Fair Evasion? Varied Transit Enforcement in New York City

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Abstract

Fare Evasion and its enforcement is an ever-more relevant issue in New York City. In this paper, a data set of fare evasion arrests and weighted census data is created and analyzed using a difference-in-differences regression model in order to understand the impact of the Manhattan District Attorney's 2018 policy to curtail the prosecution of those arrested for fare evasion in the New York City Subway. Results suggest that, despite an overall reduction in arrests, Black and Hispanic communities still saw an increase in fare evasion policing. Income inequality is suggested as an indicator of the number of arrests as well. Furthermore, the proportion of Black arrests was found to increase following the implementation of the policy, especially in areas which contain greater Black and Hispanic populations.

1 Introduction

The activities of the New York Police Department regarding the arrest of individuals caught evading subway fare has been the source of increasing controversy, locally and nationwide. On June 30, 2017, Cyprus R. Vance Jr., District Attorney (DA) of Manhattan, announced that his office would "end criminal prosecution of fare evasion in Manhattan"(Vance 2017). On the same day as his Manhattan counterpart, Brooklyn District Attorney Eric Gonzalez announced on Twitter that Brooklyn would end prosecution as well, though no official start date was given (Gonzalez 2017).[1] One year after the enforcement of the policy began, the office of the Manhattan District Attorney reported that subway fare evasion arraignments had decreased by 95.55% combined with internal NYPD reforms resulting in an 89% decrease in fare evasion arrests (Vance 2018).

There are three choices an NYPD officer has when an individual is caught evading the fare in a subway station. The officer can exercise their own discretion, allowing the individual to go free; they can issue a summons processed by the Transit Adjunction Bureau, resulting in up to a $100 fine; and they can choose to make an arrest (Stolper and Jones 2017). It is generally considered that an officer would arrest an individual if they do not have identification, have outstanding warrants, or have been previously stopped for fare evasion. The issuance of a Desk Appearance Ticket (DAT), a court summons in New York City, is considered an arrest by the NYPD.

According to the original report from Vance, fare evasion arrests are categorized as "Thefts of Service", a class A misdemeanor and the most common charge in Manhattan Criminal Court. The enforcement of Vance's "Decline-to-Prosecute" strategy went into effect on February 1st 2018. The policy consists of issuing summons "in lieu of arrest", in the form of "offering pre-arraignment diversion to those individuals who are arrested for [fare evasion] and issued a desk appearance ticket". The individual with a DAT must successfully participate in a diversion program in order to not be prosecuted, in which case the individual

[1]Since no actionable policy was released by the Brooklyn DA's office, the borough is considered "untreated" in the experiment of this paper

is not required to make a court appearance. (Vance 2017). Individuals who were arrested without a DAT were not guaranteed this opportunity.

In June 2018, New York Governor Andrew Cuomo announced that 500 new uniformed officers would be added to the Metropolitan Transit Authority's train stations and bus stops for fare enforcement purposes, citing a $120 million increase to $225 million in lost revenue to the transit system (Cuomo 2018). However, in a report from Elizabeth Keating of the office of the MTA Inspector General questions this figure, noting that this figure was derived from a sample set that was not representative of normal MTA ridership (Keating 2019). Importantly, these are MTA Security officers, not members of the NYPD.

In this paper, I start by reviewing literature on the current state of fare evasion enforcement, and it's relationship with Broken Windows policing and relationships between uniformed officers and people of color within the context of transportation policing. I present a novel data set created from publicly available arrest records using geographic and categorical filtering methods. Finally, a difference-in-differences regression is presented, and its results and implications therein are discussed.

2 Literature Review

2.1 Fare Evasion in New York City

As of the time of writing, the academic study of fare evasion arrests in New York is relatively limited to journalism, qualitative social analysis, and descriptive statistics, providing a theoretical and intuitive basis for statistical analysis in this paper. One such study, conducted in 2016 by Stolper et al. at New York's Community Service Society, finds that fare evasion arrests are likely to be racially skewed, with Black men aged 16-36 representing half of all fare evasion arrests despite representing 13.1% of poor adults in the city. Within Brooklyn, the study also found that the racial distribution of adults in poverty does not match the racial distribution of fare evasion arrests, with Black individuals accounting for 66% of fare evasion arrests in 2016 despite making up 29% of adults in poverty, while the same respective distributions are relatively even for Hispanic individuals. 12% of fare evasion arrests were White, while 39% of adults in poverty at the time were White. They also qualitatively analyze visualizations of poverty and arrest rates, concluding that while impoverished areas are more likely to be subject to higher rates of fare evasion arrests, not all impoverished areas contain relatively large amounts of arrests (Stolper and Jones 2017). In this paper I will seek to update these descriptive statistics from 2016 to 2019, as well as to statistically verify Stolper et al.'s claims. Results will display whether these disparities exacerbated as fare evasion arrests decreased over time.

