

Social Data Analysis I, Fall 2022
Final Project
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Research Question

As we know it, major metropolitan cities across the United States still contain incredibly high levels of racial, social, and economic segregation, even after laws were passed meant to mitigate it (ex. Fair Housing Act of 1968). I came into graduate study deeply interested in understanding this segregation, the conditions that created it, the mechanisms that perpetuate it, and the consequences of it. For the purpose of this project, I decided to look at the spatial organization of New York City and the ways it's tied to characteristics like race and socioeconomic status. By exploring how neighborhoods in New York City differ in their access to resources like city services, quality education, or even hot water, I might be able to uncover the ways city government is perpetuating racial and economic inequality, not by accident but rather through a set of policy decisions.

The question I decided to ask is one where we understand the spatial and racial dynamics of city service requests and their responses. This research question was further fueled by the discovery of NYC Open Data, an online data portal that includes data on New York City for analysis to be done for and by New Yorkers. With NYC Open Data I was able to find a dataset that collects all 311 service request records from 2010 to present: over 3 million records from all five boroughs, with complaint types ranging from noise in the park to heat or hot water repair. By exploring the data preliminarily, I was intrigued to learn more about the possible spatial variation in what types of complaints were made, how long it took the city to respond, and even what types of agencies were dispatched to address the complaint (i.e. Department of Housing vs. NYPD).

While this started out as a neighborhood research question, I quickly wanted to know how uneven access to resources spatially relates to unequal access to resources racially and economically. Through all of these thoughts, my ultimate research question began to formulate: What is the relationship between neighborhoods, racial composition of those neighborhoods, and access to city services in New York City?

What we know

A brief literature review on New York City neighborhoods and 311 service requests provided some initial insight. The [NYC City Council](#) is a good initial supplementary source, highlighting interesting descriptive statistics and even providing some accessible visualizations. For instance, one of the first facts I discovered was that

311 service requests are predominantly conducted either by phone call or website visits, rather than by using the downloadable phone application or by sending a text message. This may have implications in terms of how different communities have access to different types of technology. Other initial data points included that most service requests regard illegal parking and noise complaints – to be expected in New York City – and that most frequently, the responding agency was the New York City Police Department, as opposed to the Departments of Housing, Sanitation, or Transportation.

Aside from these descriptive statistics and limitations, other research that stood out include an article in *Nature* that uses [311 service requests as indicators of neighborhood distress and opioid use](#) and an article in the *Journal of Regional Science* using evidence from [311 calls to understand the geography of unsheltered homelessness](#). Specifically, these articles used 311 request data as predictors of possible public health outcomes and social determinants, which served as useful validation that exploring 311 data spatially can and does prove useful in discovering indicators of social phenomena.

That being said, a last piece of useful literature in the *Urban Affairs Review* investigated 311 call data itself by exploring its [promises and pitfalls](#). In quantitative and computational work, data ethics, transparency, and reliability are constant considerations in the researcher's mind; this project was no exception. The main argument in the *Urban Affairs Review* is understanding that 311 request data is not always a useful proxy and has specific limitations when interpreted as a generic measure of political engagement or neighborhood condition, and should be used intentionally and accordingly.

Data & methods

As mentioned, the dataset I decided to use comes from one of the more popular repositories for analysis done on and for New York City residents: [NYC Open Data](#). NYC Open Data is “free public data published by New York City agencies and other partners... an opportunity to engage New Yorkers in the information that is produced and used by City government.” More specifically, I discovered a popular dataset named [311 Service Requests](#) from 2010 to present.

The description of the dataset is short: “All 311 Service Requests from 2010 to present. This information is automatically updated daily.” 311 service requests are requests using the phone number 311 – a non-emergency phone number that people can contact to find information about city services, make complaints, or report problems like graffiti or road damage. Examples of 311 service requests may also include soliciting responses to illegal parking, noise complaints, or even heat or hot water issues. The dataset itself has 41 columns and over 3 million rows, each row being a single 311 service request in the City of New York since the year 2010. For the purpose of this project, however, I decided to focus on 311 service just during the summer of 2022; exploring all 311 service requests would've been too computationally intensive, and focusing on the summer as opposed to other months of the year felt appropriate because that's when

New Yorkers are interacting the most, kids are out of school, and city services are often solicited. Examples of column variables include service request open date, service request close date, incident zip code, location type, city, borough, and city agency that responded to the request.

In order to include demographic characteristics of the neighborhoods where the 311 service requests were made, I merged a second dataset from NYC Open Data named *Demographic Statistics by Zipcode*. I was able to append this zipcode-specific demographic data to the 311 service request dataset by using R's `left_join` function on the zipcode variable. The new dataset now contains information on the 311 service request, what type of request was made, where and when it was made, what government agency responded, how long it took them to close the case, and the racial makeup (in percentages) of the neighborhood where the case occurred.

