Responding to Gentrication?

311 Call Resolution Times and Neighborhood Change in Washington, D.C.

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Abstract

This is our informative abstract of fewer than 200 words. It describes what we investigate, how we investigate it, and what we find.

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1 Introduction

In this section, we introduce the reader to the phenomenon we investigate. We describe the way in which our analysis contributes to an important intellectual debate, or how it answers a pressing political or social question. We introduce our hypotheses, data, and results. We signpost for the reader what's coming in the rest of the paper.

2 Defining Gentrification

Gentrification usually refers to the socioeconomic and demographic changes that occur when relatively disadvantaged neighborhoods experience an influx of more privileged residents. While there is no universal definition in the academic literature, quantitative measures of gentrification often rely upon a combination of variables, such as median household income, median home value, median rent, percent of housing stock less than 20 years old, home ownership rate, poverty rate, percent of adults over 25 with a Bachelor's degree, race, and age (see Bhavsar, Kumar, and Richman (2020) for metastudy). As described by Bhavsar, Kumar, and Richman (2020) and illustrated by Freeman (2005) and Maciag (2015), many studies adopt a two-stage approach in classifying an area as gentrified or not. The first stage involves determining whether a neighborhood — usually a census tract — is eligible to gentrify, meaning that it is below a certain percentile with respect to the selected variables, when compared with the surrounding city or metro area (an area that is already affluent is not considered to have gentrification potential). The second stage involves determining whether the neighborhood has actually gentrified after a certain period of time, meaning that it has experienced relative growth that exceeds a certain percentile, when compared with the surrounding area.

Our definition uses median household income, median home value, and educational attainment as criteria for gentrification. Our cutoff for eligibility is below the 40th percentile, while the threshold for gentrification is relative growth above the 50th percentile, with economic indicators adjusted for inflation. This definition has both a theoretical and a practical basis: our criteria capture important aspects of gentrification and our eligibility cut-offs make for a rigorous test, while also resulting in a sufficient number of tracts classified as gentrified for us to proceed with the study. By our definition, there were 54 census tracts eligible for gentrification in 2012, out of a total of 179 census tracts in DC. By 2019, 15 of these 54 had gentrified, while 39 remained ungentrified. Notably, most of the gentrification occurred in the District's northeast quadrant, while most of eligible tracts that did not gentrify were east of the Anacostia River.