Stolper et al. also compares fare evasion policy in New York with other cities, such as San Francisco, which does not issue criminal citations for fare evasion and instead issues the "equivalent of a parking ticket"(Stolper and Jones 2017). In figures provided to the Community Service Society by the NYPD, the department claims to "only arrest people for evading the fare (instead of writing a civil summons) when that person has an outstanding warrant, has a criminal record, or has been cited for fare evasion three times in the past two years."(Stolper and Jones 2017). However, the methods of enforcement for these conditions remain unclear, as does the decision to issue a criminal summons.

2.2 Broken Windows

Within the context of racial profiling, much of the literature covering the relationship between the NYPD and the community members it polices focuses on the controversial Stop-and-Frisk policy, popular under the administration of Mayor Michael Bloomberg. Stop-and-Frisk remains relevant to pre-decriminalization fare evasion policing practices, as both fall under the Broken Windows model of policing. Introduced in 1982 by George L. Kelling and James Q. Wilson, the theory behind Broken Windows is as follows:

> "Social psychologists and police officers tend to agree that if a window in a building is broken and is left unrepaired, all the rest of the windows will soon be broken. This is as true in nice neighborhoods as in rundown ones. Window-breaking does not necessarily occur on a large scale because some areas are inhabited by deter-

> mined window-breakers whereas others are populated by window-lovers; rather, one unrepaired broken window is a signal that no one cares, and so breaking more windows costs nothing."(Kelling and Wilson 1982)

Kelling et al. analogize that if the first window in a building is not broken, the rest of the windows will not be broken either in order to convey the central tenet behind their policing model: zero tolerance for minor crimes, for if minor crimes are prevented before they occur (the first "broken window"), major crimes will not be committed in the future. Therefore, Broken Windows policing encourages higher rates of policing for minor crimes in areas with already high crime rates. In various cities across the country, the tactic is also known through names such as "rapid response", "get tough", "stop-and-frisk", "zero tolerance", "quality of life", and "order maintenance" (Kamalu and Onyeozili 2018) Fagan et al. summarize much of the research on the implementation of Broken Windows tactics in New York City, as well as the inter-group attitudes created between police officers and community members, saying:

> "The implementation of Broken Windows policies was disproportionately concentrated in minority neighborhoods and conflated with poverty and other signs of socio-economic disadvantage. Thus, what was constructed as 'order-maintenance policing' ('OMP') was widely perceived among minority citizens as racial policing, or racial profiling." (Fagan and Davies 2000)

Fare evasion, as a minor crime yet one which constitutes a large number of the perentage of total arrests, is a key example in the study of Broken Windows policing. This is generally accepted by the literature as well, with Ngozi et al. listing it as one of the first examples of the type of minor crimes targeted by police departments which employ the practice. (Kamalu and Onyeozili 2018) As Michelle Alexander stated in her 2010 book *The New Jim Crow*, "The nature of the criminal justice system has changed. It is no longer primarily concerned with the prevention and punishment of crime, but rather with the management and control of the dispossessed", suggesting that the criminal justice system is shifting towards Broken Windows policing in a specifically racial or class-based manner (Alexander 2010).

Ideologically opposed to Broken Windows policing is the decriminalization model, wherein minor crimes are not subject to arrest or prosecution, allowing for communities otherwise heavily affected by arrest rate to exist with stability. However, decriminalization is not shown to be an effective method of preventing the racial and socioeconomic disparities marked by Broken Windows policing. According to K. Babe Howell in the Cardozo Law Review, "New York's commitment to zero-tolerance policing has led to enormous increases in marijuana arrests (despite state decriminalization of simple possession). These increases have been marked by clear racial disparities" (Howell 2016). Understanding whether fare evasion arrests follow this trend after decriminalization allow for greater understanding of how the NYPD's enforcement decisions impact the communities they police, and whether the NYPD's enforcement decisions resemble the unequal nature of Broken Windows policing.

2.3 Black Lives Matter and Racialized Perceptions of Police

There has long been a connection between the policing of minor crimes such as fare evasion and various modern racial civil rights movements, namely Black Lives Matter. As recently as February 2020, Black Lives Matter President Anthony Beckford likened the enforcement of fare evasion policies to Bloomberg's "Stop-and-Frisk" policy. (Paula 2020) On 22 November 2019, there was a series of protests within the New York Subway System, organized by a coalition of 15 grassroots movements, including Black Lives Matter and Decolonize This Place, which specifically focused on the relationship between NYPD officers and people of color within the New York City Subway Station. According to an article in The Guardian by Lauren Aratani published shortly after the protest, "The coalition was created in response to incidents that happened one weekend in October and went viral on social media, including a video that showed police drawing their guns and storming a subway car. The NYPD said a witness informed the police that the young man had a gun, and he fled when police approached him previously" Aratani (2019).

