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Face Masking Violations, Policing, and COVID-19 Death Rates: A Spatial Analysis in New York City ZIP Codes

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Face Masking Violations, Policing, and COVID-19 Death Rates: A Spatial Analysis in New York City ZIP Codes

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Abstract

The use of face masks during a pandemic and compliance with state and local mandates has been a divisive issue in the United States. We document variation in face masking violation rates involving police enforcement in New York City and examine the association between police-enforced face masking violations and COVID-19-related death rates. We assemble a Zone Improvement Plan (ZIP) code–level data set from the New York City Open Data, Department of Health, and the American Community Survey (2014–2018). We use maps to demonstrate the spatial patterning of police-enforced face masking violation rates and COVID-19-related death rates. Using a Bayesian spatial analysis approach to model police-enforced face masking violations, we find considerable variation in police-enforced face masking violation rates and COVID-19-related death rates across New York City and similarities in their spatial distribution, with higher rates for both measures found in Brooklyn and the Bronx. The positive association between police-enforced face masking violation rates and COVID-19-related death rates holds after including other covariates. The percentage of non-Hispanic Blacks, Hispanics, and households with limited English proficiency are positively associated with police-enforced face masking violations. This study extends the COVID-19 literature by reporting more aggressive enforcement of face masking rules in minority and limited-English-proficiency communities.

Keywords: COVID-19, face masking, New York City, policing, spatial analysis

Since the beginning of the COVID-19 pandemic, debate about the effectiveness of wearing face masks (face masking hereafter) to reduce the spread of the virus has been heated (Feng et al. 2020), and it is particularly so in the United States. Some suggest that the limited evidence for how much face masking prevents the transmission of the viruses that cause COVID-19 and other influenza-like illnesses is the root of this debate (Greenhalgh et al. 2020; Xiao et al. 2020). Even though a recent study reports that the daily COVID-19 growth rates, on average, declined by 2 percentage points three weeks after states' face masking orders were enacted in the United States (Lyu and Wehby 2020), recommendations on face masking in public still vary by state. As of 29 October 2020, thirty-three states and the District of Columbia mandated face masking in public (Markowitz 2020).

New York City was one of the areas hit hardest and earliest by COVID-19 and New York State was among the first to mandate face masking (on 17 April 2020) as a means to combat the pandemic. Individuals who violate the mandate are subject to a maximum fine of $1,000 for each violation (New York State 2020), and the New York City Metropolitan Transportation Authority can also impose a fine on individuals who do not follow the face masking rule (Kramer 2020). Individuals can report a face masking violation to the authorities and the police department will enforce face masking or take actions to fix a violation as appropriate.

Most current research focuses on exploring the factors (e.g., racial or ethnic composition and socioeconomic conditions) associated with COVID-19-related outcomes (Chow et al. 2020; Cordes and Castro 2020; Sun et al. 2020; Do and Frank 2021), such as death rates or prevalence. Little is known about whether and how these COVID-19 outcomes shape the public's awareness of face masking violations and even less explored is whether enforcement by the police is related to the context in which a face masking violation is reported. Importantly, during the pandemic, there has been a growing concern about how public health policies are enacted by law enforcement (Dunbar and Jones 2021). The goal of this study is to fill these gaps. Specifically, we argue that there are three reasons why poor COVID-19 outcomes (i.e., high mortality) might be positively associated with police-enforced face masking violations. We discuss them next.

First, social cognitive theory suggests that environment influence, actions of others, and the results of others' actions are important determinants of individuals' preventive behavior (Bandura, Smith, and Hitt 2005; Hagger et al. 2016). In areas with high COVID-19 mortality rates, residents are sensitive to others' actions that might undermine health, and there could be a high expectation that any unlawful activities should be corrected. As such, agencies tend to take actions to fix face masking violation in areas with poor COVID-19 outcomes.

Second, in light of the person-to-person nature of COVID-19 spread, the police are at a high risk of infection because they often closely work with strangers and the most marginalized populations (Richards et al. 2006; Jennings and Perez 2020). Law enforcement officers might feel a stronger threat to not only their health but also their family's health when responding to dispatch calls in communities with high COVID-19 mortality rates than in those areas with low mortality rates. The stronger threat to health and safety might thus be associated with more police-enforced violations.

Finally, several incidents of intentional contamination of police officers via spitting or coughing have been reported (Bates 2020; Margolin 2020) and the increasing potential for intentional contamination poses an additional health risk to both civilians and law enforcement officers. Coupled with the concern about being in close proximity to strangers without face masking during the pandemic (Kecinski et al. 2020), officers taking actions to resolve the complaints about face masking violations might become a justified decision, especially in areas with high COVID-19 mortality rates.