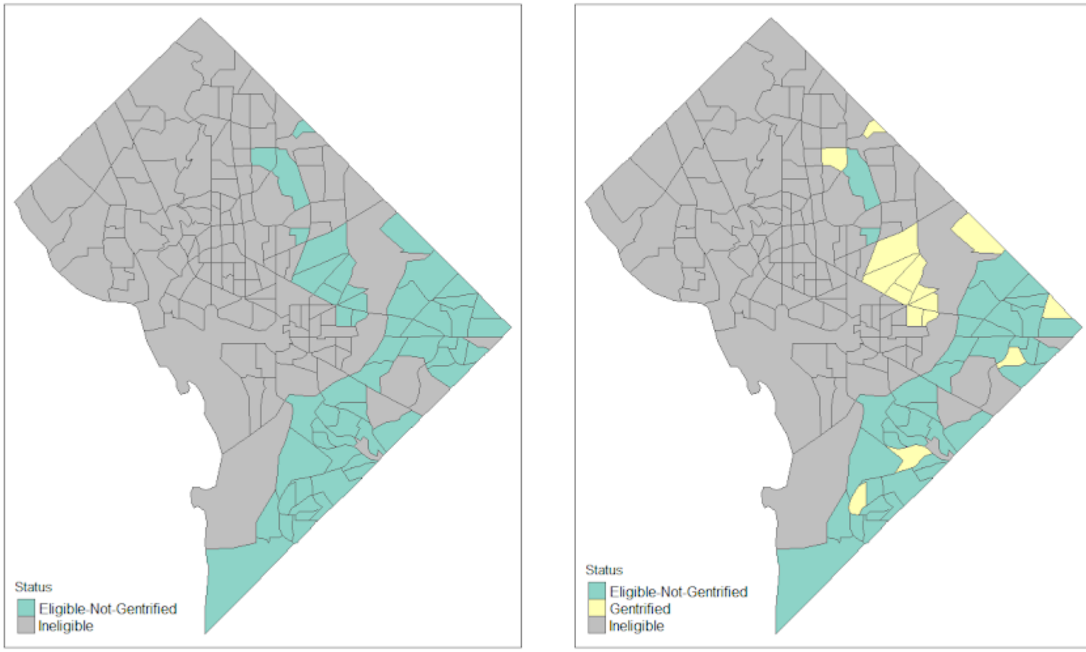

Figure 1: 2012 Census Tracts (left) and 2019 Census Tracts (right)

3 311 Call Data

We obtained data on 311 service requests in the District from Open Data DC. While data is available from 2009 through the present, we chose 2012 through 2019 as our study period. We selected 2012 because that was the year when DC started recording large call volumes; there were 250,000 calls or more each year from 2012 onwards, whereas the years prior to 2012 had fewer than 35,000 calls each. We selected 2019 as our end point because that was the last full year before the COVID-19 pandemic, which may have impacted both service requests and the indicators used to determine whether a neighborhood was gentrified. By using the widest time interval for which we were confident that we could make a fair comparison, we aimed to maximize the number of gentrified tracts in our study.

The 311 data contained the type of service requested, the location where the service was required, the date of the request, the date and time the request was received, and the date and time the request was resolved. We calculated resolution time by finding the difference between the date received data from the date resolved. Although there are more than 200 different service codes, some of which vary from year to year, we selected 15 of the 20 most common call types for this analysis, excluding calls that were more likely to have been placed by visitors to a tract than residents (e.g., parking meter repair) and service requests that did not require a physical response (e.g. D.C. government information). The selected call types and their combined frequencies in 2012 and 2019 are shown below in Figure 2.

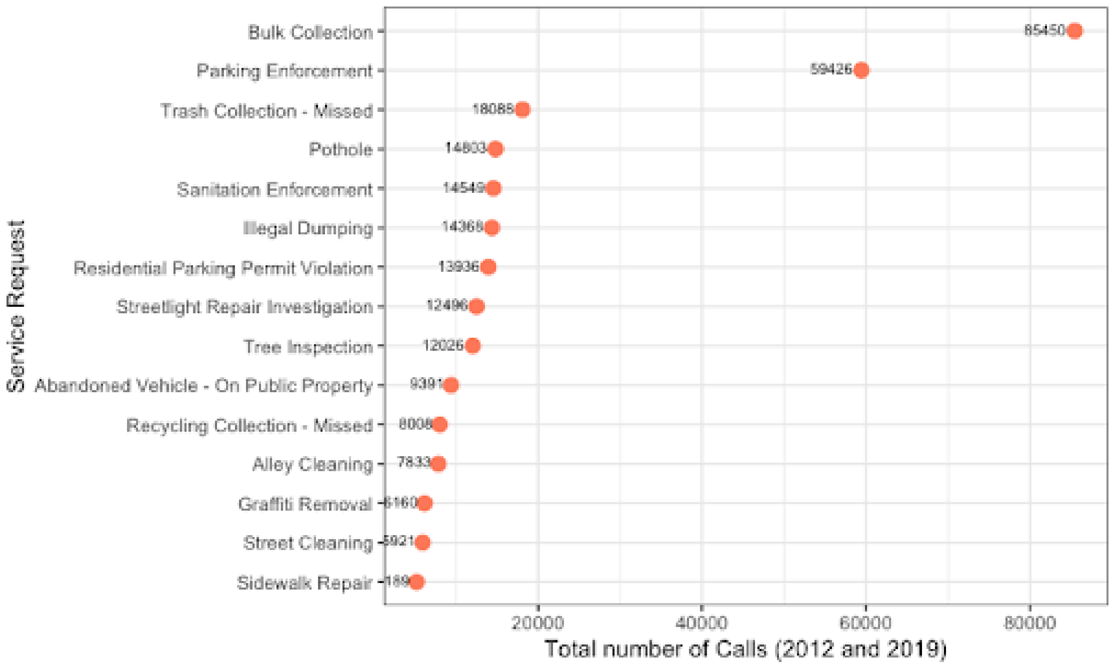

Figure 2: Most Frequent Call Types (2012 and 2019)