The events surrounding protests against police activity indicate a outwardly antagonistic relationship between groups representing people of color and the NYPD. While such a relationship is expressed in a variety of avenues, these protests specifically indicate that this relationship is perceived to be expressed through law enforcement on public transportation. The implications are twofold. First, the events which inspired the protest indicate the possibility of excessive violence from law enforcement on the subway implies a possible bias from police officers towards individuals of color on the subway. More importantly to this study, the presence of such social movements implies that police are aware of their perception to these racial groups, and that they may alter behavior in response.

3 Research Questions and Hypothesis

In this paper, I seek to understand the effect of the Manhattan District Attorney's policy on the number of fare evasion arrests which occurred in Manhattan per subway station per fiscal quarter. Furthermore, I examine the change in relative number of arrests per subway station per fiscal quarter of the Black, White, Hispanic, and Asian racial sub-groups.

Based on reported statistics from the office of the Manhattan District Attorney discussed in Section 2, I predict a decrease in fare evasion arrests at the aggregate level.

Hypothesis 1 (H1): *The DA's policy decreased the number of fare evasion arrests.*

However, historical patterns suggest that relative rates of arrest for people of color could increase following the implementation of the policy, and therefore I predict a relative increase in Black and Hispanic arrests, but a decrease in White arrests.

Hypothesis 2 (H2): *The DA's policy increased the relative number of Black fare evasion arrests.*

Hypothesis 3 (H3): *The DA's policy decreased the relative number of White fare evasion arrests.*

Hypothesis 4 (H4): *The DA's policy increased the relative number Hispanic of fare evasion arrests.*

Hypothesis 5 (H5): *The DA's policy decreased the relative number of Asian fare evasion arrests.*

4 Data

4.1 Experimental Data

While a data set has been published by the NYPD regarding fare evasion arrests, including breakdowns of the percentage of arrests which resulted in a DAT, it does not include station- or arrest-level data. According to Stolper et al. (2017), the official data do not contain "any useful information about law enforcement patterns at the station level." Therefore, an arrest-level data set of fare evasion arrests is created from the NY Open Data Arrest Data Set (Historic and Year-to-Date versions). Each row of the data set represents a single arrest, with columns for the perpetrator's race, age range, sex, the arresting officer's precinct, the Latitude-Longitude location of the arrest, and the date it occurred. The data set is filtered to only contain dates from 2010 until the present. This is an intuitive cut-off point since it avoids long term exogenous effects from shifts in prosecution due to new District Attorneys, as 2010 was the beginning of Vance's term as DA.

New York Penal Law 165.15(3) gives law enforcement the legal basis to arrest an individual for fare evasion under the category "Theft of Services". Therefore, the data are filtered into only arrests made under the correct law code. A data set of subway complex locations from the CUNY Baruch NYC Geodatabase is used to filter the arrests such that only those which occurred within 475 meters of the center of a subway station remain.(nyc 2020)[2][3] Each arrest is then assigned to the nearest subway station. Arrests are aggregated by year, quarter, and subway station, giving a final data set of the count of arrests at each subway station each quarter. The CUNY Baruch data set also contains ridership data for each subway station up to 2017 - the annual ridership in 2017 is used to control for relative

[2] A subway complex is a set of subway stations of different lines in the same geographic location

[3] 475 meters approximates the size of a subway complex as a circle

ridership across subway stations.

Data from the American Community Survey is used to add demographic information to the subway station level arrest data set. A buffer zone of 1/4 mile, approximating walking distance, is drawn around each subway station, and demographic indicators for each subway station are obtained by calculating a weighted mean of based on the proportion of each census tract within a subway station's walking-distance buffer zone. The indicators used are proportion of Black, Hispanic, White, and Asian residents, Gini Index, and mean income (ACS 2017).

4.2 Descriptive Statistics

Table 1 displays the total number of arrests in each borough before and after the policy implementation. This data suggests a reduction of the total number of arrests across all boroughs during the tested period, as well as differences between boroughs.

	Before Policy	After Policy
Brooklyn	8,072	2,437
Manhattan	12,464	1,418
Queens	3,379	956
The Bronx	8,072	1,862

Table 1: Number of Arrests 696 days before/after policy implementation

Figure 1 displays these differences, showing a general downward trend for fare evasion arrests in all boroughs, yet a sharp drop in arrests in Manhattan at the point of policy enactment. This visually implies that the reduction in arrests in Manhattan was different from the outer boroughs, though it follows the outer borough trend of decreased fare evasion arrests over time. Fixed effects controlling for yearly time trends, as well as for each borough, will be used to account for these differences.