Drawing on these reasons and using a unique data set from Zone Improvement Plan (ZIP) codes in New York City, this study aims to achieve two goals: (1) to investigate whether COVID-19 death rates are positively associated with police-enforced face masking violations and (2) to understand whether other contextual factors at the ZIP code level, beyond COVID-19 death rates, are associated with police-enforced face masking violations.

Methods

Measures and Data Sources

Dependent Variable

The number of calls about face masking violations that have been reported to and enforced by the police (police-enforced violations hereafter) serves as the dependent variable. The number of all 311 calls about face masking violations is treated as the offset variable. We note that not every 311 call will lead to police enforcement, even though the police department responds to every 311 call complaint about face masking violation. The 311 call data were obtained from New York City Open Data (New York City Open Data Team 2020) and covered calls between 28 March 2020 and 3 September 2020. There were 11,109 complaints related to face masking violations during this period, and 4,596 (41.4 percent) were responded to and enforced by the police (the remainder of the calls are those responded to by the police but no action or enforcement was deemed necessary).

Covariates

In addition to COVID-19-related death rates (per 1,000 population), we consider three groups of covariates: sociodemographic features, household and labor force features, and neighborhood disorganization.

Data on COVID-19-related death rates come from the New York City Department of Health and Mental Hygiene (see https://github.com/nychealth/coronavirus-data) from 29 February 2020 to 3 September 2020.[1] ZIP code–level data on other covariates are from the 2014–2018 American Community Survey five-year estimates, unless otherwise noted.

Sociodemographic features include six variables: percentage of population aged sixty-five and above, percentage of Hispanics, percentage of non-Hispanic Blacks, percentage of Asians, logged population density (1,000 people per square mile), and disadvantage index. The disadvantage index is a composite score created by applying principal component analysis to the following variables: percentage of population with a bachelor's degree or higher (factor loading = –0.832), logged household income (–0.942), percentage of population living below poverty level (0.884), unemployment rate (0.870), percentage of female-headed households (0.915), and percentage of households receiving public assistance income (0.914). The principal component analysis results suggest that one factor explains almost 80 percent of the overall variation.

Household and labor force features include seven variables: percentage of household overcrowding, average household size, percentage of households with limited English proficiency, percentage of workers who travel an hour or more, percentage of essential workers, income inequality, and percentage of adults (aged nineteen through sixty-four) who are uninsured. A household is considered overcrowded if there is more than one person per room. Essential workers are those who are employed in "COVID-essential" occupations.[2] Income inequality is measured by the 80/20 ratio, which is the ratio of household income at the 80th percentile to income at the 20th percentile. Higher values reflect higher levels of income inequality.

Finally, for neighborhood disorganization, we use three variables: crime rates, other 311 service call rates, and instability. Crime rates are defined as the number of violent (e.g., murder and robbery) and property (e.g., burglary and larceny) crime incidents per 1,000 population. Other 311 service call rates are defined as the number of 311 calls that are not related to face masking violations per 1,000 population. Both variables are from New York City Open Data. Because these variables are highly skewed, we use log-transformed values in the analysis. Instability is measured by the percentage of population moving to the current residence in the past year.

Bayesian Spatial Modeling

We use negative binomial regression, which relaxes the equivalence assumption and allows for overdispersion, to model the number of police-enforced face masking violations. It can be expressed as follows:

$$\mu_i = E[y_i] = \exp(\ln(T_i) + \beta_0 + \textstyle\sum_{k=1}^{K} \beta_k x_{ki}) \tag{1}$$

where μ_i refers to the mean number of police-enforced face masking violations (i.e., $E[y_i]$) and T_i indicates the number of all face masking violations reported to the police, which is used as the offset variable. Should both parameters be combined, a negative binomial regression estimates the mean rate of police-enforced cases per violation (i.e., percentage of police-enforced face masking violations). β_0 is the intercept and coefficient β_k is a parameter that assesses the relationship between covariates x_k and μ_i.

Beyond that conventional model specification, we expand Equation 1 by considering different sets of error terms, which can be expressed as Equation 2:

$$\mu_i = \exp(\ln(T_i) + \beta_0 + \textstyle\sum_{k=1}^{K} \beta_k x_{ik} + h_i + w_i) \tag{2}$$

where h_i is a random error specific to each ZIP code i. It is independent and identically distributed and follows a normal distribution with a mean of 0 and a variance parameter α_h^2, which is defined as $1/\tau_h$ (τ_h is a precision parameter). w_i refers to the spatially structured errors and is designated such that the conditional distribution of w_i given other locations w_{-i} that are defined as neighbors can be expressed as

$$w_i | w_{-i} \sim N\left(\textstyle\sum_{j\sim i} w_j / n_i\, , \alpha_w^2 / n_i\right) \tag{3}$$

where α_w^2/n_i refers to the variance parameter and is defined as $1/\tau_w$ (τ_w is the precision parameter for spatial errors), $j \sim i$ denotes that the ZIP code j is a neighbor of the ZIP code i, and n_i is the total number of neighbors of the ZIP code i. Explicitly, given a set of neighbors, w_i is assumed to have a mean equal to the mean of neighbors and a variance that is a function of the number of neighbors. Such a specification of spatially structured error has been commonly used in the conditional autoregressive (CAR) model (Besag, York, and Mollié 1991). The spatially structured errors capture the processes associated with omitted variables in the analysis. A neighborhood list is created based on the first-order queen contiguity approach, which defines a neighbor when two ZIP codes share a common boundary or vertex.