Close inspection of resolution times across all selected call types revealed irregularities in the 2012 data — while most calls had resolution times of 32 days or less, there were more than 800 observations with resolution times of 500 days or more. Furthermore, there was a large gap, with no resolution times between 32 and 205 days (see Figure 3 (left)). Finally, many of the service requests were resolved on the same dates, suggesting that they were closed on an arbitrary timeline, rather than when the service was actually completed. Based on this discovery, we decided to filter out observations for which the resolution time was greater than 31 days in both 2012 and 2019. This decision led us to discard about 6.8% percent of our data, including all requests for sidewalk repair, and left us with about 70,000 observations for analysis. We are more confident that the remaining data are reliable, based on the distributions shown in the histograms in Figure 3 (right).

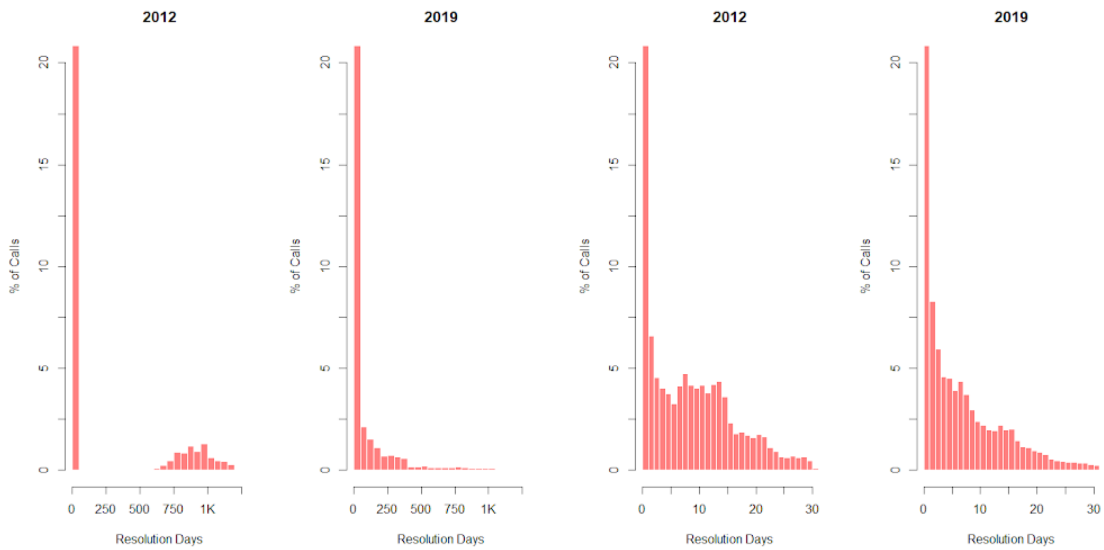

Figure 3: Before Filter (left) and After Filter (right)

4 Changes in Resolution Time by Gentrification Status

As Figure 4 illustrates, call frequency increased dramatically between 2012 and 2019, yet call resolution times improved. Whereas the call resolution times were markedly better for ineligible tracts than gentrified or eligible-not-gentrified tracts in 2012, resolution times seem to have been more equitable in 2019