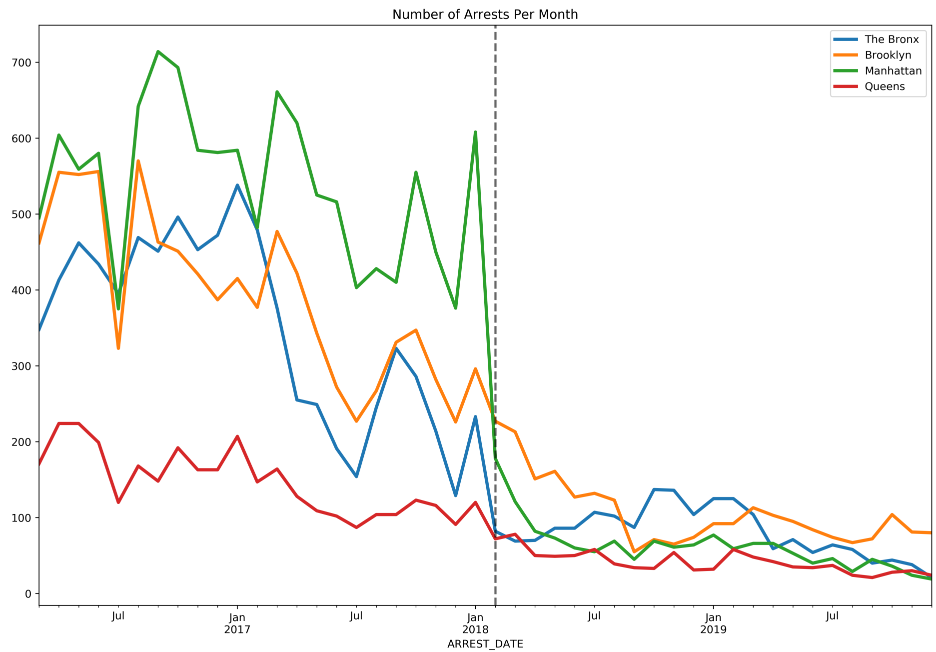

Figure 1: Number of Arrests Per Month in each Borough

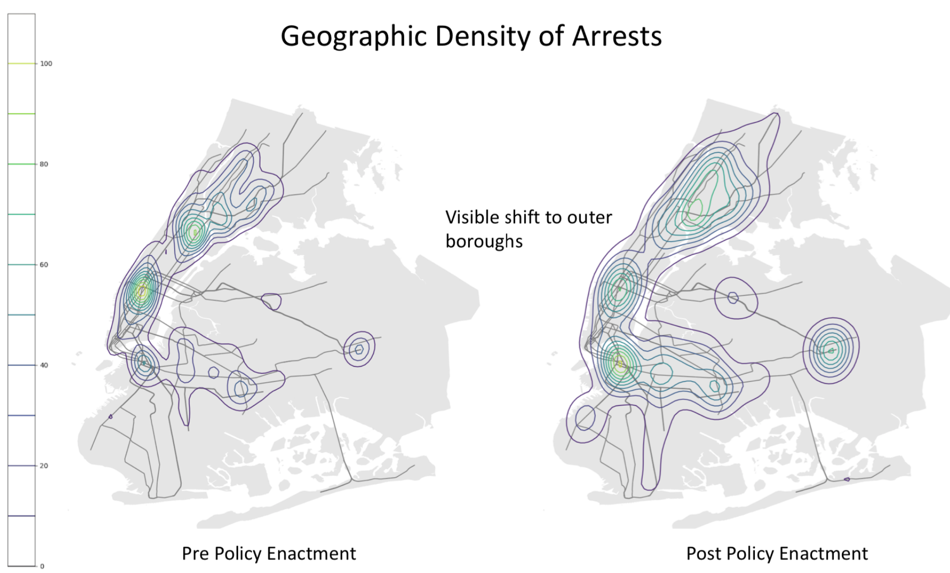

Figure 2: Change in density of Arrests

Figure 2 displays a Kernel Density Estimation of the location of arrests within New York City, visualizing bivariate probability distributions of the locations of arrests by latitudinal and longitudinal location. There is a visible shift in the density of arrests from being centered around Manhattan to being more evenly distributed across boroughs, with the most dense area for arrests being Downtown Brooklyn, close to Jay St - Metrotech and surrounding stations. This suggests that the implementation of the Manhattan DA's policy correlates with a change in the distribution of arrests, namely a movement of arrest activity to outside of Manhattan.

As seen in Table 2, while most demographic information remains largely consistent, arrest rate varies wildly across the time period studied and treatment groups. As explained below, $Period$ is a dummy variable indicating whether the year-quarter is Q1 2018 or later, as the policy went into effect in this quarter. $Treated$ is a dummy variable indicating whether the subway station is in the treated group, which in this case is the borough of Manhattan. When time trends are not accounted for, arrests for all racial groups are lower in Manhattan after the enactment of the treatment, though this represents an aggregation across all subway stations. Despite this decrease, changes at the de-aggregated level of each subway station may indicate more nuanced changes in the number of arrests.