Although other spatial econometrics models can be applied to our data set, we chose the CAR model for the following reasons. First, the CAR model allows us to account for the potential biases caused by spatial structure and to separate structured effects from nonstructured effects. Second, the potential influence of covariates from neighboring ZIP codes is not the focus of this study and as such spatial econometrics models, such as spatial lag or Durbin, are not needed. Third, the CAR model follows the Markov property, which can be easily applied to spatial generalized linear modeling (Goodchild and Haining 2004; Ver Hoef et al. 2018).

We use the integrated nested Laplace approximation (INLA) method (Rue, Martino, and Chopin 2009) to obtain the Bayesian estimates for the models just discussed. For all hyperparameters, we use the log-Gamma distribution (with a shape of 0.5 and a rate of 0.005) as the prior distribution. The default initial values by the INLA package are used in the analysis. The INLA generates the posterior distributions of parameter estimates (e.g., β_k), and we will present the results with the mean values with 95 percent credible regions. The deviance information criterion (DIC) will be used to compare different models. In principle, a DIC difference that is greater than ten between two models suggests that the one with the lower value is preferred (Spiegelhalter et al. 2002).

Results

To facilitate the interpretation of results, we include two maps showing the boroughs and ZIP codes in New York City, respectively (Figure 1), and descriptive statistics for the five boroughs (Table 1). Several observations emerge from the descriptive findings. First, the average number of police-enforced face masking violations per ZIP code in New York City was almost twenty-six between 28 March 2020 and 3 September 2020. We observe a significant variation between boroughs, however. ZIP codes in Brooklyn, on average, reported more than forty police-enforced violations, whereas those in Staten Island averaged thirteen. Second, regarding COVID-19-related death rates through 3 September 2020, ZIP codes in Manhattan have the lowest rate at 1.38 (per 1,000 population), compared with the 2.72 COVID-19-related deaths per 1,000 population among ZIP codes in the Bronx. Third, in terms of sociodemographic features, there is no significant difference in percentage of the population aged sixty-five and over, but racial and ethnic composition varies greatly by borough. ZIP codes in the Bronx have the highest average percentage of Hispanics (53.08 percent), and non-Hispanic Blacks make up almost 30 percent of the population among ZIP codes in Brooklyn. In Queens the population is approximately 25 percent Asian. As for the disadvantage index, ZIP codes in Manhattan are the least disadvantaged and those in the Bronx are the most disadvantaged.

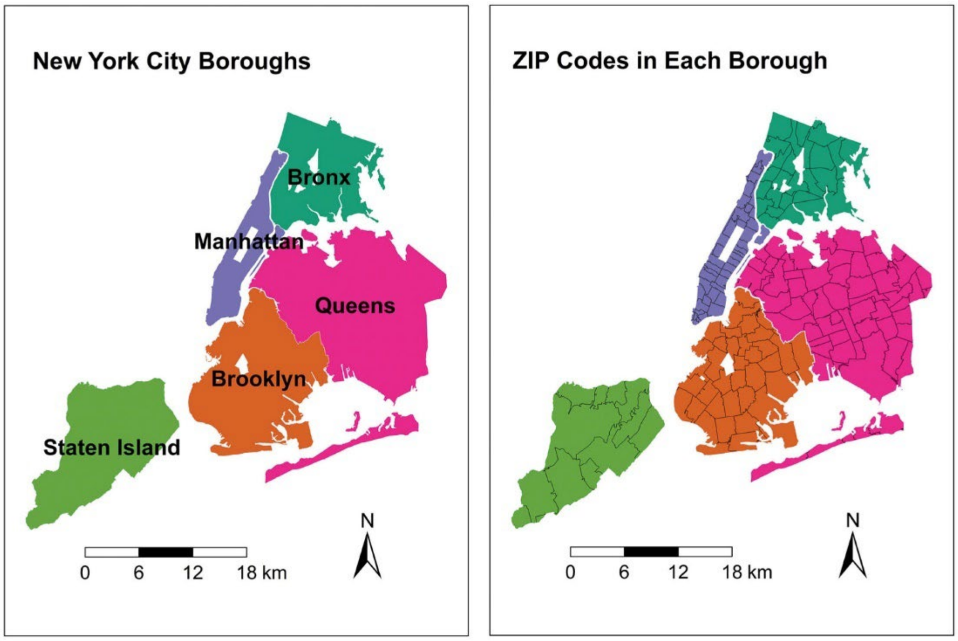

Figure 1. Maps of boroughs and ZIP codes in New York City.