I am primarily interested in exploring the geographic and demographic variables included in my merged 311 Service Request dataset. My hypothesis is that there exists a relationship between the geographic location, racial makeup of that location, and certain characteristics of the 311 Service Requests, including but not exclusively:

- *Case created date: vs. case closed date:* does service request response time vary by geographic location?
- *Racial makeup of the neighborhood where the complaint was made:* do we see differences in complaints and their responses depending on the racial makeup of the neighborhood?
- *Complaint type:* what types of complaints are most frequent and where?
- *Agency that responded:* do different agencies respond more quickly in different neighborhoods?

To understand the association between variables mentioned above, I'll be using linear multivariate regression, with case completion time as the dependent variable and all other variables as predictor variables. Towards the end, I'll also be exploring possible statistical interactions between variables.

With this merged data, I'll be able to explore my research question: *What is the relationship between neighborhoods, racial composition of those neighborhoods, and access to city services in New York City?* My hypothesis is that neighborhoods that are predominantly Black, Latinx, and/or majority non-U.S. citizen have longer response times to 311 calls and are therefore underserved by city services.

Results

Simple single regression(s)

I started with some simple single regressions between the main variables of interest, including the case completion time, the type of complaint that was issued, the racial makeup of the neighborhood (i.e. percentage Black, percentage Latinx, percentage

white), and the agency that responded. Some initial results, all statistically significant, include:

- Social Conflict complaints (ex. Noise in the park) get responded to faster than City Service complaints (ex. Hot water issue) by 16,000 minutes (11 days) on average
- NYPD is by far the fastest responding agency, as opposed to the Departments of Sanitation, Housing, or Public Transportation
- For every 1% increase in the Black population in the neighborhood, response time goes down (faster) by 22 minutes on average
- For every 1% increase in the Latino population in the neighborhood, response time goes up (slower) by 5 minutes on average
- For every 1% increase in the White population in the neighborhood, response time goes up (slower) by 13 minutes on average

Initially interpreting these results, I was a bit worried that my hypothesis proved wrong and that increased percentages in the Black population actually resulted in cases being completed faster. While this also might make sense, due to hypervigilance and surveillance associated with policing Black communities, I remained skeptical. My intuition was telling me that Black communities, while surveilled, continue to be underserved by city services. Once I began controlling for specific variables in the multivariate regression, the story began to flip.

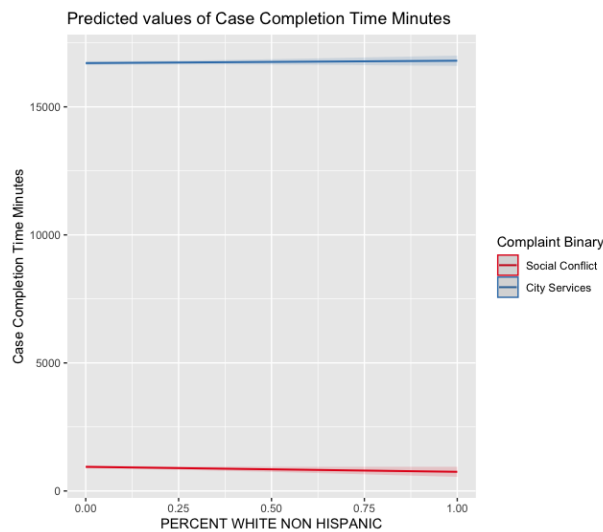
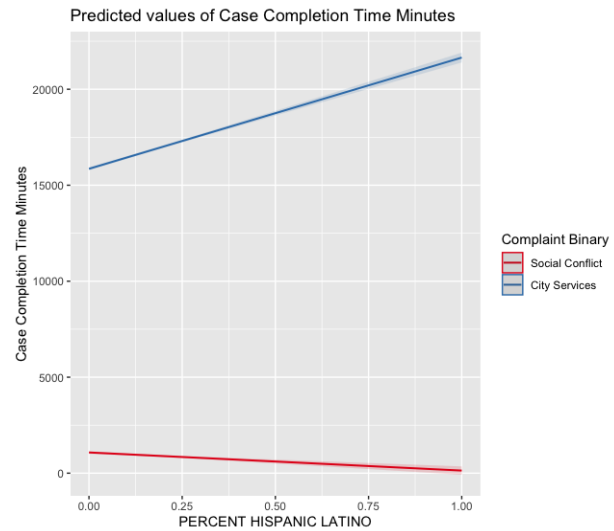
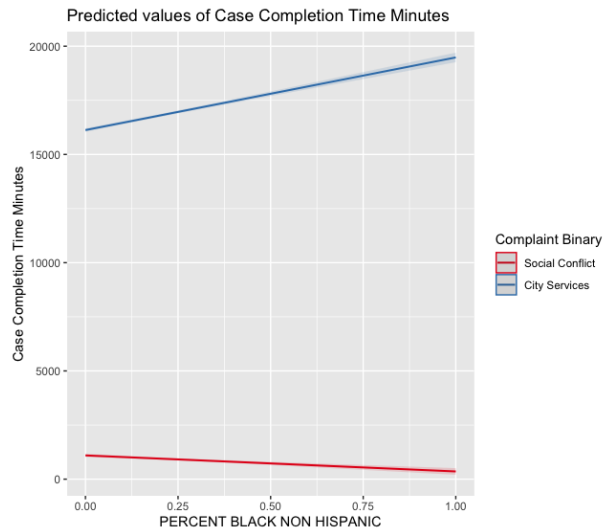
Multivariate regression(s) & interactions

