Coffee Shop, an Indicator of Gentrification and Crime

A Study of Neighborhood Gentrification in New York City, 2006 to 2017

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**Abstract** 

This study explores the associations between gentrification and neighborhood crime (robbery) by measuring a symbol of neighborhood cultural and economic shift: coffee shops. The paper utilizes longitudinal Poisson regression models with neighborhood fixed effects model. To measure gentrification, it selects counts of coffee shops, lagged crimes and variables in Census data as independent variables, and the annual counts of robbery as dependent variable. The model reveals that there is a negative relation between coffee shops and neighborhood crimes. Given neighborhoods, the model could be used to predict the future trend of robbery in New York City.

**Keywords:** fixed effect, neighborhood, gentrification, robbery, coffee shops.

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### 1. Introduction

The term "gentrification" is originally coined by British sociologist Ruth Glass to describe a phenomenon that contradicts the urban development—the displacement of lower income family caused by an influx of higher income family in a neighborhood (Lee, 2010). Beginning in 1970s, scholars have conducted series studies on this topic. Although researchers have not reached a census on the definition of gentrification (Lees, Slater, and Wyly, 2008), it commonly believes that it involves an invasion by affluent groups of a lower-income groups in a neighborhood and a displacement of the originals residents (Hamnett, 1984: 284). Along with the change of social composition of neighborhoods, a change in the nature of housing block (tenure, price, condition, etc.) can also be observed (Barton and Gruner, 2014). Gentrification also shifts "the essential character and flavor of that neighborhood" (Kennedy and Leonard, 2001). In another word, gentrification is a social process that influence economy, culture and demography in neighborhood level.

One dimension of gentrification is its relations with crimes. Theories have widely discussed this topic and leading theories have concluded that gentrifiers results in the reduction of crimes, especially property crimes and violence crimes in the gentrified neighborhood. The first quantitative study on this topic was done by McDonald (1986). This initial study has some limitations—his result was not well-supported as neither equation nor model were included in his paper and he did not take factor bias into consideration. Other studies try to omit variable bias in mainly two ways: introducing instrumental variable (Lee, 2010), and using fixed-effects regression (Kreager et. al, 2011; Papachristos et al, 2011). Lee (2010) uses LMI census tracts to test if there is a short-term increase of crime rates (assaults, robberies, automobile thefts, and thefts from automobiles) after gentrification, but she neglects higher income family would fail to provide a whole picture of gentrification and studying on one event makes her result not persuasive. Other studies rely heavily on housing data. Taylor and Covington (1988) and Covington and Taylor (1989) study the association between crime and gentrification from 1970 to 1988 in Baltimore. But the problem of using housing data is that a neighborhood with higher house value does not necessarily gentrified,

many factors might contribute to it. While identifying gentrification, most studies only take the first two features of the definition of gentrification, changes social composition and nature of housing blocks, but changes in cultures had been neglected.

Recently, there are some researchers start to include some symbols, coffee shops (Papachristos et al., 2011; C. M. Smith, 2014) and mortgage lending information (Kreager et al., 2011) to represent the shifts in culture in neighborhoods. This innovative method is more applicable, affordable and it gives a more refined definition of gentrification. However, the new approach has only been utilized to study gentrification in Chicago, a racial-segregated city. None research has used culture indicator to analyze the association between crime and gentrification in a city with high ethno-racial diversity.

The present study examines the relationship between gentrification and crimes(Robbery) by measuring a symbol of neighborhood cultural and economic shift: coffee shops in New York City from 2006 to 2017. This study tests if Papachristos's study is applicable in city with high ethno-racial diversity, and explores an appropriate model to predict robbery using the number of coffee shops crime and census data.

Our analysis is presented in three stages: (1) conducting principal component analysis; (2) performing descriptive analysis of the distribution of crime and coffee shops in New York City from 2006 to 2017; (3) conducting longitudinal analysis of neighborhood levels to predict crime.

# 2. Theory

#### 2.1 Theory about gentrification and crime

The definition of gentrification already reveals the basic and obvious consequence of it: the rise of property prices, rent, the associated property taxes and shifts of culture of neighborhood. Deep and subtle impacts include effects on employment, crime, policy, space etc.

