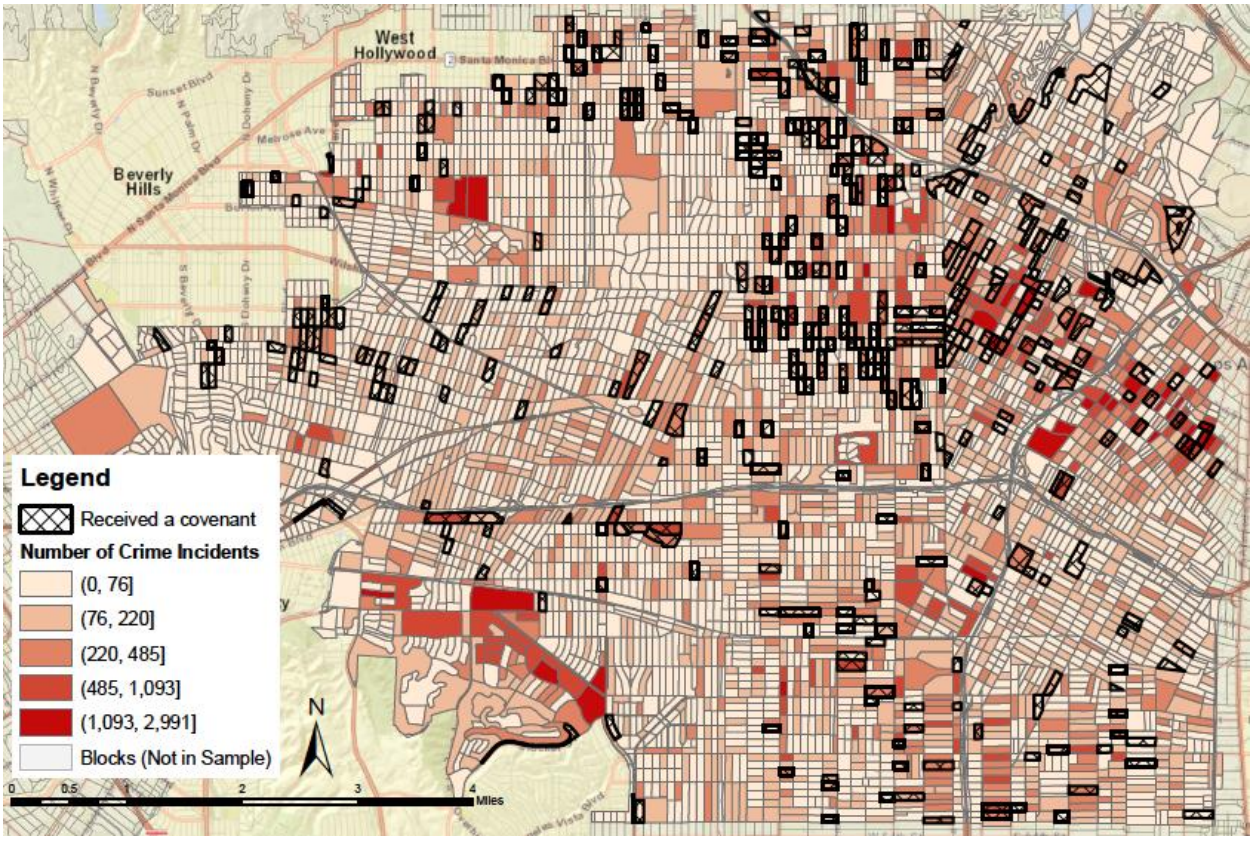
Note: Distances for each block for all years were calculated in the Zone 7 Los Angeles State Plane Projection (ESPG: 2229). Dummy variables were calculated from a continuous variable constructed in Python, which was originally in feet. Note that if a block was treated in year t, it is excluded from the figure calculations.

I calculated a block's distance from an affordable housing covenant in all years of my study. Figure 4 displays how the distance between new affordable housing projects is changing in Los Angeles. Observe that the number of non-treated blocks that are greater than one mile away is decreasing rapidly throughout the years of my study. Similarly, the number of non-treated blocks that are at least half a mile away from a covenant is steadily increasing as well. This indicates that more blocks are near another block that received an affordable housing covenant. It also indicates that the spatial concentration of treated blocks is growing during the years of my study. Therefore, the results of this graph suggest that the spatial distance between treated blocks is decreasing as the number of affordable housing covenants is increasing. I plan to include these time-varying controls in any modeling to control for the increases in the spatial concentration of affordable housing from 2010 to 2019.

Further, Figure 5 illustrates the aggregate spatial concentration of crime and affordable housing covenants from 2010 to 2019 in Central Los Angeles. While my data consists of all Census Blocks and all affordable housing covenants in Los Angeles, I chose to highlight Central LA in my map to better show the spatial concentration of crime and its visual association with affordable housing. One visual takeaway from this map is that there exist areas of concentrated affordable housing. This may indicate that if a block was already close to another block that received an affordable housing covenant, then this block is more likely to receive an affordable housing covenant as well. Theoretically, this makes sense as some urban spaces within a city are easier to approve development in than in others – so urban development is often concentrated. O'Neill et al. found that in Los Angeles, 73% of all approved developments from 2014 to 2017 were found in neighborhoods of moderate or low resource (O'Neill et al., 2022, p. 102). Further, another visual takeaway is that areas with large clusters of affordable housing covenants tend to have larger

clusters of reported crime incidents. Therefore, this map also indicates that the spatial concentration of affordable housing could be an important determinant of how new developments impact crime, and the variation in the spatial distance of affordable housing is what I plan to control in my modeling.

Figure 5: Spatial concentration of total crime and treated blocks across 2010 to 2019 in Central Los Angeles, by U.S. Census Block[4]



Map is in Zone 7 Los Angeles State Plane Projection (ESPG: 2229).