Proceeding with multivariate regression allowed me to control for certain variables as well as identify possible interactions. What I discovered is that while single regression shows that increases in Black populations are associated with faster response times, once I control for complaint type and responding agency, increases in Black populations are actually associated with slower response times. More specifically, findings from the multivariate regression include:

- For the same types of complaints and the same responding agency, a 1% increase in Black population in the neighborhood was associated with response times getting larger (slower) by 6 minutes on average
- For the same types of complaints and the same responding agency, a 1% increase in Latino population in the neighborhood was associated with response times getting larger (slower) by 11 minutes on average
- For the same types of complaints and the same responding agency, a 1% increase in White population in the neighborhood was associated with response times getting lower (faster) by 2 minutes on average

As we can see, once we control for the same types of complaints and the same responding agency, Black and Latino population increases are associated with slower city service responses, while White population increases are associated with faster city service responses.

More interesting however was introducing interactions to the dataset, which is best illustrated by the plots below:



Interpreting these plots can best be understood as: for increases in the Black population in the neighborhood, city services complaints (ex. Heat or hot water) get responded to slower on average, while social conflict complaints (ex. Noise in the park) get responded to faster on average. For increases in the Latino population in the neighborhood, the story is the same, but the effect is actually more drastic. For white population increases however, social conflict and city service complaints get responded to with relative consistent timing.

Conclusion

Through all of these analyses, all statistically significant, I was able to confidently conclude that while single regression tells one story, multivariate regression and interactions tell another. More specifically, increases in Black or Latino populations in neighborhoods cause case completion times to increase (get slower) when controlling for the same types of complaints that are made and the same government agency that is dispatched to respond. This is not the case with increases in the White population in the

neighborhood, where typically, case completion times are lower (faster) the larger the white population in the neighborhood.

Even more captivating though was the finding via statistical interactions. I discovered that the case completion time also varies in terms of the type of complaint the city is responding to and how large the Black or Latino populations in the neighborhood are. Increases in Black or Latino populations are associated with city service complaints (ex. Heat and hot water) taking longer for the city to respond to, while the same population increases are associated with social conflict complaints (ex. Noise in the park) being responded to faster, most often by the NYPD. The plots in the Results section of this paper best illustrate this phenomenon. This suggests another hypothesis, that Black and Latino neighborhoods are underserved by basic city services but overserved by policing and surveillance services. Possible further research may include collecting 911 call records and comparing them to the 311 request analysis done here to understand how different types of city services are prevalent in different communities.

Appendix

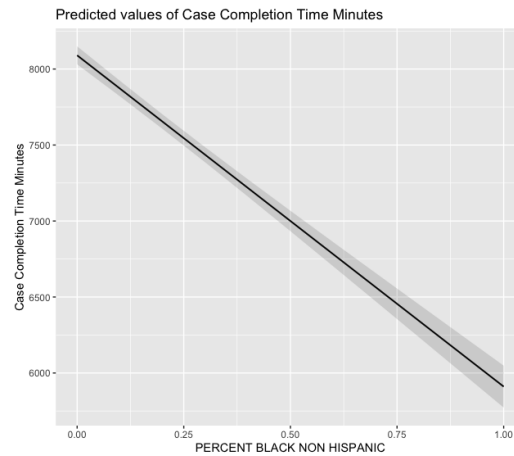
Single Regressions

```
Call:
lm(formula = Case.Completion.Time.Minutes ~ PERCENT.BLACK.NON.HISPANIC,
    data = joined_data_clean)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-8090  -7979  -6806  -2631  183266
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)      8090.12      30.08    269 <2e-16 ***
PERCENT.BLACK.NON.HISPANIC -2179.77      83.84    -26 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 18470 on 582077 degrees of freedom
(15498 observations deleted due to missingness)
Multiple R-squared:  0.00116, Adjusted R-squared:  0.001158
F-statistic: 675.9 on 1 and 582077 DF, p-value: < 2.2e-16
```