Sociology theories had looked in the association and find the negative relations between them (Kennedy and Leonard, 2001:5; Lee, 2010). Barton and Gruner (2014) assessed the relation from a

theoretic point of view. Social disorganization theory and the civic communities perspective theory suggest that gentrification results in short-term increases in crime. But overtime it is expected to see a long-term decrease in crime. Routine activities and defended community theories have the same conclusion with the above two theories from different perspectives. Human ecology theory also supports in that gentrification would weaken the social ties and the neighborhood's ability to against the crime (Lee, 2010; McDonald, 1986; Taylor & Covington, 1988; Van Wilsem, J., Wittebrood, K. & De Graaf, N.D, 2006). Broken windows thesis, however, argues there is a negative linear relation between crime rates and gentrification as gentrification causes investment of capital into disadvantaged neighborhoods, which associated with a reduction of disorder, makes residents more willing to engage with their local community (Kennedy and Leonard 2001; Taylor 2001).

To sum up, all theories agrees that there is a negative association between gentrification and crimes, but they differ in whether the relation is linear and the reasons behind it.

#### 2.2 Coffee Shop as an indicator

Scholars have been seeking the indicators of gentrification for years. They are also looking for "a proliferation of consumption amenities in a previously disinvested area that is a response to supply or demand (Brown-Saracino, 2010)". Papachristos et al (2011) believe that coffee shops are the ideal indicator. Previous studies have shown that an increasing number of coffee shops in a neighborhood usually represents a subtle change of culture is happening there (Lloyd; 2005). And quantitative and descriptive studies have discussed about the association of Starbucks and gentrification (Kennedy and Leonard 2001; Thompson and Arsel 2004; Papachristos et al., 2011).

Papachristos et al. (2011) summarizes the theoretical reason of using coffee shop as an indicator of gentrification. First, coffee shop owners recreate high-culture ideas tied to art and philosophy for its customers (Roseberry 1996; Simon 2009; Thompson and Arsel 2004), which makes coffee shop becomes a "third place" for residents to communicate and socialize from home and work (Oldenburg, 1999). Two,

coffee house is loved by higher-income gentrifies as it represents a leisure lifestyle because it meets the more affluent people's demand to meet friends and relax, which is not required or less required by the ungentrified neighborhoods. Third, compare with census data, the number of coffee shops does not have time limitation. Unlike census data, it could be summed per year or per month, which makes it possible to capture a subtler change in the neighborhood.

In this paper, we choose the number of coffee shops and census data of neighborhoods as indicators to identify gentrification. As gentrification theoretically would lead to the decrease of crimes, we examine if the gentrification indicators associate with robbery crimes.

### 3. Data

The paper uses data collected from nation website and database: New York City Open Data, New York City Police Department (NYPD), United States Census Bureau and New York Government. There are four parts of data: neighborhood, crime, coffee shops and census.

The paper uses neighborhood as units since gentrification is a process of a renovation of lower-income neighborhood (Hamnett, 1984: 284) and previous studies also study gentrification by analyzing it in neighborhoods (Ley, 1996; Lee, 2010; Barton and Gruner, 2014; Kreager, Lyons, & Hays, 2011). The data, ZIP Code Definitions of New York City Neighborhoods, was obtained from New York government website, which lists the zip codes of all neighborhoods in NYC.

As for crime data, the paper uses NYPD Complaint Data Historic and NYPD Complaint Data Current YTD obtained from NYPD website. The historic crime data includes all crimes on records reported to the NYPD from 2006 to 2016, with 5,580,035 observations. The current crime data has 468,761 crime records in the year of 2017.

In terms of the counts of coffee shops in neighborhoods, there are two parts: downloaded data and crawled data. We uses Sidewalk\_Cafes(legally operating), Sidewalk Café Licenses and Applications and

Sidewalk\_Cafes data sets collected from New York Open Data. These three data sets include all business with a DCA license which is needed to open coffee shops in New York City. However, these datasets only include one record for chain stores, impossible to trace all branches of coffee shops from it. An alternative to NYC Open Data's data is crawled from Google Maps using Google Earth software. Google Earth saves all records of coffee shops in neighborhoods on Google Maps to KML files. This method allows us to get a complete data of coffee shops in NYC.

Census data, US 2000 Census and US 2010 Census, is collected from United States Census Bureau. These two censuses have detailed information about population, age, business and industry, education, governments, housing, income, origins and languages, poverty, race and Hispanic origin, veterans for every zip code in New York.

# 4. Analysis and Result

### 4.1 Principal Component Analysis

Previous quantitative studies on gentrification and crime utilizes census data to identify gentrification. Keeping this tradition, we select six census indicators: the percentage of Black population, the percentage of White population, the percent of population with bachelor's degree, the log of mean family income and the percentage of population that is below 200% poverty line. The high correlation of above mentioned indicators could result in insignificant variables in the models (Papachristos et al., 2011). Adding the counts of coffee shops as one dependent variable could increase the possibility that capturing a subtler change in the neighborhood.