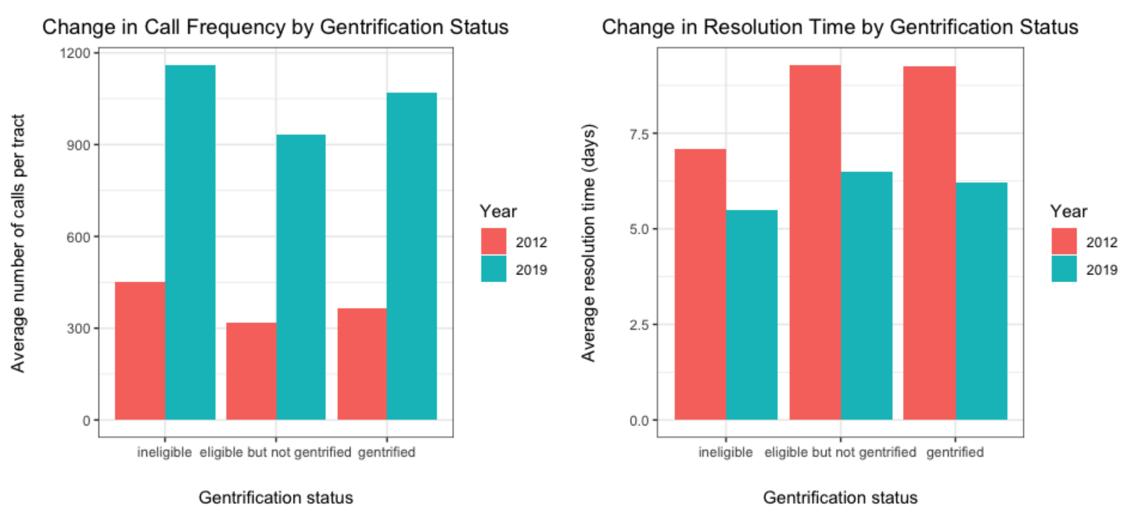

Figure 4: Change in Call Frequency (left) and Change in Resolution Time (right)

Below, Figure 5 shows that resolution times followed roughly the same trend across gentrification statuses for every year from 2012 to 2019. Ineligible tracts experienced a 1.57-day decrease in resolution time, eligible-but-not-gentrified tracts experienced a 2.80-day decrease in resolution time, and gentrified tracts showed a 3.02-day decrease in resolution time. That is to say, the resolution time for gentrified tracts improved the most. However, the ineligible tracts, which were the most affluent tracts as of 2012, started and ended with the best resolution times.