	Period = 0 Treated = 0	Period = 0 Treated = 1	Period = 1 Treated = 0	Period = 1 Treated = 1
Ridership	8183.422	25417.23	8183.422	25417.23
	(7716.14)	(29267.13)	(7717.334)	(29278.38)
Arrests	11.49061	15.83863	2.448432	2.095287
	(19.75466)	(24.8305)	(5.730268)	(5.827621)
Black Arrests	6.680796	8.369109	1.47236	1.143443
	(12.76378)	(14.67811)	(3.854244)	(3.388656)
White Arrests	.6352104	1.487705	.1955446	.204918
	(1.432862)	(2.644221)	(.7423601)	(.5896687)
Asian Arrests	.2101898	.3509221	.0523927	.0379098
	(.723982)	(.9936045)	(.3277924)	(.2300442)
Hispanic Arrests	3.867781	5.469518	.7153465	.6834016
	(7.557724)	(8.869602)	(1.801269)	(2.163371)
Percent Black	.2438998	.1258619	.2438998	.1258619
Population	(.2443567)	(.1680758)	(.2443945)	(.1681404)
Percent White	.3910809	.5911734	.3910809	.5911734
Population	(.2391324)	(.2309536)	(.2391694)	(.2310424)
Percent Asian	2.14154	2.733063	2.14154	2.733063
Population	(3.358565)	(3.012922)	(3.359084)	(3.014081)
Percent Hispanic	.3376549	.2158863	.3376549	.2158863
Population	(.2159676)	(.2155033)	(.2160011)	(.2155862)
Income	44458.99	75192.65	44458.99	75192.65
	(30646.85)	(61951.93)	(30651.59)	(61975.75)
Gini Index	.3945931	.3829835	.3945931	.3829835
	(.1691444)	(.235944)	(.1691706)	(.2360347)
N	9696	3904	2424	976

Mean Values, Standard Deviation in Parentheses

Table 2: Balance Table of Variables

5 Methods

5.1 Estimating the change in Arrests

To test the effect of the Manhattan DA's policy to stop prosecuting fare evasion on the number of fare evasion arrests I run a multivariate difference in differences regression with fixed effects. The dependent variable is the number of arrests at subway station s in year y quarter q. The model is tested on the entire data set, consisting of the number of arrests at each subway station each quarter, beginning Quarter 1 of 2010 and ending Quarter 4 of 2019, inclusive.

Period is a dummy variable indicating whether the year-quarter is Q1 2018 or later, as the policy went into effect in this quarter. *Treated* is a dummy variable indicating whether the subway station is in the treated group, which in this case is the borough of Manhattan. *Ridership* represents the average weekday ridership at each subway station s in 2017.[4] A, B, C, and D represent the weighted percent Black, White, Asian, and Hispanic populations respectively in the area around a subway station, using means from the 2013-2017 American Community Survey for New York City tracts. From the same data set, E and F represent economic variables Income and Gini Index respectively for the walking-distance buffer around each subway station. γ_y and γ_b represent vectors of fixed effects for years and boroughs respectively. Model 1 is as follows:

$$\begin{aligned}\Delta(Arrests)_{syq} = \beta_0 + \beta_1(Period) + \beta_2(Treated) + \beta_3(Period * Treated) \\ +\beta_4(Ridership_s) + \beta_5(A_s) + \beta_6(B_s) + \beta_7(C_s) + \\ \beta_8(D_s) + \beta_9(E_s) + \beta_{10}(F_s) + \beta_{11}(\gamma_y) + \beta_{12}(\gamma_b) + \epsilon\end{aligned} \tag{1}$$

[4] Ridership was not seen to change drastically between years, and accurate ridership data is not available after 2017.

5.2 Estimating Racial Effects

In testing the overall change in arrests, it is possible that Model 1 is prone to Simpson's Paradox, where de-aggregated data show different trends than their aggregated counterparts. For the second stage, Model 1 is modified to test differences in the arrest rate for various races. Model 2, shown below, is similar to Model 1, with the addition of property r indicating the racial group to which each arrested individual belongs. The new control $Arrests$ represents a control for the total number of arrests at each subway station each year-quarter, and $Population$ represents the proportion of race r in the population of the area walking-distance to subway station s. Including these controls and running the model for each racial subgroup allows comparative analysis of the effect of the Manhattan DA's policy on the relative number of arrests of each race controlling for the prevalence of each race in an area, which allows for robust analysis of potential racial bias in arrest patterns. A and B represent economic indicators Income and Gini Index respectively, and γ_y and γ_b represent the same fixed effects as Model 1, controlling for time and geographic trends of arrests for race r. Model 2 is as follows:

$$\begin{gathered}\Delta(Arrests)_{syqr} = \beta_0 + \beta_1(Period) + \beta_2(Treated) + \beta_3(Period * Treated) \\ +\beta_4(Ridership_s) + \beta_5(Arrests_{syq}) + \beta_5\beta_6(Population_{sr}) + \\ \beta_7(A_s) + \beta_{11}(B_s) + \beta_{12}(\gamma_{yr}) + \beta_{13}(\gamma_{br}) + \epsilon\end{gathered} \tag{2}$$