Table 1. Descriptive statistics of all variables and comparisons among New York City boroughs

	Bronx $n = 25$		Brooklyn $n = 25$		Manhattan $n = 44$		Queens $n = 59$		Staten Island $n = 12$		New York City $n = 177$		One-way ANOVA
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	
Dependent variable													
Police-enforced face mask violations	32.44	14.33	40.05	19.83	24.50	14.80	16.90	13.04	13.08	11.42	25.56	17.70	***
Independent variables													
COVID-19-related death rates	2.72	0.85	2.24	1.17	1.38	0.95	2.42	1.11	1.79	0.97	2.12	1.14	***
Sociodemographic features													
% Population aged 65 and above	13.25	5.31	13.45	4.83	14.28	6.00	15.25	4.56	14.49	2.90	14.30	5.04	
% Hispanics	53.08	18.16	19.41	13.01	20.47	19.13	24.21	15.22	20.49	11.63	26.10	19.44	***
% Non-Hispanic Blacks	27.84	15.41	29.30	28.62	11.52	17.06	17.09	24.79	11.13	11.56	19.37	23.12	**
% Asians	3.53	3.21	11.29	11.06	14.32	10.26	24.06	16.37	7.48	3.96	14.95	13.95	***
Log of population density	10.41	0.99	10.59	0.41	10.96	0.82	9.95	0.71	9.10	0.45	10.34	0.88	***
Disadvantage index	1.26	1.00	0.27	0.74	–0.67	1.04	–0.18	0.55	–0.14	0.56	0.00	1.00	***
Household and labor force features													
% Household overcrowding	11.33	5.00	10.14	5.30	6.46	3.19	7.99	4.95	4.45	2.47	8.29	4.90	***
Average household size	2.76	0.28	2.67	0.38	2.10	0.36	2.93	0.48	2.83	0.16	2.64	0.50	***
% Households with limited English proficiency	16.99	8.16	15.30	12.08	8.59	7.49	15.40	12.02	6.41	2.51	13.30	10.66	***
% Workers traveling an hour or more	35.20	5.23	28.02	11.18	10.18	6.22	32.09	8.79	35.52	3.07	26.47	12.60	***
% Essential workers	77.42	9.62	62.69	15.17	43.08	14.37	69.35	10.59	67.85	5.09	62.46	17.10	***
Income inequality	18.33	3.25	21.84	7.62	28.61	10.87	13.86	3.54	25.28	16.18	20.60	9.82	***
% Uninsured adults	13.79	4.42	11.55	4.40	6.79	4.13	12.23	6.18	7.76	3.79	10.65	5.57	***
Neighborhood disorganization													
Log of crime rates	3.67	0.87	3.62	0.62	2.99	1.10	2.71	0.88	2.49	0.60	3.09	0.97	***
Log of other 311 service call rates	5.17	0.47	4.81	0.30	4.72	0.65	4.81	0.30	4.73	0.16	4.83	0.45	**
Instability	8.83	2.62	9.85	3.62	16.57	5.26	8.75	4.07	5.90	1.27	10.74	5.30	***

Note: ANOVA = analysis of variance. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Fourth, the percentage of workers commuting over an hour and percentage of essential workers are the lowest among ZIP codes in Manhattan and high among ZIP codes in the Bronx. Income inequality is also the highest (28.61) in Manhattan, whereas other ZIP codes share a more equal distribution of income. Finally, crime rates and the rates of other 311 service calls are higher among ZIP codes in the Bronx and Brooklyn than in other boroughs.

Beyond these descriptive statistics, we visualize the spatial distributions of the rate of police-enforced face masking violation and COVID-19-related death rates in Figure 2 (by quintiles). The maps suggest that ZIP codes with high rates of police-enforced face masking violations (Figure 2A) are concentrated in the Bronx, eastern Queens, northern Brooklyn, and northern Staten Island, and these areas seem to echo the clusters of COVID-19-related death rates (Figure 2B), such as the ZIP codes in the Bronx and eastern Queens. The similarity in the spatial distributions of these variables suggests that COVID-19-related death rates might be positively associated with police-enforced face masking violations.