Multi-Family Blocks vs. Single-Family Blocks

Using data from the Othering and Belonging Institute, I can discover the number of blocks that permit single-family developments and the number of blocks that permit multi-family

[4] See Figure 14 in Appendix to see a generated map with all covenants. In order other words, Figure 14 displays both block crime incidents and affordable housing covenants (as point data) in Central LA.

developments. Out of the 18,437 used in my analysis, 11,538 blocks permit single-family development, and 9,393 blocks permit multi-family development. Note that a block can permit both single- and multi- family development. I am interested in understanding what is the causal impact of affordable housing on crime for blocks that permit single-family development and for blocks that permit multi-family development. The reason is that residential entitlements are more likely to receive community opposition when they are placed in areas of restrictive, low-density zoning (O'Neill et al, 2022; Fischel, 1999). More specifically, single-family zoning ordinances are also known for their role in delaying below-market-rate development (Menendian et al., 2022). Because of this community opposition that is more prevalent in areas where zoning ordinances are unfriendly to low-cost, high-density housing, understanding whether perceptions of affordable housing (i.e., affordable housing is known to increase neighborhood crime) are realized empirically becomes even more important.

Level of Aggregation

While I could have chosen to aggregate crime incidents at any areal unit (i.e. neighborhood, block group, or census tract level), I chose to create my unit of analysis at the block level. Theoretically, the law operates in a way that gives neighborhood owners the ability to oppose development at the parcel level. Therefore, community opposition to development occurs at a more localized level. Given that this is my interest, I would like to study the impacts of affordable housing covenants at and around the parcel level. Census Blocks are the smallest level of aggregation for enumeration by the U.S. census. Further, blocks, unlike neighborhoods, have associated population data, which can be used to calculate crime rates, so they are the best geographic unit for this analysis.

IV. Models Specified

Denoting the outcome for block b in year t, the primary model estimated is:

$$(1)\quad Y_{bt} = \beta c_{bt} + \gamma_b + \delta_t + \tau \mathbf{X_{bt}} + \epsilon_{bt}$$

where c_{bt} is an indicator variable that represents whether the block has an affordable housing covenant in year t, γ_b is a full set of block fixed effects, δ_t *i*s a full set of year dummies, and $\mathbf{X_{bt}}$ is a vector containing time-varying block-level controls that control for a block's distance from an affordable housing covenant. Time-varying block-level controls will help with the identification of the treatment effect. My identifying assumption is that census blocks that received an affordable housing covenant would not otherwise have changed differently than those blocks that never received an affordable housing covenant. If my identifying assumption holds, then β is the causal impact of an affordable housing covenant on block crime.

To empirically support my identifying assumption, I also construct a secondary event study model. Denoting the outcome for block b in year t, the secondary model estimated is:

$$(2)\quad Y_{bt} = \gamma_b + \delta_t + \tau \mathbf{X_{bt}} + \sum_{k=-3}^{3} \beta_k D_{bt}^{k} + \eta_{bt}$$

where $\gamma_{b,}$ δ_t, and $\mathbf{X_{bt}}$ are defined above and D_{bt}^{k} is a dummy variable that takes the value 1 if the block is k years away/from receiving an affordable housing covenant. If my identifying assumption is true, it must be the case that coefficients on the terms D_{bt}^{-3} and D_{bt}^{-2} in this model are statistically insignificant. These coefficients establish the expected behavior of block crime patterns before receiving treatment, so these coefficients signal whether there are fundamental differences in the trends in crime rates two to three years before the block received an affordable housing covenant.

Note the empirical results of this secondary model cannot prove my identifying assumption, but it can generate confidence in its plausibility.

V. Model Estimation and Results

Table 6 shows my regression estimates for Model 1. Regression (B) includes the time-varying controls. In both Regression (A) and (B), the coefficient on C_{vt} is negative but not significant. Assuming my identifying assumption holds, this means that the introduction of an affordable housing covenant has no impact on neighborhood crime.

Table 6: Regression Estimations for Model (1)

	Coefficients	
	(A)	(B)
DID Estimate (C_{vt})	-0.209	-0.269
	(0.149)	(0.167)
$1_{\{Dist \leq .25\ Mile\}}$ ($\in \mathbf{X_{bt}}$)		0.0767
		(0.0958)
$1_{\{.25 < Dist \leq .5\ Mile\}}$ ($\in \mathbf{X_{bt}}$)		-0.259***
		(0.0819)
$1_{\{.5 < Dist \leq 1\ Mile\}}$ ($\in \mathbf{X_{bt}}$)		-0.162***
		(0.0602)
Block fixed effect?	Yes	Yes
Year fixed effect?	Yes	Yes
Number of Blocks	18,437	18,437
Total Observations	184,370	184,370
R-squared	0.066	0.066

Notes: **Dependent variable**: block crime rates per 100 persons. **Sample block crime rate mean**: 4.34. Table presents the robust standard errors in parentheses. $1_{\{Dist \leq .25\ Mile\}}$ is an indicator variable, which takes values 1 if the block is not treated in year t and the block is less than a quarter of a mile away from an affordable housing covenant. *** significant at the 1-percent level.