Table 1. Principal Component Analysis

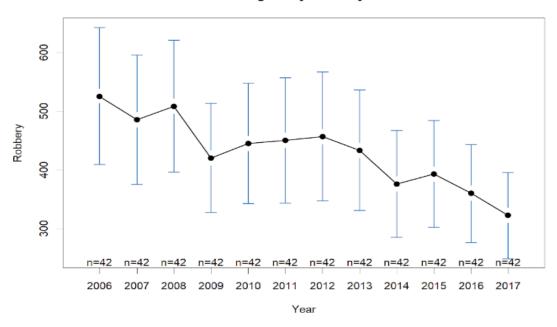
	Factor Loading	Cronbach's Alpha	
Panel A: Census Indicators with Coffee	Shop Variable		
Neighborhood Change		0.899	
Percentage of bachelor's degree	0.936		
Log of mean family income	0.991		
Percentage of population below 200% poverty line	-0.692		
Counts of Coffee Shops	0.626		
Racial Demographics Change		0.908	
Percentage of White	-0.827		
Percentage of Black	0.95		
Panel B: Census Indicators with Coffee	Shop Variable		
Neighborhood Change		0.902	
Percentage of bachelor's degree	0.818		
Log of mean family income	1.099		
Percentage of population below 200% poverty line	-0.777		
Racial Demographics Change		0.908	
Percentage of White	-0.823		
Percentage of Black	0.948		

As is shown in Table 1, to test if adding coffee shops factor would decrease the correlation among, we run the similar Principal Component Analysis twice, with and without the counts of coffee shops. Using 'fa' function in R, it automatically divided variables in two factors, which we name 'Neighborhood Change' and 'Racial Demographics Change.' Then, utilizing 'alpha' function in r, we get the Cronbach's' Alpha value, a measurement of internal consistency. The higher alpha value means the stronger correlation of variables. Table 1 reveals that the alpha value decreases from 0.902 to 0.899 (see neighborhood change alpha in the Panel A and Panel B) after including the counts of coffee shops and factor loading of the number of coffee shops is 0.626, relative smaller than other loading values. The

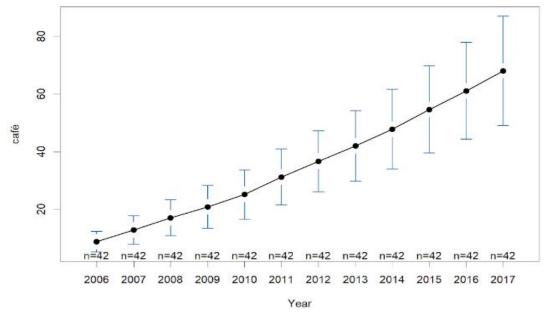
results show that the counts of coffee shops make its own contribution to our analysis: it decreases the intercorrelations among the dependent variable.

## **4.2 Descriptive Analysis**

### Heterogeineity across years



### Heterogeineity across years



**FIG. 1.** Annual Average Number of Robbery, and Coffee Shops in New York City, 2006 to 2017 for 42 Neighborhoods.

To understand the trend of robbery and gentrification better, we conduct a descriptive analysis, using plots to identify and describe gentrification and robbery in NYC from 2006 to 2017.

We have to consider neighborhood effects as data of robbery and coffee shops differs significantly in different neighborhood, for example, there might be 10 coffee shops in A neighborhood but there are more than 200 coffee shops in B neighborhood in the same year. Plotting total amounts of crimes and coffee houses has obvious disadvantage: we could fail to capture the general changing trend of all neighborhood. Thus, we choose to plot the annual average number of coffee shops and robbery in NYC from 2006 to 2017, with blue vertical lines indicating the range of each year's data.

Figure 1 shows that the number of robbery in neighborhoods is negatively related with the counts of coffee shops, which agrees with the theory we discussed in part 2. The annual average counts of coffee shops of forty-two neighborhoods in NYC increase from less than twenty to sixty from 2006 to 2017. The dramatic increase accompanies with a decrease in the counts of robbery, from 520 to around 350. However, as the increase of coffee shops shows a linear trend, there are two noticeable rises of robbery in 2008 and 2015. The interesting fact might relate with policy and other factors; the reason of the increasing will not be discussed in this paper.