6 Results

6.1 Aggregate Policy Effect

Table 3 shows results of Model 1, testing whether the Manhattan District Attorney's policy to stop prosecuting fare evasion arrests had an effect on the total number of arrests within the treated borough. The results suggest that there was an average of 4.7 fewer arrests at each subway station in Manhattan each quarter as a direct result of the policy. This raises questions regarding the mechanisms through which this reduction occurred, and the model does not describe whether this change was due to a reduction in the number of police officers at a subway station or due to a change in the behavior of individual officers. However, the results of Model 1 suggest that the Manhattan policy of eliminating the prosecution of individuals for fare evasion led to a significant decrease in arrests. Though 4.7 is a relatively small number for an individual subway station, on aggregate this accounts for a substantial number of arrests, and there was likely a much larger reduction in stations with higher ridership. In popular subway stations, such as Penn Station (which faced a 25% reduction in arrests between Q4 2017 and Q1 2018), there was likely a much larger reduction in arrests due to the policy.

Within the area walking distance from a subway station, racial demographics are shown to significantly impact the expected change in arrests. A one percent increase in the Black and Hispanic populations leads to an increase of approximately 12 and 13 arrests per station per quarter respectively, at a 99% confidence level. Meanwhile, a one percent increase in White and Asian populations is shown to significantly decrease the number of arrests in a subway station by 12 and 0.2 arrests per subway station per quarter respectively. This demonstrates that despite the overall reduction in arrests, the likelihood of an individual being arrested is higher in areas with a higher Black and Hispanic population. It is unclear whether this is due to higher rates of fare evasion in Black and Hispanic areas, or to racially biased placement of police officers in subway stations with a higher proportion of nonWhite travelers.

	Model 1a Arrests	*Model 1b* Arrests	*Model 1c* Arrests
Period	-9.042***	-9.042***	-8.485***
	(0.437)	(0.394)	(0.628)
Treated	4.348***	4.532***	5.240***
	(0.365)	(0.380)	(0.568)
Period * Treated	-4.701***	-4.701***	-4.701***
	(0.816)	(0.736)	(0.732)
Ridership		0.000333***	0.000335***
		(0.00000808)	(0.00000805)
Percent Black Population		12.25***	10.99***
		(1.091)	(1.122)
Percent White Population		-11.08***	-12.32***
		(1.136)	(1.166)
Percent Asian Population		-0.218***	-0.209***
		(0.0494)	(0.0498)
Percent Hispanic Population		13.02***	13.73***
		(0.919)	(0.967)
Income		-1.40**	-1.14*
(per $10,000)		(0.492)	(0.494)
Gini Index		10.57***	9.993***
		(0.983)	(1.008)
_cons	11.49***	2.633*	1.381
	(0.196)	(1.043)	(1.202)
Year and Borough Fixed Effects	No	No	Yes
N	17000	17000	17000
R^2	0.052	0.230	0.239

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Change in Arrests

Including Income and Gini Index as controls contributes to the explanation of the significant coefficients on the racial population variables. Controlling for such economic indicators extracts whether the increase in fare evasion arrests is due to a generally lower income, which occurs in areas of New York with a higher Black and Hispanic population. While income is found to have a slightly significant effect, the magnitude is low, with an additional arrest for every additional $10,000 of average income in an area. This indicates more than simply increased poverty and rates of crime as explanatory to the significant coefficients of the racial demographic variables. Moreover, Gini Index is found to have a strong positive effect on the number of arrests - a 0.1 increase in the Gini Index of an area around a subway station leads to 1 more arrest per station per quarter after the policy implementation. Marginal and low magnitude impacts of income paired with strong effects from income inequality suggests policing is occurring with bias towards nonWhite individuals, and that such policing is more likely in areas with a high Black or Hispanic population and with high income inequality, regardless of whether the area is generally low-income.

6.2 Racial Effects

Table 4 shows the impact of the policy on the number of arrests for each racial sub-group. The results suggest that changes in the arrest rate are different on aggregate than for each racial group, and that there are significant differences between arrests rates of each group. Despite the decrease in total arrests as a result of the policy, holding all else constant the relative number of Black arrests increased by 0.7 arrests per subway station per quarter, significant at a 99% confidence level. The policy resulted in a decrease of White arrests by approximately 0.6 arrests per station per quarter, also significant at a 99% confidence level. Asian arrests are suggested to have decreased marginally yet significantly in comparison to the tested racial sub-groups. The relative number of Hispanic arrests were found to not change significantly as a result of the policy.