I will now interpret the set of time-varying controls. Observe that the coefficients on $1_{\{.25 < Dist \leq .5\ Mile\}} \in \mathbf{X_{bt}}$ and $1_{\{.5 < Dist \leq 1\ Mile\}} \in \mathbf{X_{bt}}$ are both negative and significant at the 1% level. This means that, relative to being greater than a mile away from an affordable housing

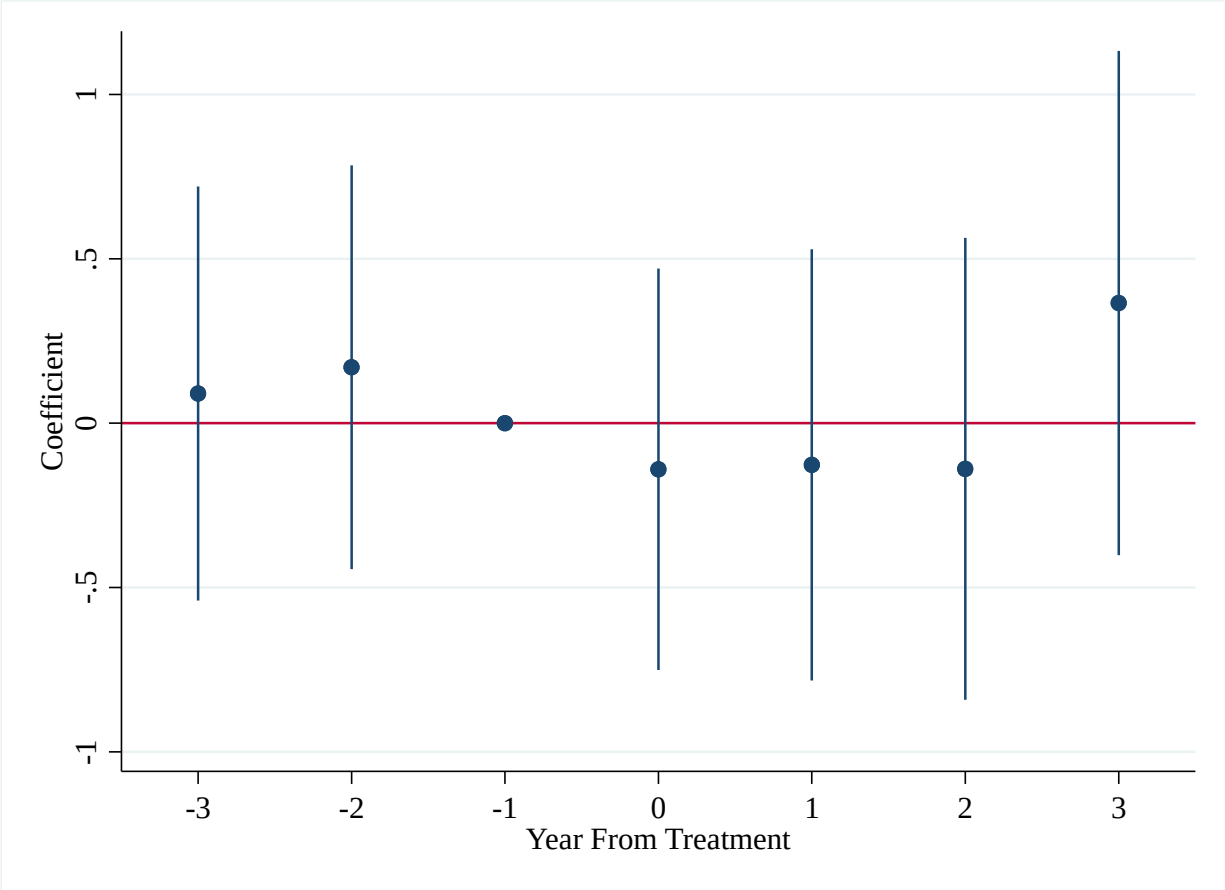
covenant, a block that is between a quarter and a half mile away from a covenant is associated with a 0.26 decrease in block crime rates. Further, relative to being greater than a mile away from an affordable housing covenant, a block that is between half a mile and one mile from an affordable housing covenant is associated with a 0.16 decrease in block crime rates. However, $1_{\{Dist \leq .25\ Mile\}} \in \mathbf{X_{bt}}$ is positive but not significant. Meaning, relative to being greater than a mile away from an affordable housing covenant, a block that that less than a quarter of a mile away from an affordable housing covenant is not associated with any change in crime. These results suggest that it is the centers between large concentrations of affordable housing and areas with no affordable housing that experience the least levels of crime.

A comparative analysis between Regression (A) and Regression (B) also relays an interesting story. Existing literature on the extraneous impacts of affordable housing has suggested that below-market rate developments do not affect crime, but large concentrations of affordable housing developments can lead to an increase in crime (Agnew, 2010). I find that, when I control for the concentration of affordable housing through a set of time-varying controls, the treatment effect does not change substantially nor does its significance change. This means that the concentration of affordable housing may not be as large of a determinant of crime as previous literature suggests.

Figure 7 shows a coefficient plot for the coefficients on D_{bt}^{k} in Model (2). Observe that coefficients on D_{bt}^{-3} and D_{bt}^{-2} are statistically insignificant. This means that a block being three or two years away from receiving treatment is not associated with any changes in block crime. Further, the insignificance of the coefficients on D_{bt}^{-3} and D_{bt}^{-2} gives some plausibility to our identifying assumption in Model (1). Therefore, I have confidence in saying that, before being

treated, the census blocks that experienced an affordable housing covenant designation were on a similar trend with respect to crime as blocks that did not receive an affordable housing covenant.

Figure 7: Coefficient Plot for Model (2)



Note: Coefficient estimations and standard errors for Model (2) are in Table 12 of the appendix. Coefficient plot shows the 95% confidence interval the coefficient on D_{bt}^{k} for k ∈{-3, -2, 0, 1, 2, 3).

Multi-Family Blocks vs. Single-Family Blocks

Column 1 of Table 8 shows the estimation results of Model (1) when I discard blocks that do not permit single-family development. Similarly, Column 1 of Figure 7 shows the estimation results of Model (1) when I discard blocks that do not permit multi-family development. Note that for these estimations results, I did not include the set of time-varying controls. The theoretical reason is that a census block's distance from an affordable housing covenant is likely to be

associated with whether the block allows for single- or multi-family structures. Areas of restrictive, low-density zoning are less likely to experience development. They are also areas of greater affluence, so below-market rate structures are less likely to occur in these areas (Menendian et al., 2022). Therefore, controlling for this variation is not the best for identification.