Having presented the negative association between robbery and coffee shops, we move to a discuss special changes of gentrification indicators in NYC. Figure 2 to figure 5 depicts the distribution of the changes of numbers of coffee shops, robbery, the changes of proportion of people with higher education degrees, proportion of White people from 2006 to 2017 of all 42 neighborhoods in NYC.

# Coffee Shop Increase from 2006 to 2017

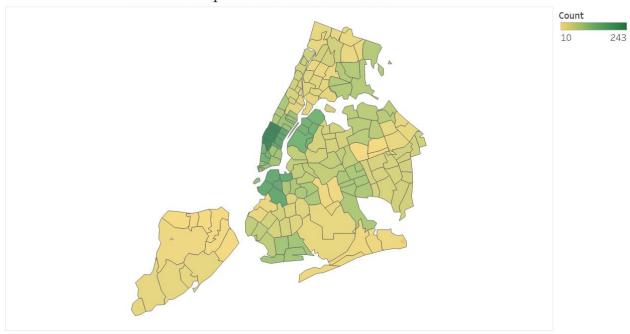


FIG. 2. Maps of New York City Depicting Coffee Shop from 2006 to 2017.

# Robbery Decrease from 2006 to 2017

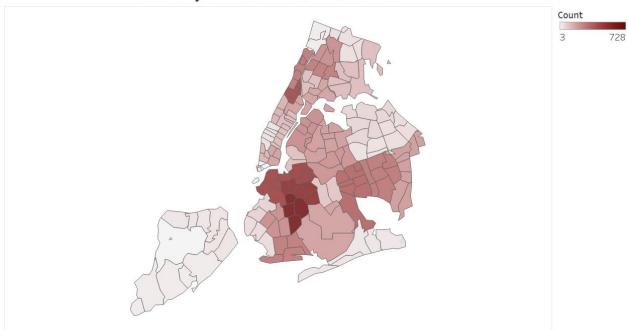


FIG. 3. Maps of New York City Depicting Robbery from 2006 to 2017.

# Percent with Bachelor Degree Change from 2006 to 2017

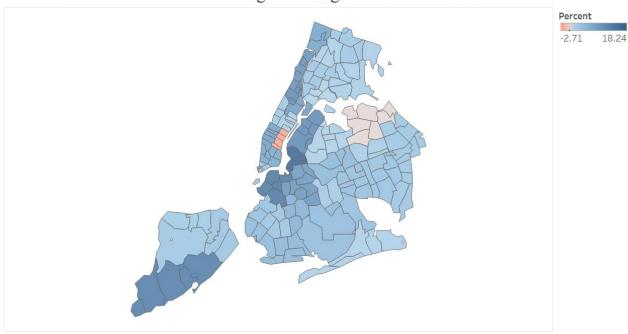
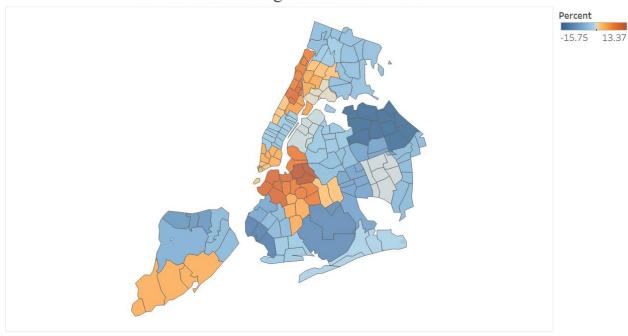


FIG. 4. Maps of New York City Depicting Higher Education Degree from 2006 to 2017.

# Percent White Change from 2006 to 2017



**FIG. 5.** Maps of New York City Depicting White from 2006 to 2017.

Compare figure 2 and figure 3, we find that not all neighborhood that have experienced a great decrease in Robbery would have a noticeable increase in the number of coffee shops. But in the contrary, most neighborhoods that have a huge growth of the number of coffee shops expect to see a significant decrease in robbery. Thus, the number of coffee shops alone cannot fully explain the changes of robbery and gentrification.

From figure 3 and figure 5, we notice that there is a more obvious pattern, the neighborhoods with a great increase in White population have experienced a significant decrease in robbery. It becomes the motives for us to include the percent of White people into the final model, though the previous research in Chicago (Papachristos et al., 2011) did not consider this variable significant.

Compare figure 2 with figure 4, we observe that neighborhood with a surge in the number of coffee shops (with deep green) are likely to have more residents with higher degree (with deep blue). This result accords with the theory that coffee shops represent the higher-income (received higher education) groups lifestyle.