	Black Arrests	White Arrests	Asian Arrests	Hispanic Arrests
Period	0.118	0.131**	-0.0309	-0.400***
	(0.122)	(0.0466)	(0.0241)	(0.112)
Treated	0.570***	0.363***	0.0723***	0.830***
	(0.0986)	(0.0395)	(0.0196)	(0.0976)
Period*Treated	0.763***	-0.594***	-0.102***	-0.151
	(0.141)	(0.0541)	(0.0279)	(0.129)
Ridership	-0.0000193***	0.0000177***	0.00000970***	0.00000737***
	(0.00000160)	(0.000000612)	(0.000000317)	(0.00000147)
Total Arrests	0.591***	0.0530***	0.0113***	0.315***
	(0.00145)	(0.000561)	(0.000281)	(0.00132)
Percent Black Population	6.306***			
	(0.129)			
Percent White Population		1.088***		
		(0.0520)		
Percent Asian Population			0.0181***	
			(0.00164)	
Percent Hispanic Population				6.373***
				(0.143)
Income	1.55***	-4.92e-03	-2.91e-03	3.24e-06***
(Per $10,000)	(0.0879)	(0.0357)	(0.0168)	(0.0813)
Gini Index	-2.795***	0.239**	0.0726	0.801***
	(0.192)	(0.0745)	(0.0372)	(0.172)
_cons	-1.928***	-0.989***	-0.254***	-2.394***
	(0.124)	(0.0487)	(0.0239)	(0.141)
Year and Borough Fixed Effects	Yes	Yes	Yes	Yes
N	17000	17000	17000	17000
R^2	0.927	0.471	0.218	0.827

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Change in Arrests by Race

The population of each racial sub group was found to effectively control for the number of arrests experienced by that group, as each coefficient is positive and significant. The coefficient of the Hispanic Population variable indicates that changes in arrests for Hispanic individuals were correlated with population concentration. According to Table 5, which displays the Beta coefficients of the results of Model 2 (allowing comparison across races) the effect of population percentage on Hispanic arrests is higher than that of any other race. This suggests that Hispanic arrests are concentrated in Hispanic areas to a higher degree than Black arrests are concentrated in Black areas, White arrests in White areas, etc. Moreover, when the results of Model 1 are taken into account, each additional percentage of Hispanic population in accounted for an increase of 13 arrests (aggregated across races) per subway station per quarter. This suggests that, within the context of fare evasion arrests, the policy did not change bias against Hispanic individuals, though it may have strongly affected bias against Hispanic communities.

Differences between the results for Black and Hispanic arrests suggest differences in the mechanisms motivating the changes for each racial group. Unlike for Hispanic arrests, the relative number of Black arrests is shown to have increased significantly as a result of the policy despite controlling for Black population and the overall time-trend in Black arrests through fixed effects. Interestingly, income is found to have a significant effect on Black arrests in the positive direction, implying that Black individuals are more likely to be arrested in higher-income areas, despite the general trend of Black individuals living in lower-income areas. This could imply that there is a higher incidence of Black individuals being arrested while commuting to or from higher income areas. The coefficient for Gini Index is also interesting in this case, since it implies that there is a lower incidence of Black arrests in areas with higher income inequality. This could be interpreted to mean that Black individuals are more likely to be arrested in areas with homogeneous income levels. Combined, the economic indicators imply that there is a higher incidence of Black arrests in homogeneously higher-income areas. The high R^2 squared value when Model 2 tests changes in Black Arrests indicates that the policy and variables discussed account for most of the changes in patterns to Black arrests, and point to the policy, economic indicators, and racial demographics as primary causes of changes in Black arrests uniquely experienced by Manhattan across the tested time period.

The results of Model 2 suggest that the only racial sub-group which experienced a relative decrease in arrests as a result of policy was White. This decrease appears to be relatively widespread across subway stations of varying demographics, as neither income or Gini Index are found to be significant predictors of White arrests. Asian arrests are found to decrease marginally (though this may be due to the relatively small number of Asian arrests overall), and while significant each additional percentage of Asian population is found to affect the number of Asian arrests the least compared to other races (according to Table 5).

7 Discussion and Conclusion

The results above are strong indicators for an increase in racial bias in the arrest patterns of the New York Police Department as a result of the Manhattan DA's policy to stop prosecuting fare evasion arrests. The policy was successful insofar as it led to an aggregate decrease of the total number of arrests, and for the total number of arrests of each race. The mechanism through which this occurred could be a direct reduction in transportation policing from the NYPD, though the recent increase in MTA police could mean that policing remains level, and that the reduction in arrests led to an increase in other enforcement actions such as fines. However, the policy clearly increased the relative number of arrests of Black individuals, when time trends and population demographics are controlled for. This effect was not seen significantly for Hispanic individuals, while White individuals saw significantly fewer arrests. Based on the press release associated with the policy discussed in this paper, the motivations for the adaptation of the policy were at least somewhat racial in nature, with direct reference to biases in enforcement. City councilmember Rory I. Lancman stated "For too long, prosecution of fare evasion as a crime has disproportionately impacted people of color . . . and even put immigrants at risk of deportation"(Vance 2017). The mention of a racial motivation for the policy did not result in a racially egalitarian implementation, despite intentions to do so. It is possible that policies which attempt to decrease racial bias by reducing the severity of punishment rather than eliminating it entirely are prone to increases in bias. Furthermore, events after the implementation of the policy, such as the grassroots coalition protest mentioned in Section 2.3, which took place more than a year after the prosecutions ended, indicate that the public has perceived an increase in racial bias for fare evasion enforcement after the policy went into effect. It is also possible that the presence of the protests had an exogenous impact on the aggregate or racial arrest rates, with police officers responding to the protests by changing their arrest behaviors.