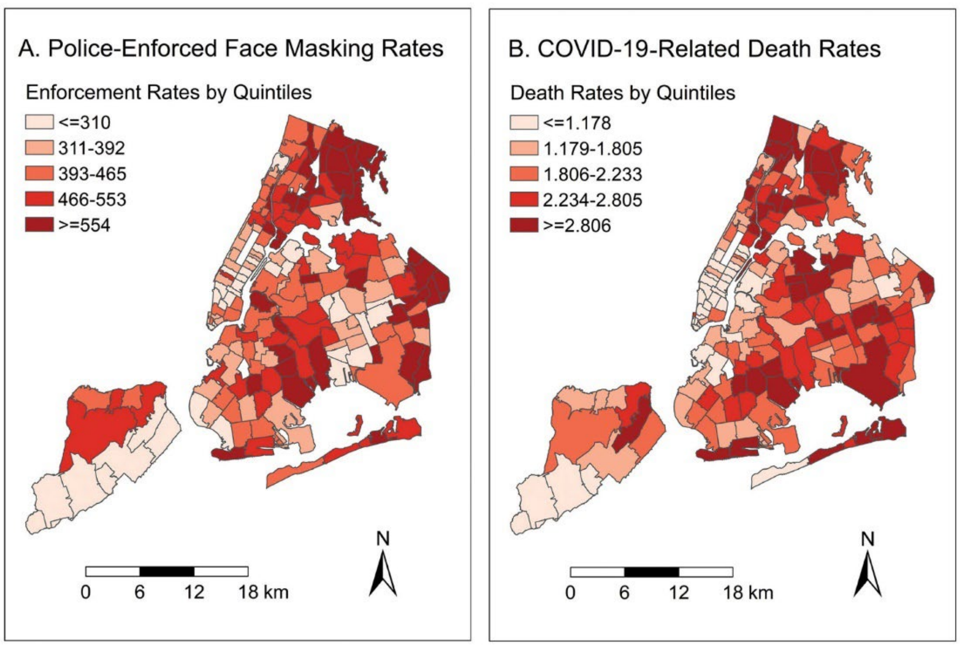

Figure 2. Maps of police-enforced face masking rates and COVID-19 death rates in New York City.

Table 2 shows the spatial negative binomial regression results (the maps of the combined effects of these models are in Appendix A). Model 1 considers only COVID-19-related death rates, and the results indicate that one additional COVID-19-related death (per 1,000 population) in a ZIP code is associated with a 14.9 percent increase in the number of police-enforced face masking violations ((1.149 – 1) * 100%). Including sociodemographic features in Model 2 explains more than 60 percent of the positive association between COVID-19-related death rates and the number of police-enforced face masking violations because the magnitude of this association drops from 14.9 percent to 5.7 percent ((1.057 – 1) * 100%). This decrease in the association between COVID-19-related deaths and police-enforced violation might imply that racial and ethnic composition serves as a mechanism for this association. Because minorities have been disproportionately affected by COVID-19, especially in the early stage of the pandemic, areas with high concentrations of minorities can be associated with high COVID-19 mortality rates, which might explain the association found in Model 2.

In Model 3, the household and labor force features seem to suppress the relationship of COVID-19-related death rates with the number of police-enforced face masking violations. Specifically, one additional COVID-19-related death is associated with a 6.1 percent increase in the dependent variable in Model 3, which is slightly higher than that in Model 2. The final model further considers neighborhood disorganization variables, but the results indicate that these variables do not alter the relationship between COVID-19-related death rates and the number of police-enforced face masking violations. The findings from Model 3 and Model 4 indicate that limited English proficiency might be another possible mechanism linking COVID-19-related death rates with police-enforced violations, but the percentage of workers commuting more than an hour seems to operate in an opposite direction. Neighborhood disorganization variables do not seem to play a role in accounting for the positive association between COVID-19 deaths and police-enforced face masking violations.

Beyond COVID-19-related death rates, several important findings are worth noting. First, the concentrations of non-Hispanic Blacks and Hispanics are positively associated with the number of police-enforced face masking violations, and these associations are consistent from Model 2 to Model 4. Based on Model 2, for example, a 10 percentage point increase in non-Hispanic Blacks is associated with a 5 percent increase ((1.005◦10-1) * 100% = 5.11%) in the number of police-enforced face masking violations in a ZIP code, and this association is enhanced in Model 4 to roughly 7 percent. Similarly, in the full model, the number of police-enforced face masking violations is increased by 5 percent as the percentage of Hispanics increases by 10 percentage points.

Second, ZIP codes with more households with limited English proficiency tend to have more police-enforced face masking violations. Explicitly, every 10 percentage point increase in households with limited English proficiency is related to a 12.66 percent increase in police-enforced face masking violations ((1.012◦10-1) * 100% = 12.67%). This relationship is not changed even after the neighborhood disorganization variables are considered. Finally, the percentage of workers commuting more than an hour is negatively associated with police-enforced face masking violations. Our results suggest that the number of police-enforced face masking violations decreases by almost 8 percent ((1-0.992◦10) * 100% = 7.72%) if the percentage of workers commuting more than an hour increases by 10 percentage points.