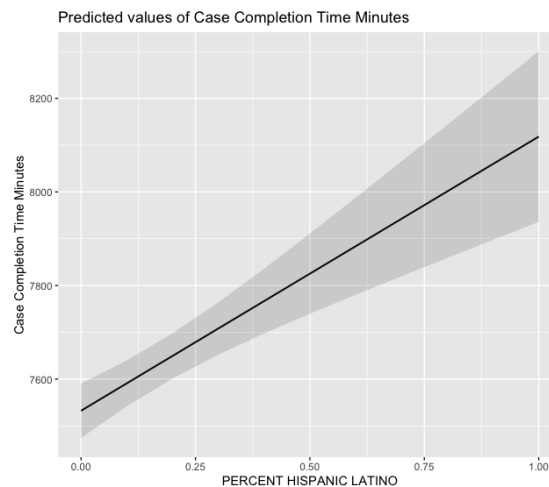


```
Call:
lm(formula = Case.Completion.Time.Minutes ~ PERCENT.HISPANIC.LATINO,
    data = joined_data_clean)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-8118  -7519  -7409  -2753  183823
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)      7532.44      29.64  254.143 < 2e-16 ***
PERCENT.HISPANIC.LATINO  585.71     106.77   5.486 4.12e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 18480 on 582077 degrees of freedom
(15498 observations deleted due to missingness)
Multiple R-squared:  5.169e-05, Adjusted R-squared:  4.998e-05
F-statistic: 30.09 on 1 and 582077 DF, p-value: 4.123e-08
```

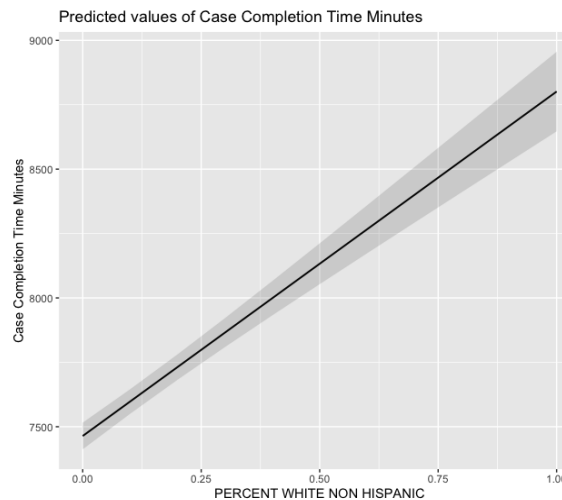


```
Call:
lm(formula = Case.Completion.Time.Minutes ~ PERCENT.WHITE.NON.HISPANIC,
    data = joined_data_clean)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-8801  -7436  -7314  -2790  183892
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)      7464.08      26.33  283.44 <2e-16 ***
PERCENT.WHITE.NON.HISPANIC 1337.20      85.32  15.67 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 18480 on 582077 degrees of freedom
(15498 observations deleted due to missingness)
Multiple R-squared:  0.0004218, Adjusted R-squared:  0.0004201
F-statistic: 245.6 on 1 and 582077 DF, p-value: < 2.2e-16
```



```
Call:
lm(formula = Case.Completion.Time.Minutes ~ Complaint.Binary,
    data = joined_data_clean)

Residuals:
    Min       1Q   Median       3Q      Max
-16611  -6644   -913   -756 182947

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    16611.25     33.27   499.2  <2e-16 ***
Complaint.BinarySocial Conflict -15657.40     43.84  -357.2  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 16750 on 597575 degrees of freedom
Multiple R-squared:  0.1759,    Adjusted R-squared:  0.1759
F-statistic: 1.276e+05 on 1 and 597575 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = Case.Completion.Time.Minutes ~ as.factor(Agency.Name),
    data = joined_data_clean)

Residuals:
    Min       1Q   Median       3Q      Max
-36889  -3448   -99    12 173619

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    32444.5     116.0   279.70  < 2e-16
as.factor(Agency.Name)Department of Consumer Affairs -30199.9     240.9  -125.38  < 2e-16
as.factor(Agency.Name)Department of Education         -19828.7     1383.4   -14.33  < 2e-16
as.factor(Agency.Name)Department of Environmental Protection -27302.2     143.2  -190.62  < 2e-16
as.factor(Agency.Name)Department of Health and Mental Hygiene -20069.8     280.0   -71.68  < 2e-16
as.factor(Agency.Name)Department of Homeless Services    -30613.5     180.8  -169.32  < 2e-16
as.factor(Agency.Name)Department of Housing Preservation and Development -9500.3     127.6   -74.47  < 2e-16
as.factor(Agency.Name)Department of Parks and Recreation  -3218.1     171.1   -18.81  < 2e-16
as.factor(Agency.Name)Department of Sanitation          -20446.2     132.8  -153.93  < 2e-16
as.factor(Agency.Name)Department of Transportation    -18930.4     141.2  -134.08  < 2e-16
as.factor(Agency.Name)New York City Police Department  -32308.6     119.0  -271.42  < 2e-16
as.factor(Agency.Name)Office of Technology and Innovation -6308.2     2054.7   -3.07  0.00214
as.factor(Agency.Name)Taxi and Limousine Commission    4444.8     267.4    16.62  < 2e-16

(Intercept) ***
as.factor(Agency.Name)Department of Consumer Affairs ***
as.factor(Agency.Name)Department of Education ***
as.factor(Agency.Name)Department of Environmental Protection ***
as.factor(Agency.Name)Department of Health and Mental Hygiene ***
as.factor(Agency.Name)Department of Homeless Services ***
as.factor(Agency.Name)Department of Housing Preservation and Development ***
as.factor(Agency.Name)Department of Parks and Recreation ***
as.factor(Agency.Name)Department of Sanitation ***
as.factor(Agency.Name)Department of Transportation ***
as.factor(Agency.Name)New York City Police Department ***
as.factor(Agency.Name)Office of Technology and Innovation **
as.factor(Agency.Name)Taxi and Limousine Commission ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15350 on 597564 degrees of freedom
Multiple R-squared:  0.3076,    Adjusted R-squared:  0.3076
F-statistic: 2.212e+04 on 12 and 597564 DF,  p-value: < 2.2e-16
```