Results suggest that the NYPD directly reacted to credible commitment from the District Attorney's office that it would stop prosecuting fare evasion arrests by reducing the number of individuals it arrested for fare evasion. Whether this was due to internal decisions from the NYPD or individual officers with changing incentives is unclear. The question of whether this response constitutes a form of Broken Windows Policing, however, is less clear. There was shown to be a relative increase in Black arrests as a result of the policy, and as discussed in Section 2.1 Broken Windows policing is racial in nature. Furthermore, as Broken Windows policing is linked to racial and socioeconomic profiling, Hispanic and Black communities having higher rates of arrest, both for each of those races respectively and on aggregate, suggests that those areas and races are profiled. However, Broken Windows Policing also concerns the placement of police officers in areas predicted to have higher rates of minor crimes in order to prevent increased crime in the future. It is impossible to directly measure the relationship between placement of officers and bias in law enforcement due to the confidential nature of data involving the exact arrests from individual officers, or knowing the rates at which officers are assigned locations (in this case, subway station). Despite the particular mechanism being unclear, increased arrest rates of Black individuals and in communities of color with a clear decrease in White arrests points to racial motivation at the individual level for Black people, and at the community level for Black and Hispanic communities.

While some results point to racial bias and the presence of Broken Windows Policing as the mechanisms they are driven by, others are more difficult to explain. The prevalence of Gini Index as a strong positive indicator on the aggregate model, yet as a strong negative indicator for the arrest of Black individuals is one such example. Areas with a higher rate of income inequality could have more arrests due to a higher number of reports from other individuals in the area, though there is little quantitative evidence proving that higher income individuals are more likely to report fare evasion. Other exogenous explanations for increased arrest rates where there is higher income inequality could be linked to gentrification, as there could be high rates of income inequality in gentrifying areas, accompanied by a higher rate of fare evasion arrests as subway stations in gentrifying areas become more popular.

If Models 1 and 2 are to be interpreted as indicating racial bias, their results indicate a very particular mechanism through which it is expressed. Bias is seen to be present against Black individuals, through the results of Model 2, and against Black communities, through the results of Model 1. However, while the proportion of Hispanic individuals in a community is significant to both models, the policy was not found to have a significant effect on the number of Hispanic arrests. Bias is shown to Black individuals, but not Hispanic individuals, yet it is shown to both communities of color. This could display a disparity between biases of the NYPD and that of individual police officers. If it can be assumed that officers are placed at or near the subway stations in which the arrests occur, demographic results of Model 1 could indicate bias in the central decision-making body of the NYPD against *communities* of color. Meanwhile, the results of Model 2 indicate bias against specifically Black *individuals*, with an increase in Black arrests at the subway station level. It is possible that the NYPD assigns officers to communities of color, both Black and Hispanic, while officers individually carry stronger bias against Black individuals.

While a relationship between race, economic class, and law enforcement in the New York City subway system has been established, a deeper examination of the mechanisms driving this relationship is needed. Future work could examine the incentive structures present in the interactions between prosecutors and law enforcement. Future work could also analyze the District Attorney's announcement as an exogenous shock to the NYPD as a whole through a regression discontinuity in time design. Finally, in order to determine whether the observed fare evasion arrest patterns are systemic, future work should apply similar research techniques to other cities and enforcement agencies.

8 Appendix

	Black Arrests	White Arrests	Asian Arrests	Hispanic Arrests
Period	0.004	0.030**	-0.017	-0.022***
	(0.97)	(2.80)	(-1.28)	(-3.58)
Treated	0.021***	0.094***	0.044***	0.051***
	(5.79)	(9.20)	(3.68)	(8.51)
Period*Treated	***	***	***	
	(5.40)	(-10.97)	(-3.66)	(-1.16)
Ridership	-0.029***	0.189***	0.244***	0.019***
	(-12.07)	(28.98)	(30.61)	(5.00)
Total Arrests	0.952***	0.599***	0.300***	0.850***
	(407.52)	(94.56)	(40.10)	(239.87)
Percent Black Population	0.119***			
	(49.06)			
Percent White Population		0.157***		
		(20.94)		
Percent Asian Population			0.079***	
			(10.99)	
Percent Hispanic Population				0.193***
				(44.54)
Income	0.056***	-0.001	-0.002	0.020***
	(17.66)	(-0.14)	(-0.17)	(3.99)
Gini Index	-0.043***	0.026**	0.019	0.021***
	(-14.57)	(3.21)	(1.95)	(4.65)
Year and Borough Fixed Effects	Yes	Yes	Yes	Yes
N	17000	17000	17000	17000
R^2	0.927	0.471	0.218	0.827

Standardized beta coefficients; t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Change in Arrests by Race (Beta coefficients)

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