Table 2. Bayesian negative binomial regression of the number of police-enforced face covering violations

	Model 1		Model 2		Model 3		Model 4	
	M	95% CR	*M*	95% CR	*M*	95% CR	*M*	95% CR
Intercept	0.311	[0.281, 0.345]	0.409	[0.221, 0.748]	0.429	[0.156, 1.168]	0.460	[0.109, 1.911]
COVID-19-related death rates	**1.149**	**[1.100, 1.199]**	**1.057**	**[1.002, 1.115]**	**1.061**	**[1.000, 1.124]**	**1.062**	**[1.001, 1.126]**
Sociodemographic features								
% Population aged 65 and above			1.004	[0.991, 1.017]	0.998	[0.982, 1.015]	0.999	[0.981, 1.016]
% Hispanics			**1.006**	**[1.001, 1.010]**	**1.005**	**[1.000, 1.010]**	**1.005**	**[1.000, 1.011]**
% Non-Hispanic Blacks			**1.005**	**[1.002, 1.009]**	**1.006**	**[1.003, 1.010]**	**1.007**	**[1.003, 1.011]**
% Asians			1.002	[0.998, 1.007]	0.999	[0.993, 1.004]	0.999	[0.993, 1.005]
Log of population density			0.958	[0.908, 1.012]	0.945	[0.881, 1.014]	0.949	[0.883, 1.021]
Disadvantage index			1.038	[0.947, 1.137]	0.998	[0.877, 1.137]	1.002	[0.879, 1.143]
Household and labor force features								
% Household overcrowding					0.986	[0.971, 1.001]	0.987	[0.972, 1.003]
Average household size					1.085	[0.889, 1.323]	1.077	[0.878, 1.322]
% Households with limited English proficiency					**1.012**	**[1.002, 1.022]**	**1.012**	**[1.002, 1.022]**
% Workers traveling an hour or more					**0.992**	**[0.984, 0.999]**	**0.991**	**[0.983, 0.999]**
% Essential workers					1.005	[0.994, 1.015]	1.005	[0.994, 1.016]
Income inequality					0.999	[0.993, 1.005]	1.000	[0.993, 1.006]
% uninsured adults					0.992	[0.976, 1.009]	0.994	[0.977, 1.011]
Neighborhood disorganization								
Log of crime rates							0.950	[0.884, 1.021]
Log of other 311 service call rates							1.006	[0.875, 1.156]
Instability							0.999	[0.984, 1.014]
θ (overdispersion hyperparameter)	3.606	[2.828, 4.204]	8.013	[4.806, 9.866]	8.541	[4.925, 10.410]	8.485	[4.893, 10.355]
DIC	1,148.68		1,106.58		1,108.09		1,111.06	
	M	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Marginal variance of structured effects	0.1620	0.1220	0.0569	0.0218	0.0495	0.0196	0.0499	0.0197
Marginal variance for unstructured effects	0.0079	0.0063	0.00639	0.0046	0.0056	0.0040	0.0058	0.0042

Note: $N = 177$. The numbers in the table indicate rate ratios and values shown in bold suggest that the credible region does not include 1. CR = credible region; DIC = deviance information criterion.

Discussion and Conclusion

The findings presented lead us to the following conclusions related to our research goals. First, for New York City ZIP codes, we obtain evidence that high COVID-19 death rates are positively associated with the number of police-enforced face masking violations. Although this association can be partially explained by sociodemographic features of a ZIP code, it remains an important factor in our full model. That is, after the police department responds to the face masking complaints, the police are more likely to take action to fix the complaints in ZIP codes with high COVID-19 death rates than in those with low rates. This association confirms that exposure to heightened risk factors might enhance preventive behaviors, especially when the actions of others might lead to infections or other negative health consequences, such as stress.

Second, in addition to COVID-19 death rates, our analysis indicates that ZIP codes with more minorities tend to have more police-enforced face masking violations. This finding echoes several reports suggesting that minority communities tend to be the focus of law enforcement (Goldberg and Annese 2020; The Legal Aid Society 2020) regarding social distancing. This study extends this literature by suggesting that minority communities experience more aggressive enforcement of face masking rules than White communities, which echoes the concern about how police officers enact public health policies with different racial and ethnic groups (Dunbar and Jones 2021). This finding also suggests that racial and ethnic composition could be a mechanism linking COVID-19 death rates and police-enforced face masking violations. Moreover, percentage of households with limited English proficiency is positively related to police-enforced face masking violations. A plausible explanation is that limited English proficiency could be a barrier to communication with law enforcement, especially for the initial police interaction or emergency situations (Meischke et al. 2010; Coppersmith 2018). Thus, police-enforced face masking violations are more common in ZIP codes with more households with limited English proficiency. Racial and ethnic composition and households with limited English proficiency could both be mechanisms that should be examined with formal mediation analysis.