Multivariate Regressions

Call:

```
lm(formula = Case.Completion.Time.Minutes ~ as.factor(Complaint.Binary) +  
    PERCENT.BLACK.NON.HISPANIC + as.factor(Agency.Name), data = joined_data_clean)
```

Residuals:

Min	1Q	Median	3Q	Max
-37151	-3387	-102	46	174039

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	32553.20	117.82	276.294
as.factor(Complaint.Binary)Social Conflict	1490.80	93.96	15.867
PERCENT.BLACK.NON.HISPANIC	617.85	70.41	8.775
as.factor(Agency.Name)Department of Consumer Affairs	-31909.32	261.50	-122.022
as.factor(Agency.Name)Department of Education	-19781.76	1406.28	-14.067
as.factor(Agency.Name)Department of Environmental Protection	-27831.59	146.20	-190.363
as.factor(Agency.Name)Department of Health and Mental Hygiene	-20341.42	282.49	-72.009
as.factor(Agency.Name)Department of Homeless Services	-32675.51	217.81	-150.018
as.factor(Agency.Name)Department of Housing Preservation and Development	-9761.30	128.82	-75.774
as.factor(Agency.Name)Department of Parks and Recreation	-3514.60	173.27	-20.284
as.factor(Agency.Name)Department of Sanitation	-20578.23	134.40	-153.113
as.factor(Agency.Name)Department of Transportation	-19013.11	143.94	-132.086
as.factor(Agency.Name)New York City Police Department	-33977.49	149.58	-227.157
as.factor(Agency.Name)Office of Technology and Innovation	-1319.74	2853.09	-0.463
as.factor(Agency.Name)Taxi and Limousine Commission	3204.08	280.20	11.435

Pr(>|t|)

(Intercept)	<2e-16 ***
as.factor(Complaint.Binary)Social Conflict	<2e-16 ***
PERCENT.BLACK.NON.HISPANIC	<2e-16 ***
as.factor(Agency.Name)Department of Consumer Affairs	<2e-16 ***
as.factor(Agency.Name)Department of Education	<2e-16 ***
as.factor(Agency.Name)Department of Environmental Protection	<2e-16 ***
as.factor(Agency.Name)Department of Health and Mental Hygiene	<2e-16 ***
as.factor(Agency.Name)Department of Homeless Services	<2e-16 ***
as.factor(Agency.Name)Department of Housing Preservation and Development	<2e-16 ***
as.factor(Agency.Name)Department of Parks and Recreation	<2e-16 ***
as.factor(Agency.Name)Department of Sanitation	<2e-16 ***
as.factor(Agency.Name)Department of Transportation	<2e-16 ***
as.factor(Agency.Name)New York City Police Department	<2e-16 ***
as.factor(Agency.Name)Office of Technology and Innovation	0.644
as.factor(Agency.Name)Taxi and Limousine Commission	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15350 on 582064 degrees of freedom