All in all, the trend of robbery and coffee shop represented in maps presents that the influence of gentrification is different across neighborhoods. The neighborhoods effects have to be considered and ignoring this fact might lead to an incorrect conclusion. In the next stage of analysis, we would use quantitative methods to build model and find relations between indicators and robbery.

#### 5.3 Longitudinal Analysis

Above discussion on quantitative studies illustrates the necessity of handling neighborhood effects. Our research decides to utilize over-dispersed longitudinal Poisson models with neighborhood fixed effects. This model not only considers the factors differences on the neighborhood level, but also could effectively examine the association between coffee shops, gentrification and crimes.

Based on 2000 census and 2010 census, we build regression model for each variables in the census data and use linear interpolations as independent variables in models in order to have more detailed swift in the neighborhoods for decennial data.

The steps of longitudinal analysis are:

- (1) Fit models with different variables; (2) Select model using cross validation (leave-one-group-out);
- (3) Conduct ordinary least squares (OLS) regression analysis

### **5.3.1 Models**

Table 2. Fixed Effect Regression Models

	========	Depe	====== ndent vari	======= able:	========
		Counts of Robbery			
	(1)	(2)	(3)	(4)	(5)
Number of Coffee Shops		-0.395 (0.242)			-0.316 (0.232)
Percent with Bachelor Degree		-1,544.773*** (195.924)		•	-1,606.393*** (188.182)
Log Mean Family Income		-0.001** (0.0005)		-0.002*** (0.0004)	
Percent of People 200% Below Poverty Line		-1,263.789*** (363.364)		-1,175.694*** (360.120)	
Percent White		-270.001 (239.952)		-156.784 (230.190)	
Percent Black		1,106.425*** (230.291)		1,215.295*** (220.882)	1,272.058***   (177.169)
Lagged Robbery			-0.024 (0.046)		
Observations Total Sum of Squares: Residual Sum of Squares: R-Squared: Adj. R-Squared:	420 3003600 1684500 0.43919 0.37172	420 3003600 1474900 0.50896 0.44692	420 3003600 2109900 0.29756 0.21722	3003600 1485400	420 3003600 1479900 0.50729 0.44653
Note:	========	========		======== *p<0.1; **p<0	======== .05; ***p<0.01

In table 2, we include five models. The dependent variables for all five models are the counts of robbery in neighborhood. The independent variable in total we include the number of coffee shops, census indicators and lagged robbery. The reason of having lagged crimes is that past year' crime rate in the neighborhoods indicates neighborhood public safety. A higher rate of crimes in the past suggests a high possibility of similar crime rates in the next year (Kirk and Papachristos 2011).

Model 1 only includes neighborhood change variables, also incorporated the number of coffee shops; model 2 uses all neighborhood change and racial demographic change variables; model 3 considers the counts of coffee shops and lagged robbery as independent variables; model 4 excludes variables in model 3; model 5 includes neighborhood change variables and racial demographic change variables, except percent of population that is White. Compare these five models, we first exclude model 3, as it has the highest value of residual sum of squares and lowest r-squared and adjusted r-squared. It seems that model 2 has highest r-squared value and adjusted r-squared value. The next step of analysis is finding the best model with the highest predictive power.

#### 5.3.2 Cross Validation

To validate and compare models, we choose to use leave-one-group. The reasons for choosing this method deserve some comments. First, given the size of data, only 504 observations in total, leave-one-out performs better for small dataset compared with K-fold. Second, cross validation tends to be less biased than bootstrap. Third, using leave-one-group-out enables us to measure neighborhoods effect better. The grouping identifier for the samples is specified via the groups parameter and it yields groups of dependent samples, in our case, yields groups of different neighborhood samples.

**Table 3.** Cross Validation for Model1,2,4,5

Model	RMSE
Model 1	8.275008126331024
Model 2	8.151429171453241
Model 4	9.205339709526223
Model 5	8.15242554190971

Table 3 presents the RMSE for model 1,2,4 and 5. We choose model 2 as the final model in that it has lowest RMSE and it has the highest R squared value (see Table 2).

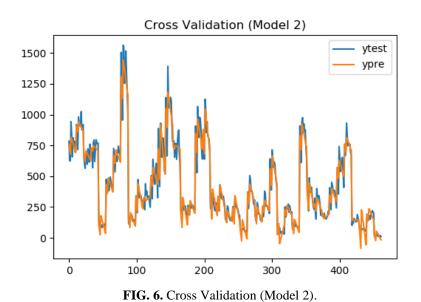


Figure 6 illustrates the test value and predict value. Although RMSE is larger than 1, our model captures the rise and the fall of test data. The model could be used to predict the trend of robbery in NYC given the neighborhood, census and coffee shops data.