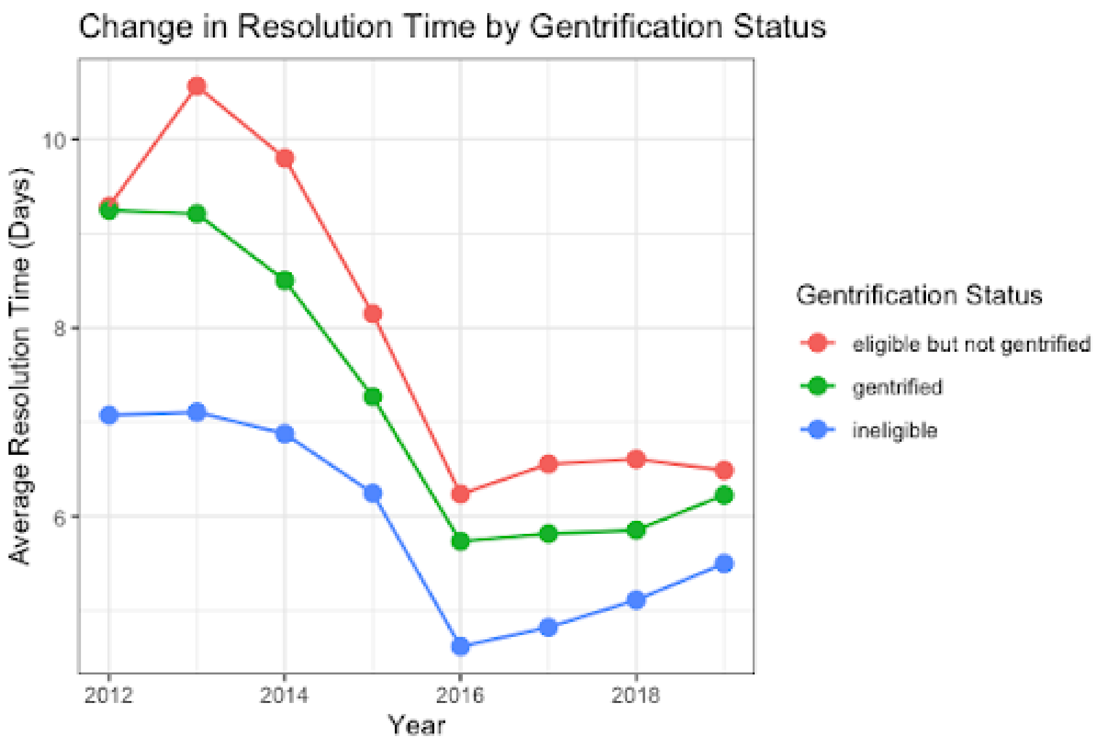

Figure 5: Change in Resolution Time by Status (2012-2019)

5 Difference-in-Difference Analysis

We used a series of difference-in-difference models to determine whether gentrification had a statistically significant effect on call resolution times. The plots below show the changes in resolution times from 2012 to 2019, for tracts that gentrified and tracts that were eligible to gentrify but did not. The counterfactual in each plot shows what would have happened in the gentrified tracts had gentrification not occurred (with the assumption that the trend in the gentrified tracts would have paralleled the trend in the eligible-but-not-gentrified tracts). The difference between the 2019 value for the gentrified tracts and the 2019 value for the counterfactual represents the effect of gentrification. (Data Science for Public Service 2019)

A difference-in-difference model requires a treatment group and a control group, as well as a pre-intervention condition and a post-intervention condition. Treating the gentrified tracts as the treatment group, the eligible-but-not-gentrified tracts as a control group, and gentrification itself as the intervention, we used regression to generate the following equation:

$$\text{Resolution Days}_i = \beta_0 + \beta_1(\text{Treatment}_i) + \beta_2(\text{Post}_i) + \beta_3(\text{Treatment:Post}_i) + \epsilon_i$$

where β_0 represents the intercept, β_1 represents the difference between the treatment and control group before gentrification, β_2 represents the difference in the control group before and after gentrification, and β_3 represents the difference-in-difference estimator (Data Science for Public Service 2019). The coefficients for all models can be found in the appendix at the end of this paper.

We first present a pair of difference-in-difference models based on 54 tracts — the 15 that were gentrified and the 39 that were eligible but not gentrified — including one model in which we controlled for call type and one in which we did not. Next, we present a similar pair of models in which 10 gentrified tracts were matched with 10 eligible-but-not-gentrifed tracts based on pre-gentrification attributes, again controlling and not controlling for call type. Finally, we present models for the two most common call types — bulk collection and parking enforcement — with matching.