(15498 observations deleted due to missingness)

Multiple R-squared: 0.3101, Adjusted R-squared: 0.3101

F-statistic: 1.869e+04 on 14 and 582064 DF, p-value: < 2.2e-16

Call:

```
lm(formula = Case.Completion.Time.Minutes ~ as.factor(Complaint.Binary) +  
    PERCENT.WHITE.NON.HISPANIC + as.factor(Agency.Name), data = joined_data_clean)
```

Residuals:

Min	1Q	Median	3Q	Max
-36984	-3403	-190	-6	173916

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	32690.34	117.78	277.543
as.factor(Complaint.Binary)Social Conflict	1518.22	93.91	16.166
PERCENT.WHITE.NON.HISPANIC	-201.60	71.08	-2.836
as.factor(Agency.Name)Department of Consumer Affairs	-31934.94	261.53	-122.108
as.factor(Agency.Name)Department of Education	-19785.90	1406.36	-14.069
as.factor(Agency.Name)Department of Environmental Protection	-27845.70	146.25	-190.403
as.factor(Agency.Name)Department of Health and Mental Hygiene	-20365.83	282.49	-72.093
as.factor(Agency.Name)Department of Homeless Services	-32723.44	217.91	-150.172
as.factor(Agency.Name)Department of Housing Preservation and Development	-9734.52	128.79	-75.582
as.factor(Agency.Name)Department of Parks and Recreation	-3547.51	173.26	-20.475
as.factor(Agency.Name)Department of Sanitation	-20592.94	134.40	-153.225
as.factor(Agency.Name)Department of Transportation	-19029.94	143.94	-132.204
as.factor(Agency.Name)New York City Police Department	-33968.91	149.62	-227.035
as.factor(Agency.Name)Office of Technology and Innovation	-1311.44	2853.26	-0.460
as.factor(Agency.Name)Taxi and Limousine Commission	3138.28	280.27	11.197

Pr(>|t|)

(Intercept)	< 2e-16 ***
as.factor(Complaint.Binary)Social Conflict	< 2e-16 ***
PERCENT.WHITE.NON.HISPANIC	0.00456 **
as.factor(Agency.Name)Department of Consumer Affairs	< 2e-16 ***
as.factor(Agency.Name)Department of Education	< 2e-16 ***
as.factor(Agency.Name)Department of Environmental Protection	< 2e-16 ***
as.factor(Agency.Name)Department of Health and Mental Hygiene	< 2e-16 ***
as.factor(Agency.Name)Department of Homeless Services	< 2e-16 ***
as.factor(Agency.Name)Department of Housing Preservation and Development	< 2e-16 ***
as.factor(Agency.Name)Department of Parks and Recreation	< 2e-16 ***
as.factor(Agency.Name)Department of Sanitation	< 2e-16 ***
as.factor(Agency.Name)Department of Transportation	< 2e-16 ***
as.factor(Agency.Name)New York City Police Department	< 2e-16 ***
as.factor(Agency.Name)Office of Technology and Innovation	0.64578
as.factor(Agency.Name)Taxi and Limousine Commission	< 2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15350 on 582064 degrees of freedom

(15498 observations deleted due to missingness)

Multiple R-squared: 0.31, Adjusted R-squared: 0.31

F-statistic: 1.868e+04 on 14 and 582064 DF, p-value: < 2.2e-16

Call:

```
lm(formula = Case.Completion.Time.Minutes ~ as.factor(Complaint.Binary) +  
    PERCENT.HISPANIC.LATINO + as.factor(Agency.Name), data = joined_data_clean)
```

Residuals:

Min	1Q	Median	3Q	Max
-37333	-3357	-91	82	174101

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	32516.88	117.77	276.114
as.factor(Complaint.Binary)Social Conflict	1489.59	93.93	15.859
PERCENT.HISPANIC.LATINO	1103.83	89.62	12.317
as.factor(Agency.Name)Department of Consumer Affairs	-31938.37	261.48	-122.144
as.factor(Agency.Name)Department of Education	-19832.65	1406.19	-14.104
as.factor(Agency.Name)Department of Environmental Protection	-27856.84	146.20	-190.537
as.factor(Agency.Name)Department of Health and Mental Hygiene	-20351.31	282.46	-72.051
as.factor(Agency.Name)Department of Homeless Services	-32660.17	217.80	-149.954
as.factor(Agency.Name)Department of Housing Preservation and Development	-9819.46	128.97	-76.137
as.factor(Agency.Name)Department of Parks and Recreation	-3519.48	173.24	-20.315
as.factor(Agency.Name)Department of Sanitation	-20564.04	134.40	-153.006
as.factor(Agency.Name)Department of Transportation	-19010.19	143.93	-132.077
as.factor(Agency.Name)New York City Police Department	-33976.90	149.56	-227.181
as.factor(Agency.Name)Office of Technology and Innovation	-1333.95	2852.90	-0.468
as.factor(Agency.Name)Taxi and Limousine Commission	3214.61	280.17	11.474

Pr(>|t|)

(Intercept)	<2e-16 ***
as.factor(Complaint.Binary)Social Conflict	<2e-16 ***
PERCENT.HISPANIC.LATINO	<2e-16 ***
as.factor(Agency.Name)Department of Consumer Affairs	<2e-16 ***
as.factor(Agency.Name)Department of Education	<2e-16 ***
as.factor(Agency.Name)Department of Environmental Protection	<2e-16 ***
as.factor(Agency.Name)Department of Health and Mental Hygiene	<2e-16 ***
as.factor(Agency.Name)Department of Homeless Services	<2e-16 ***
as.factor(Agency.Name)Department of Housing Preservation and Development	<2e-16 ***
as.factor(Agency.Name)Department of Parks and Recreation	<2e-16 ***
as.factor(Agency.Name)Department of Sanitation	<2e-16 ***
as.factor(Agency.Name)Department of Transportation	<2e-16 ***
as.factor(Agency.Name)New York City Police Department	<2e-16 ***
as.factor(Agency.Name)Office of Technology and Innovation	0.64
as.factor(Agency.Name)Taxi and Limousine Commission	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15350 on 582064 degrees of freedom
(15498 observations deleted due to missingness)

Multiple R-squared: 0.3102, Adjusted R-squared: 0.3102

F-statistic: 1.87e+04 on 14 and 582064 DF, p-value: < 2.2e-16

Interactions

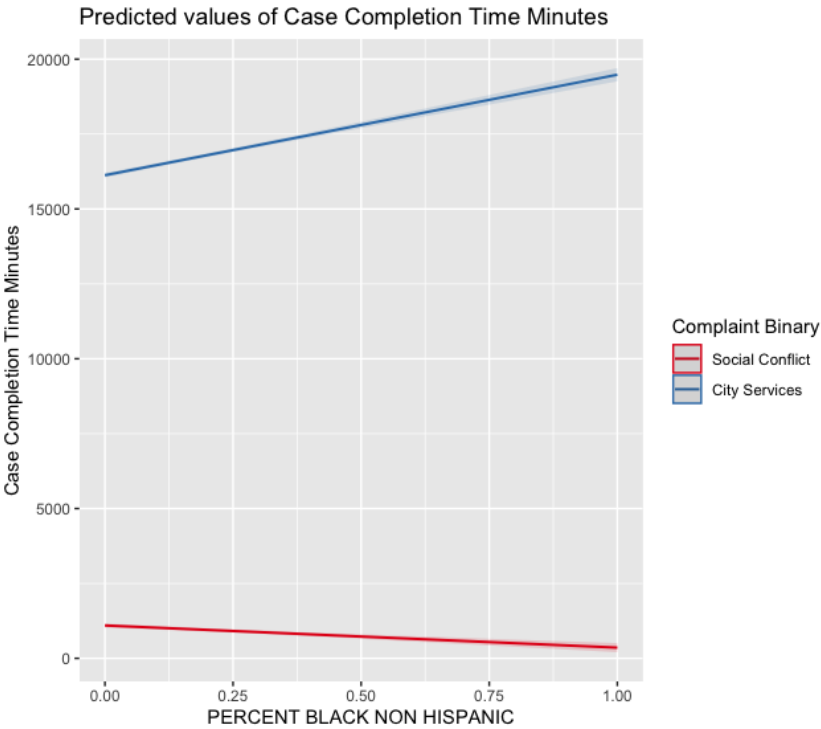
```
> stargazer(i1, type = "text")
```

=====	
	Dependent variable:

	Case.Completion.Time.Minutes

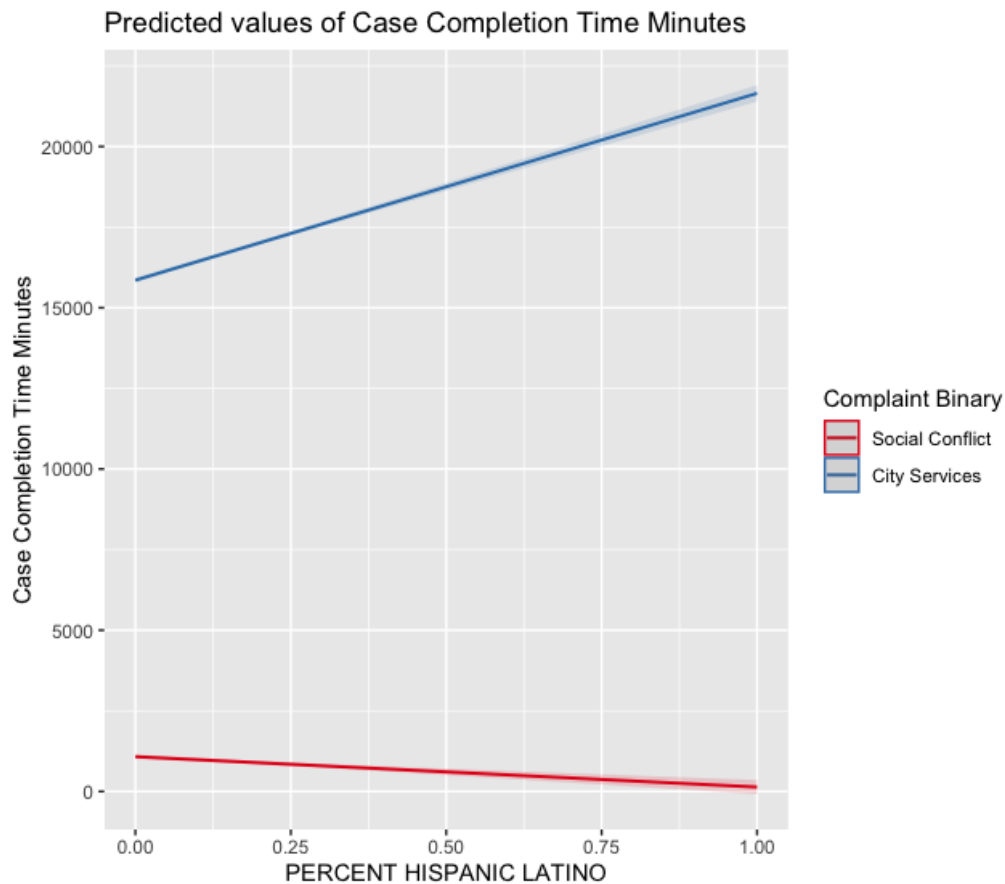
PERCENT.BLACK.NON.HISPANIC	3,355.088*** (129.766)
Complaint.BinarySocial Conflict	-15,028.490*** (54.877)
PERCENT.BLACK.NON.HISPANIC:Complaint.BinarySocial Conflict	-4,095.136*** (160.554)
Constant	16,125.900*** (40.797)

Observations	582,079
R2	0.180
Adjusted R2	0.180
Residual Std. Error	16,740.600 (df = 582075)
F Statistic	42,467.070*** (df = 3; 582075)
=====	
Note:	*p<0.1; **p<0.05; ***p<0.01
>	



```
> stargazer(i4, type = "text")
```

Dependent variable:	
Case.Completion.Time.Minutes	
PERCENT.HISPANIC.LATINO	5,794.539*** (147.355)
Complaint.BinarySocial Conflict	-14,776.760*** (53.990)
PERCENT.HISPANIC.LATINO:Complaint.BinarySocial Conflict	-6,736.787*** (195.318)
Constant	15,855.310*** (40.219)
Observations	582,079
R2	0.181
Adjusted R2	0.181
Residual Std. Error	16,728.110 (df = 582075)
F Statistic	42,820.360*** (df = 3; 582075)
Note:	*p<0.1; **p<0.05; ***p<0.01




```
> stargazer(i5, type = "text")
```

=====	
Dependent variable:	

Case.Completion.Time.Minutes	

PERCENT.WHITE.NON.HISPANIC	93.457 (111.960)
Complaint.BinarySocial Conflict	-15,766.570*** (48.457)
PERCENT.WHITE.NON.HISPANIC:Complaint.BinarySocial Conflict	-287.422* (155.037)
Constant	16,708.210*** (37.072)

Observations	582,079
R2	0.179
Adjusted R2	0.179
Residual Std. Error	16,751.030 (df = 582075)
F Statistic	42,172.570*** (df = 3; 582075)
=====	
Note:	*p<0.1; **p<0.05; ***p<0.01
>	