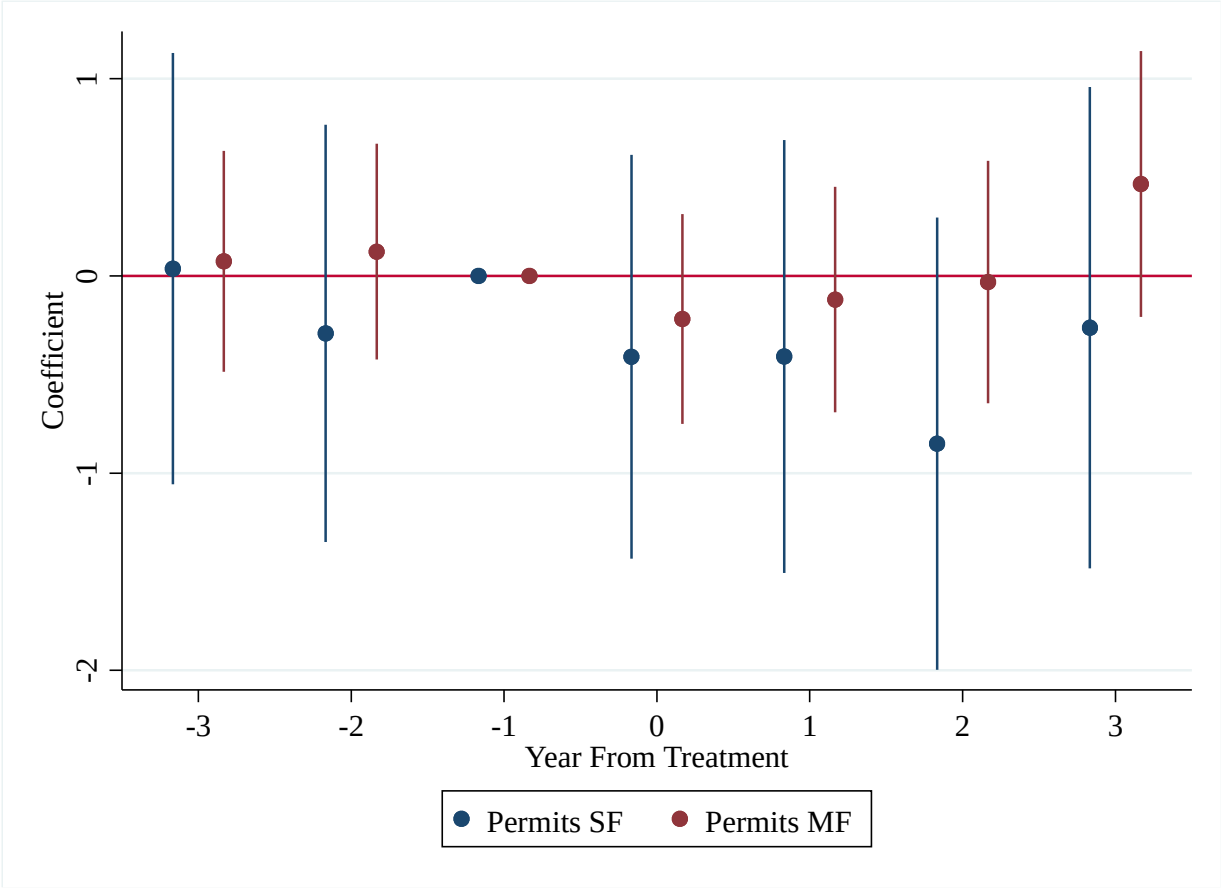
Table 8: Regression Estimations of Model (1) for Blocks that Permit Single-Family Development and for Blocks that Permit Multi-Family Development

	Coefficients	
	Permits SF	Permits MF
DID Estimate (C_{vt})	-0.519***	-0.157
	(0.149)	(0.148)
Block fixed effect?	Yes	Yes
Year fixed effect?	Yes	Yes
$\mathbf{X_{bt}}$ Included?	No	No
Number of Blocks	11,538	9,393
Total Observations	115,380	93,930
R-squared	0.083	0.077

Notes: **Dependent variable**: block crime rates per 100 persons**. Sample crime rate mean for SF blocks**: 3.59. **Sample crime rate mean for MF blocks**: 4.71. Table presents the robust standard errors in parentheses, *** significant at the 1-percent level.

Interestingly, in Column 1 of Table 8, the coefficient on C_{vt} is large, negative, and statistically significant at the 1% level. Assuming my identifying assumption remains true, this means in areas that permit single-family development, an introduction of an affordable housing covenant decreases block crime rates by .519 (in terms of number of crimes per 100 persons). Note that the sample crime rate means for blocks that permit single-family development is 3.59 (crimes per 100 persons), so the treatment imposes almost a 15% decrease in block crime. On the other hand, in Column 2 of Figure 8, the coefficient on C_{vt} is negative but not statistically significant. Again, operating under my identifying assumption, this means that in areas that permit multi-family development, the introduction of an affordable housing covenant has no impact on block crime.

Figure 9 Coefficient Plot of Model (2) for Blocks that Permit Single-Family Development and for Blocks that Permit Multi-Family Development



Note: Coefficient estimations and standard errors for Model (2) for multi-family and single-family permitting blocks are in Table 18 of the appendix. Note that this event study model does not contain time varying block controls. Coefficient plot shows the 95% confidence interval the coefficient on D_{bt}^{k} for k ∈{-3, -2, 0, 1, 2, 3).