5.1 Difference-in-difference models without matching

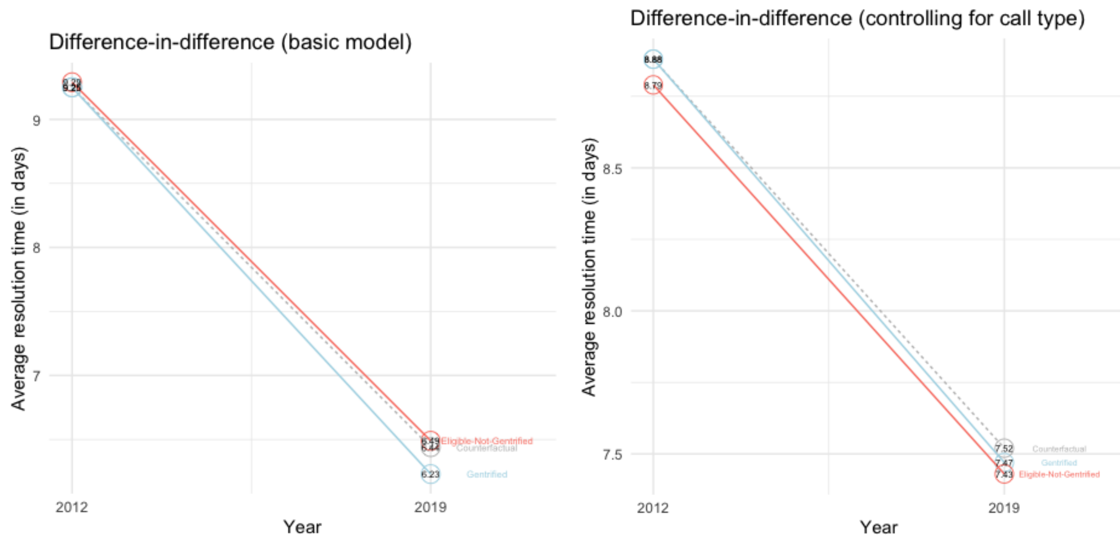

Figure 6: DiD - Basic (left) and DiD - Controlling for Call Type (right)

In the basic model (Figure 6 (left)), in which we did not control for call type, the difference-in-difference estimate is -0.22 days, suggesting that resolution times in gentrified tracts were about 5 hours and 17 minutes faster than they would have been had gentrification not occurred. However, this model has little statistical significance (p = 0.0964) and the confidence interval (- 0.48 days, .04 days) straddles 0.

Controlling for call type diminishes what little statistical significance there is. In Figure 6 (right), the difference-in-difference estimate is -0.05 days, or about 1 hour and 12 minutes, with a confidence interval (-0.24 days, 0.14 days) that again straddles 0. The p-value for the model that controls for call type is p = 0.624. Here, it is clear that gentrification may not have impacted resolution time at all, and it is likely that the mix of calls largely accounts for any difference in the rate of improvement between gentrified and eligible-but-not-gentrified tracts.

5.2 Difference-in-difference models with matching

Matching allows for clearer insights into the impact of gentrification on response times by creating a more meaningful control group. By identifying the 10 gentrified tracts and 10 eligible-but-not-gentrified tracts that were most similar to each other as of 2012, we were able to zero in on the tracts from which we could learn the most.

There are several ways to go about matching. Two of the most commonly used methods are propensity score matching and Mahalanobis distance matching. Propensity score matching, in this context, involves pairing like census tracts using a propensity score calculated by reducing pre-gentrification characteristics for each tract (MHI, median home value, and percent of adults over 25 with a Bachelor's degree) to a single dimension. This means that matched pairs will be close in propensity scores, but will not necessarily be similar with respect to a particular characteristic. On the other hand, Mahalanobis distance matching entails matching pairs of census tracts based on a Mahalanobis distance, similar to a Euclidean distance, calculated using the same pre-gentrification characteristics. With this method, each paired tract will be as similar as possible with respect to all of the attributes used for matching. (King and Nielsen 2019)

Our approach to matching blended the two methods above by utilizing the MatchIt package in R and applying the ‘genetic’ method (see Sekhon (2011) for details on GenMatch()). This allowed us to balance our pre-gentrification tract attributes. Figure 7 (left) below shows the 10 matched gentrified tracts and the 10 matched eligible-but-not-gentrified tracts, while Figure 7 (right) shows the balance achieved with regard to the pre-gentrification attributes and the distance measure for the matched tracts as compared to all 54 tracts that were deemed eligible in 2012.