We implemented several sensitivity analyses to ensure the robustness of our findings. First, we included more variables in the analysis than presented here (e.g., percentage of housing units without complete kitchen or plumbing systems), but they do not change our findings and conclusions. Second, we examined whether COVID-19 confirmed cases and positivity rates are related to police-enforced face masking violations. The results indicate that these variables are not associated with the dependent variable, confirming that only COVID-19 death rate plays a role. Third, we examined whether the number of precincts is related to the police-enforced violations. Although the estimated association is positive, this relationship is not strong enough statistically (95 percent confidence of rate ratio [0.935, 1.113]). Fourth, we conducted several models in which the total number of 311 calls about face masking violations serves as the dependent variable (offset is total number of 311 calls). The results indicate that the concentrations of minority groups, household overcrowding, and average household size are associated with the number of face masking violations. These findings can be found in Appendixes B, C, and D.

This study is subject to several limitations. First, we are unable to know the details about the police's action because the data set does not provide this information. Similarly, the information about the callers and individuals reported (e.g., race and ethnicity and gender) is not available, precluding analysis with these variables. Second, this is an ecological study specific to New York City and the findings cannot be generalized to the individual level or other populations and areas. Third, like other ecological research, this study is subject to the modifiable area unit problem (Openshaw 1983; Fotheringham and Wong 1991), and using different geographic units (e.g., tracts) might alter the findings and conclusions. Finally, whereas the COVID-19 mortality and 311 calls are available on a daily basis, other key independent variables are time invariant and a formal spatiotemporal analysis is not possible. It is thus important to note that the associations reported in this study could be confounded by temporal factors.

Despite these limitations, this study contributes to the literature in two ways. First, several scholars have found that the COVID-19 pandemic increased distress and mental burden, causing other public health problems, such as suicide and substance use (Czeisler et al. 2020; Sher 2020); however, to our knowledge, this study is among the first to link COVID-19 death rates to police-enforced face masking violations. Second, although the enforcement of COVID-19 preventive measures is more discretionary compared to other laws, our findings indicate that minority communities are still more likely to experience police enforcement than White neighborhoods, which supports the racial and ethnic disparities in law enforcement responses reported in New York City (Gelman, Fagan, and Kiss 2007; Golub, Johnson, and Dunlap 2007).

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Notes

1. The COVID data released by the New York City Department of Health and Mental Hygiene do not allow us to truncate the time span to match the 311 calls.
2. The "COVID-essential" occupations include construction and extraction occupations; farming, fishing, and forestry occupations; installation, maintenance, and repair occupations; material moving occupations; production occupations; transportation occupations; office and administrative support occupations; sales and related occupations; building and grounds cleaning and maintenance occupations; food preparation and serving related occupations; health care support occupations; personal care and service occupations; and protective service occupations.

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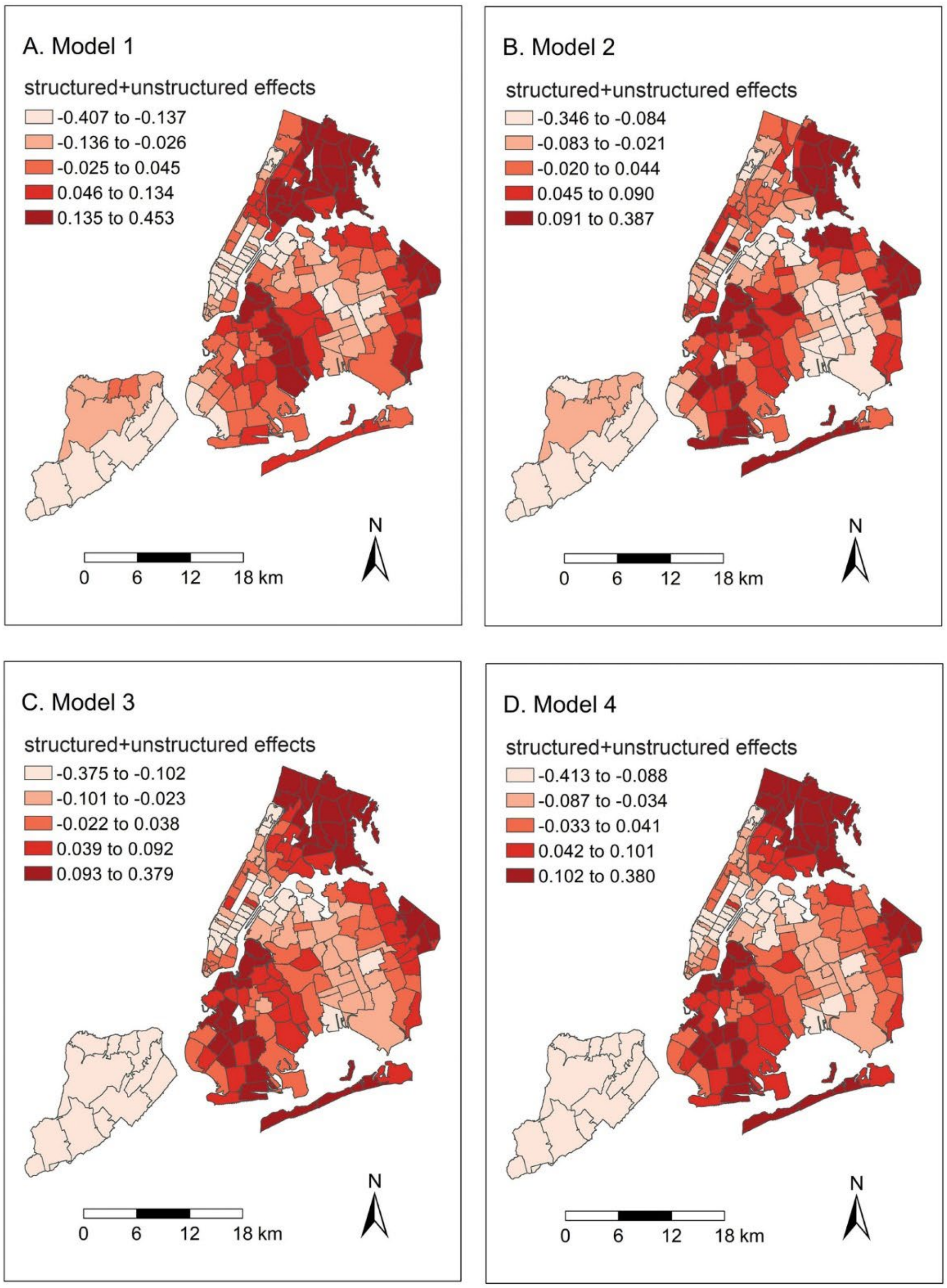
Appendix A