Figure 9 is the coefficient plot for the coefficients on D_{bt}^{k} in Model (2) when I discard blocks that do not permit single-family structures (results in blue) and blocks that do not permit multi-family structures (results in red). Like Figure 6, the coefficients on D_{bt}^{-3} and D_{bt}^{-2} for both multi-family and single-family blocks are statistically insignificant. This indicates some support to validate our results in Table 8. Meaning, the large, negative coefficient on C_{vt} in Column 1 of Table 8 is not likely to stem from trends in crime before treatment. However, the lack of large magnitude or statistical significance on the D_{bt}^{k} $(k > 0)$ coefficients in either type of block indicates that the separation by zoning category creates no meaningful change on the impact of

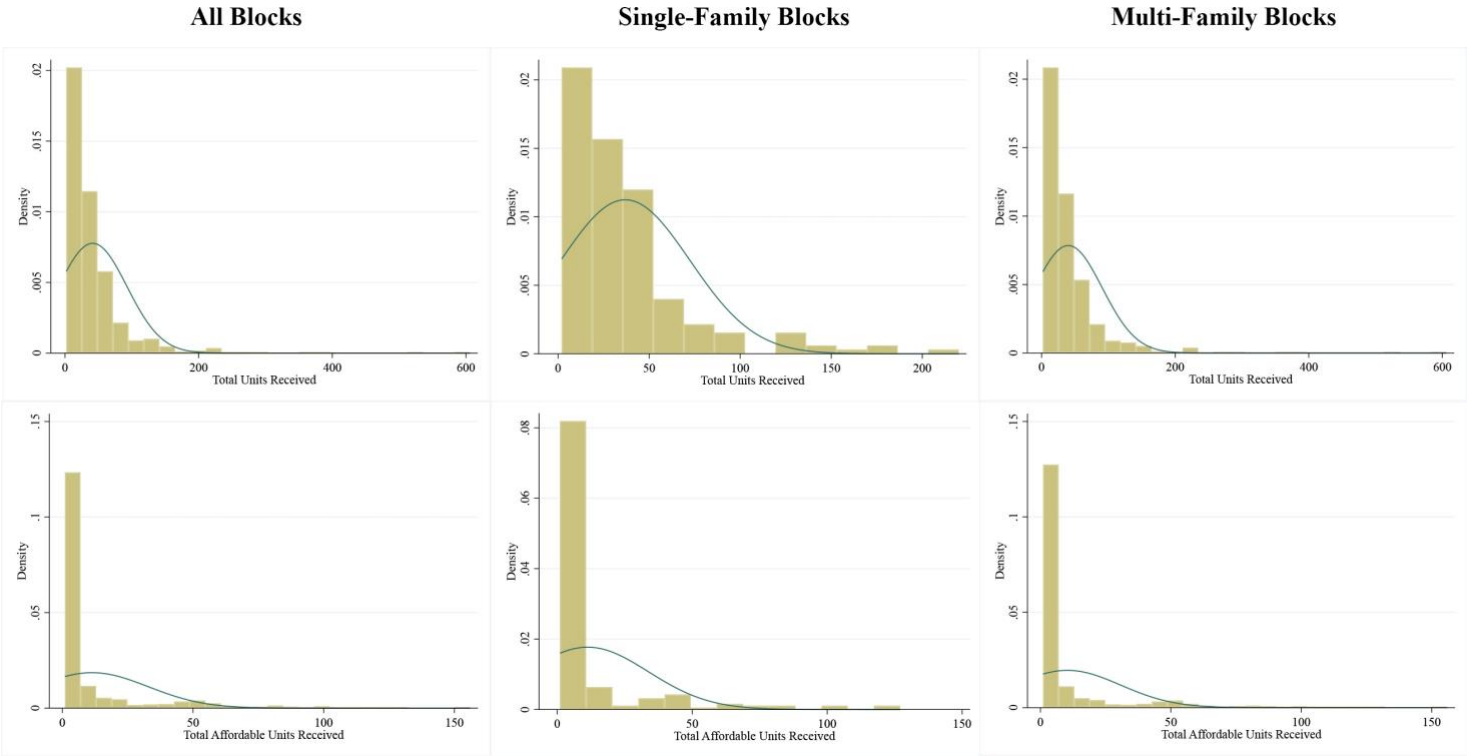
below-market-rate housing on reported crime. Combining the results of these two models, I can discern that in single-family areas, an introduction of an affordable housing covenant has either no impact or possibly a negative impact on crime.

There is some merit to the claim that the introduction of affordable housing could decrease reported crime in low dense areas, so the interpretation of my empirical results in Model 1 is not out of the blue. There is extensive economic modeling on the relationship between increasing density and crime (Twinam 2014; Bennet 1991). Tate Twinam finds that higher residential density leads to lower levels of per capita crime rates. Given this, perhaps the decrease in reported crime in low-dense, single-family areas is a result of the increases in density because of the affordable housing convent. One avenue to explore this further is to incorporate project size. Larger projects indicate larger increases in density, so it is possible to examine the empirical relationship between increasing density and reported crime. This analysis would allow us to see how development – affordable or not – is impacting single-family areas. It is also possible to see the distributional consequences of affordable development. As in, does the percentage of affordability affects the relationship between development and crime rates? While these are future questions to explore this phenomenon further, existing empirical work is in line with my results.

I will now note the differences in single-family and multi-family blocks that may influence differences in the treatment effect. First, there are more treated blocks in multi-family areas than in single-family areas. 1.7% (N=246) blocks that permit single-family development were treated whereas 8.5% (N=890) blocks that permit multi-family development were treated. Further, there exist differences in the size of the covenant. Figure 10 visualizes these differences by showing the distribution of the total units and affordable units for all treated blocks in the first column, the distribution of the total units and affordable units for all treated **single-family blocks** in the second

column, and the distribution of the total units and affordable units for all treated **single-family blocks** in the third column. Observe that the distributions for the total affordable units received are similar across all block zoning categories, but multi-family blocks received larger outlier projects that permit upwards of 150 new residential units.

Figure 10: Distributions of Total Units Received and Total Affordable Units Received in All Blocks, Single-Family Blocks, and Multi-Family Blocks



Note: All graphs exclude blocks that have not been treated. Meaning, blocks that did not receive an affordable housing covenant are not included in the histogram.