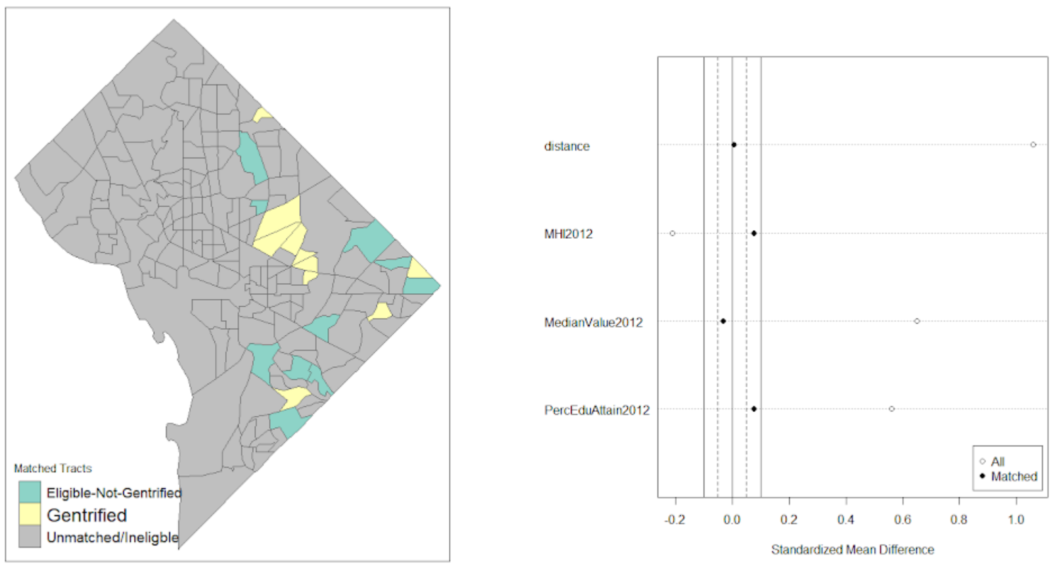

Figure 7: Matched Census Tracts (left) and MatchIt Plot (right)

Although matching reduced the number of tracts to 20, we still had more than 25,000 observations to use in our second pair of difference-in-difference models. The coefficients for these models can be found in the table provided in the appendix.

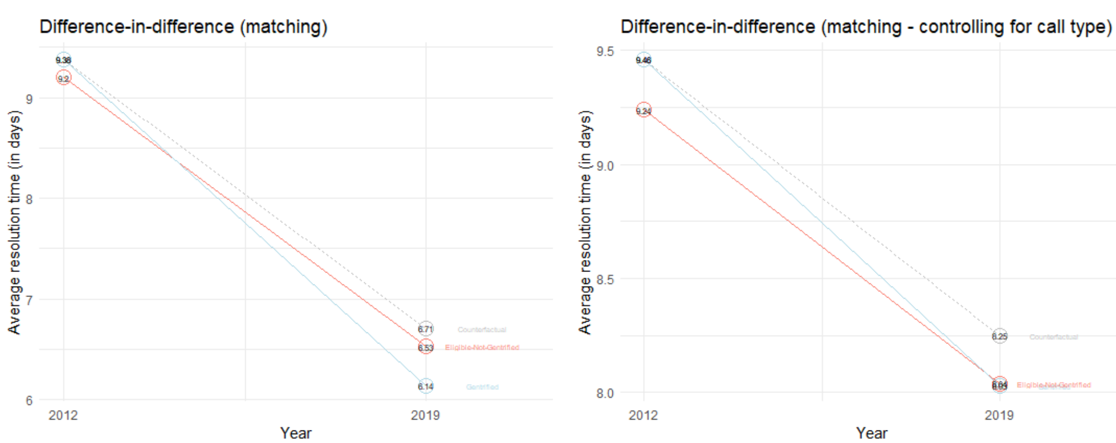

Figure 8: DiD - Basic with Matching (left) DiD - Controlling for Call Type with Matching (right)

In the basic model with matching (Figure 8 (left)), in which we did not control for call type, the difference-in-difference estimate is -0.57 days, or about 13 hours and 41 minutes faster. This model has more statistical significance (p = 0.0065) than the basic model without matching (Figure 6 (left)) and has a confidence interval of (-0.98 days, -0.16 days), which does not straddle 0. This suggests that resolution times in tracts that gentrified by 2019 were a little more than a half a day faster than they would have been had gentrification not occurred, assuming that the trend in the gentrified tracts would have paralleled that of the eligible-but-not-gentrified tracts that were most similar to them in 2012.