### 5.3.3 Ordinary Least Squares (OLS) Regression Analysis

To validate our model and check if linear model is suitable for the data, we conduct OLS analysis. Figure 7 describes the fitted value and observed value. All points are close to a regressed diagonal line (red line) and there are not obvious outliers, which indicates that the prediction error is low for model 2.

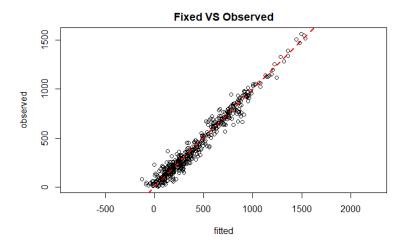


FIG. 7. Fitted Versus Observed Plot (Model 2).

One of the critical assumptions of linear models, including linear fixed-effects panel models, is normally distributed errors. The histogram of residual plot reveals that the residuals are consistent with random error, as we could see it follows normal distribution<sup>2</sup>. As for qq-plot, some curvature in the tails is tolerated and expected as long as the majority of points lie on the auxiliary line. We can draw conclusion that model 2 is well-behaved and it is appropriate to use linear model for our datasets.

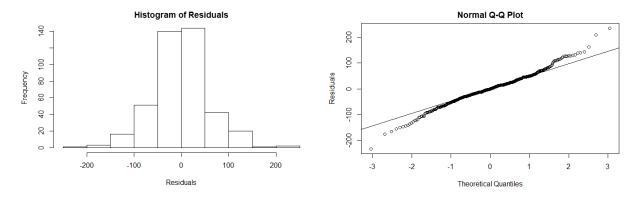


FIG. 8. Residual Plot (Model 2).

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<sup>&</sup>lt;sup>2</sup> https://www.sciencedirect.com/science/article/pii/S0168169915002902

## 6. Conclusion

The study examines if coffee shops is an indicator of gentrification and crimes, utilizing longitudinal Poisson fixed effect model to study New York City from 2006 to 2017. Principal components analysis, descriptive studies and longitudinal studies are conducted, and we found that coffee shop is an indicator of gentrification and crimes, and negatively associated with crimes.

Factor analysis indicates that coffee shops contribute to decrease the internal consistency of census data, which lower the chance to have insignificant variables while building models. Thus, it is reasonable to include it as dependent variables in longitudinal analysis. Descriptive analysis shows the trend of changes of six census factors, coffee shops and robbery. The changes of coffee shops are closely related with the other census indicators and crimes—the increase of numbers of coffee shops indicates more White residents, increasing number of people with bachelor's degree and less crimes in the neighborhood. When observing the change of crimes and census gentrification indicators on the map, we notice an interesting fact. In NYC, Brooklyn is currently most gentrified area. The number of coffee shops, proportion of White population and residents with bachelor's degree has experienced the sharpest increaser, meanwhile, the number of robbery in this borough has fallen fast. Longitudinal models provide the most direct evidence of association of coffee shops and gentrification and crimes. In table 2, the coefficients of coffee shops are negative in all models, which illustrates the negative association of coffee shops, gentrifications and crimes. The model we built has been validated using cross-validation and OLS analysis, and could be used to predict the trend of robbery in NYC.

## 7. Discussion

There were many challenges that we have overcome. First, when collecting data for coffee shops, we found the number of records on the NYC open data was extremely small. On a second look, we realized this data set does not include every branch of chain coffee shop. We had to crawl data from Google Maps using Google Earth and cleaned duplicate data, which was really time consuming. The second challenge

is R do not have suitable package for cross validation (leave one group out) on panel data. We manually coded for that part.

Honestly, this study has limitation. First, this study only captures some but not all characteristics of gentrification, further study could include other source of data to identify gentrification processes, especially data that could represent economical development, public facilities. Second, the size of datasets is not large. We focus on NYC, with 42 neighborhoods for 12 years. Future study could include more cities, or study one city for a longer period. By doing this, researchers might be able to find a model that is applicable for major cities in U.S. and has higher predictive power. Third, we only use one type of crime, robbery, as dependent variables. Previous studies have shown that gentrification has influence on both property crimes and violence crimes. If time permitted, we would build models for more types of crimes and validate if coffee shop is an indicator.

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