VI. Robustness Checks

Gaps in Crime Data

I have shown that LAPD has an unusual amount of reported crime incidents in 2012 and 2016. Though unlikely, these numbers may be reflective of the actual number of crimes occurring

in these years. Reported crime is known to occur cyclically because it is impacted by cyclical factors, such as economic fluctuations (Land, 2012). However, it is also possible that crime incidents were systematically excluded in these years. To account for this possibility, I have rerun Model (1) on a manipulated dataset where I dropped block observations in the years 2012 and 2016. Table 11 shows the regression estimations of this robustness check.

Table 11: Regression Estimations for Model (1), Dropping Observations in Years 2012 and 2016

	Coefficients	
	(A)	(B)
DID Estimate (C_{vt})	-0.113	-0.187
	(0.159)	(0.181)
$1_{\{Dist \leq .25\ Mile\}}$ ($\in \mathbf{X_{bt}}$)		0.0977
		(0.107)
$1_{\{.25 < Dist \leq .5\ Mile\}}$ ($\in \mathbf{X_{bt}}$)		-0.342***
		(0.0880)
$1_{\{.5 < Dist \leq 1\ Mile\}}$ ($\in \mathbf{X_{bt}}$)		-0.166**
		(0.0602)
Block fixed effect?	Yes	Yes
Year fixed effect?	Yes	Yes
Number of Blocks	18,437	18,437
Total Observations	**147,496**	**147,496**
R-squared	0.006	0.007

Notes: **Dependent variable**: block crime rates per 100 persons. **Sample block crime rate mean**: 5.03. Table presents the robust standard errors in parentheses. *** significant at the 1-percent level, ** significant at the 5-percent level.

This robustness check further supports my estimation results of Model (1). While the magnitude of the coefficient on C_{vt} in Regression (A) and Regression (B) has decreased relative to the original regression estimations, neither the direction nor the significance of the coefficient has changed. Although the change in magnitude would be more alarming if the DID coefficients in Table 6 were significant, the conclusions I can draw from Table 8 are the conclusions I have drawn from Table 6. Also observe the magnitude coefficient on C_{vt} decreases by 0.096. Given

that the original sample block crime rate mean is 4.34, this equates to almost a 2% decrease in block crime rates. This difference is negligible but is important to notice. Because of this difference, it cannot be the case that the coefficient of C_{vt} is only a result of the possible data gap in 2012 and 2016.

VII. Conclusions and Future Directions

My results indicate that the introduction of an affordable housing covenant has no impact on block crime when introduced. From my single-family blocks v. multi-family blocks analysis, I also show that an affordable housing covenant can be approved in areas of both low-density and high-density zoning without increasing reported crime. My results even suggest that the affordable housing introduction of affordable housing covenants in single-family areas could decrease crime. This result is striking; perhaps less dense areas could benefit from affordable housing developments. However, due to the differences in the sign and significance of the primary coefficients in my primary and secondary models, I cannot definitively say that affordable housing decreases crime in areas of single-family areas. Finally, my time-varying controls relay that when I control for the distance between newly developed affordable housing covenants, the treatment effect does not change substantially nor does its significance change. This implies that the concentration of affordable housing may not be as large of a determinant of crime as previous literature suggests.

There are limitations to my empirical strategy. For one, I assigned treatment by the year the affordable housing covenant is established. A block with an affordable housing covenant does not mean a block contains developed and occupied affordable housing units. Therefore, an ideal assignment of treatment would be the year in which affordable housing units were developed and occupied. However, this tenant-level data is difficult to retrieve. Another easier alternative is to

assign treatment by the year the certificate of occupancy of the structure is established. However, oftentimes, the certificate of occupancy may occur before the affordable housing covenant has been established, which would not be reflective of the ideal treatment of interest. For future study, I plan to assign treatment by the year the affordable housing covenant is established but using jurisdiction-level entitlement and building permit data to exclude jurisdiction-level not been developed yet. These excluded covenants (and therefore excluded blocks) were not yet treated in actuality. With this treatment assignment, I will now know which covenants are already developed and possibly creating an impact in the surrounding neighborhood.

There also exists an attribution error in my methods. Perhaps I am attributing any changes in crime that result from affordable development to development more broadly, which reflects increasing density. This attribution would also better explain the differences in my treatment effect between single-family areas and multi-family areas. Newly available data in the coming years could potentially resolve this attribution error. In 2020, Los Angeles adopted an inclusionary ordinance in the East Los Angeles/Gateway and South Los Angeles submarkets. This means that development requesting to approve five or more units are subject to building affordable units or paying an in-lieu fee ("Inclusionary Housing Ordinance"). In the coming years, I can find the blocks that receive affordable units through the inclusionary program and blocks that would have otherwise received affordable units but are only receiving market-rate units. The blocks that receive market-rate units can serve as a more comparable comparison group for my difference-in-differences model. This empirical design will also bring more clarity to the results of my multi-family blocks vs. single-family blocks analysis. This is because I attribute the statistically significant treatment effect in single-family areas due to increases in density.