However, when controlling for call type, the statistical significance is again diminished. In Figure 8 (right), the difference-in-difference estimate is -0.22 days, or about 5 hours and 17 minutes, with a confidence interval (-0.52 days, 0.08 days) that again straddles 0. The p-value for the model with matched tracts that controls for call type is p = 0.149. It again appears that gentrification may not have had any effect on resolution time, and any difference in the rate of improvement between gentrification statuses can be largely attributed to the mix of calls.

5.3 Difference-in-difference models for individual call types with matching

6 Discussion

We remind the reader what this paper was about, why it was important, and what we found. We reflect on limitations of the data or methods. If we have specific advice for someone picking up where we leave off, we provide that guidance. We avoid making trite statements like "more research should be done".

7 References

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8 Appendix

Table 1 - Difference-in-difference models without matching

	Resolution Days	
	Basic	Controlling for Call Type
Intercept	9.289***	8.785***
	(0.063)	(0.103)
Treatment	−0.044	0.092
	(0.113)	(0.084)
Post	−2.801***	−1.355***
	(0.073)	(0.055)
Alley Cleaning		3.954***
		(0.142)
Bulk Collection		4.071***
		(0.098)
Graffiti Removal		1.431***
		(0.324)
Illegal Dumping		2.831***
		(0.121)
Parking Enforcement		−7.201***
		(0.103)
Pothole		1.354***
		(0.132)
Recycling Collection - Missed		−4.552***
		(0.169)
Residential Parking Permit Violation		−7.013***
		(0.124)
Sanitation Enforcement		−3.918***
		(0.121)
Street Cleaning		3.429***
		(0.158)
Streetlight Repair Investigation		−4.169***
		(0.137)
Trash Collection - Missed		−4.782***
		(0.122)
Tree Inspection		−4.787***
		(0.140)
Treatment:Post	−0.218*	−0.048
	(0.131)	(0.098)
Observations	70,381	70,381
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 2 - Difference-in-difference models with matching

	Resolution Days	
	Basic	Controlling for Call Type
Intercept	9.199***	9.243***
	(0.130)	(0.184)
Treatment	0.177	0.217
	(0.182)	(0.133)
Post	−2.667***	−1.207***
	(0.150)	(0.112)
Alley Cleaning		3.344***
		(0.245)
Bulk Collection		3.969***
		(0.170)
Graffiti Removal		0.360
		(0.482)
Illegal Dumping		2.534***
		(0.205)
Parking Enforcement		−7.839***
		(0.177)
Pothole		0.232
		(0.226)
Recycling Collection - Missed		−5.219***
		(0.276)
Residential Parking Permit Violation		−7.588***
		(0.205)
Sanitation Enforcement		−4.351***
		(0.207)
Street Cleaning		2.905***
		(0.266)
Streetlight Repair Investigation		−4.749***
		(0.237)
Trash Collection - Missed		−5.344***
		(0.209)
Tree Inspection		−5.407***
		(0.241)
Treatment:Post	−0.570***	−0.221
	(0.209)	(0.154)
Observations	25,475	25,475
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 3 - Difference-in-difference models for individual call types with matching

	Resolution Days	
	Bulk Collection	Parking Enforcement
Intercept	13.160***	0.436***
	(0.147)	(0.097)
Treatment	0.219	0.114
	(0.206)	(0.133)
Post	−1.163***	−0.059
	(0.183)	(0.107)
Treatment:Post	−0.151	−0.041
	(0.256)	(0.147)
Observations	8,369	4,555
Note:		*p<0.1; **p<0.05; ***p<0.01