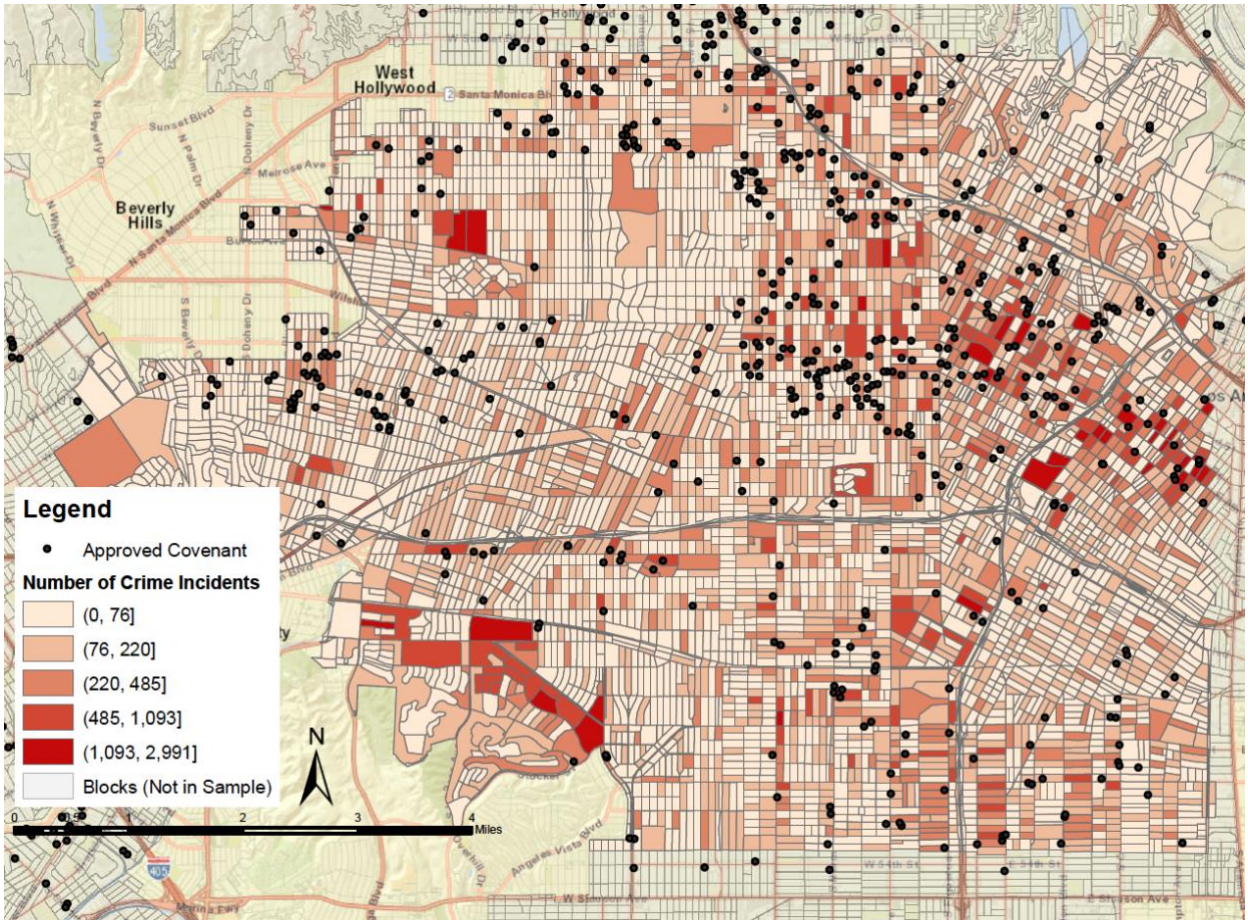
Los Angeles, and California more broadly, is in a housing crisis. Ranked as the fourth most expensive city in the world, Los Angeles needs affordable housing for its constituents. However, perceptions around affordable housing have a monumental impact on policy because of the participatory component of the approvals process for development. This paper generates empirical evidence to inform public opinion on affordable housing. I address the perception that affordable housing increases reported crime. This claim is not supported by my analysis.

VIII. Appendix

Table 13: Count of crime-reported incidents by month and year

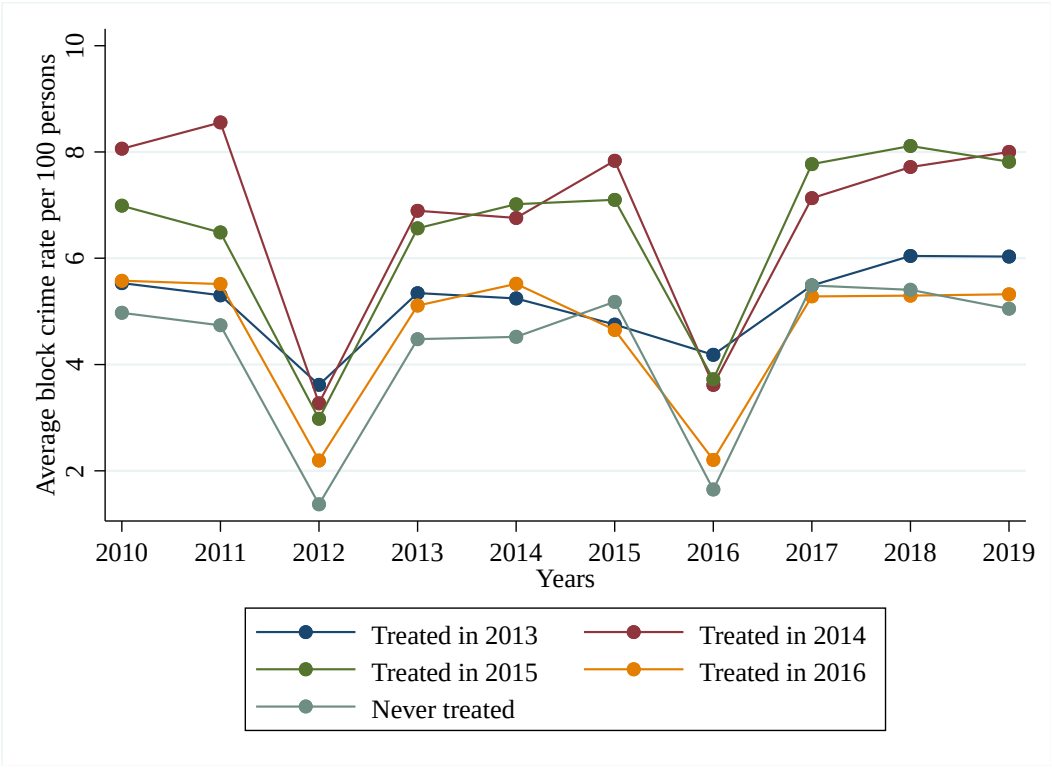
Month	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Jan.	19,469	18,097	5,963	16,765	16,181	18,386	6,816	19,671	19,401	18,454
Feb.	16,021	14,677	5,543	14,061	13,681	16,006	6,403	17,110	17,141	16,258
Mar.	18,127	16,939	5,717	16,216	15,601	18,005	6,571	19,411	19,027	18,799
Apr.	17,771	16,433	5,728	15,719	15,408	16,944	6,754	18,752	19,132	17,923
Jul.	17,716	16,938	6,163	16,595	16,699	17,939	6,846	19,452	19,941	18,642
Aug.	17,672	17,014	5,384	16,097	16,360	17,546	6,574	19,043	19,271	18,335
Sept.	17,851	17,268	5,233	16,630	17,222	18,685	6,990	20,163	19,833	19,074
Oct.	17,294	17,001	5,538	17,427	17,044	18,990	6,840	19,720	19,723	18,911
Nov.	16,628	16,241	5,248	16,220	16,743	18,276	5,889	19,420	18,445	17,990
Dec.	17,616	17,030	5,335	16,236	17,301	19,203	6,177	20,400	19,521	18,198

Figure 14: Spatial concentration of crime incidents by U.S. Census Block and affordable housing covenants from years 2010 to 2019



Map is in Zone 7 Los Angeles State Plane Projection (ESPG: 2229).

Figures 15 and 16: Evolution of average block crime rate by treatment status



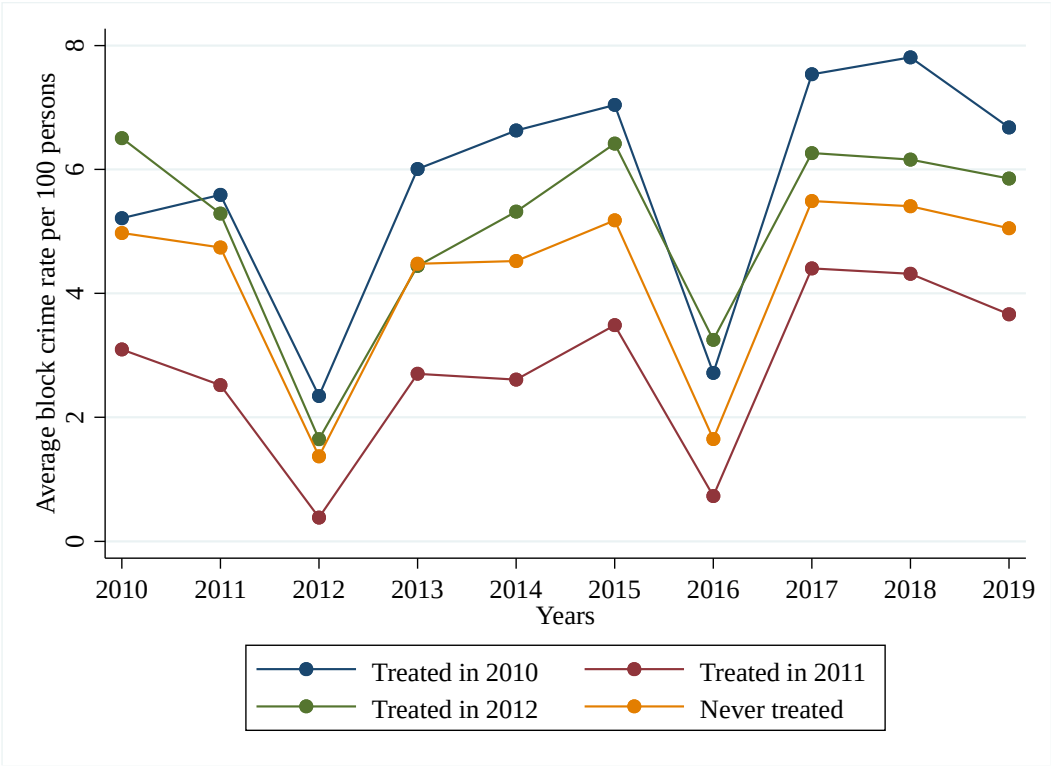


Table 17: Regression Estimations for Model (2)

	Coefficients
D_{bt}^{-3}	0.0903
	(0.321)
D_{bt}^{-2}	0.170
	(0.313)
D_{bt}^{0}	-0.140
	(0.312)
D_{bt}^{1}	-0.127
	(0.335)
D_{bt}^{2}	-0.139
	(0.359)
D_{bt}^{3}	0.366
	(0.391)
$\mathbf{X_{bt}}$ Included?	Yes
Observations	181,190
R-squared	0.731

Note: Dependent variable: block crime rates per 100 persons. Table presents the robust standard errors in parentheses. No coefficients are statistically significant.

Table 18: Regression Estimations for Model (2) for Blocks that Permit Single-Family Development and for Blocks that Permit Multi-Family Development

	Coefficients	
	Permits SF	Permits MF
D_{bt}^{-3}	0.0367	0.0741
	(0.558)	(0.286)
D_{bt}^{-2}	-0.291	0.123
	(0.540)	(0.279)
D_{bt}^{0}	-0.410	-0.218
	(0.522)	(0.272)
D_{bt}^{1}	-0.408	-0.120
	(0.560)	(0.292)
D_{bt}^{2}	-0.851	-0.0309
	(0.585)	(0.314)
D_{bt}^{3}	-0.263	0.466
	(0.623)	(0.344)
$\mathbf{X_{bt}}$ Included?	No	No
Observations	114,545	90,959
R-squared	0.611	0.765

Note: Dependent variable: block crime rates per 100 persons. Table presents the robust standard errors in parentheses. No coefficients are statistically significant.

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