Maps of combined random effects (sum of spatially structured + unstructured random effects) across four models



Appendix B

Sensitivity analysis with the number of precincts in the full model

	Model 4	
	M	95% CR of rate ratio
Intercept	0.468	[0.110, 1.958]
Sociodemographic features		
% Population aged 65 and above	0.999	[0.981, 1.017]
% Hispanics	1.005	[1.000, 1.011]
% Non-Hispanic Blacks	1.007	[1.003, 1.011]
% Asians	0.999	[0.993, 1.004]
Log of population density	0.951	[0.884, 1.024]
Disadvantage index	1.006	[0.881, 1.148]
Household and labor force features		
% Household overcrowding	0.988	[0.972, 1.003]
Average household size	1.078	[0.878, 1.323]
% Households with limited English proficiency	1.012	[1.002, 1.022]
% Workers traveling an hour or more	0.991	[0.983, 0.999]
% Essential workers	1.005	[0.993, 1.016]
Income inequality	0.999	[0.993, 1.005]
% Uninsured adults	0.994	[0.977, 1.011]
Neighborhood disorganization		
Log of crime rates	0.941	[0.865, 1.023]
Log of other 311 service call rates	1.005	[0.875, 1.156]
Instability	0.998	[0.983, 1.014]
Number of precincts	1.020	[0.935, 1.113]
θ (overdispersion hyperparameter)	8.421	[4.865, 10.292]
DIC	1,112.55	

Notes: N = 177. CR = credible region; DIC = deviance information criterion. The numbers in the table indicate rate ratios. When a CR includes 1, the relationship with the dependent variable is not statistically significant.

Appendix C

Bayesian negative binomial regression results of number of 311 calls about face masking in New York City ZIP codes

	Model 1		Model 2		Model 3		Model 4	
	M	95% CR	*M*	95% CR	*M*	95% CR	*M*	95% CR
Intercept	0.017	[.014, 0.020]	0.005	[0.002, 0.011]	0.127	[0.039, 0.418]	0.121	[0.034, 0.439]
COVID-19-related death rates	0.795	[0.739, 0.856]	1.009	[0.934, 1.089]	1.044	[0.973, 1.120]	1.044	[0.972, 1.121]
Sociodemographic features								
% Population aged 65 and above			0.993	[0.975, 1.011]	0.988	[0.969, 1.006]	0.990	[0.970, 1.009]
% Hispanics			0.988	[0.981, 0.994]	0.991	[0.985, 0.997]	0.991	[0.985, 0.997]
% Non-Hispanic Blacks			0.985	[0.980, 0.990]	0.989	[0.985, 0.994]	0.989	[0.985, 0.994]
% Asians			0.988	[0.981, 0.994]	0.994	[0.987, 1.001]	0.993	[0.986, 1.000]
Log of population density			1.175	[1.088, 1.270]	0.976	[0.897, 1.062]	0.979	[0.898, 1.067]
Disadvantage index			0.839	[0.734, 0.958]	0.938	[0.798, 1.103]	0.941	[0.799, 1.107]
Household and labor force features								
% Household overcrowding					1.042	[1.022, 1.063]	1.043	[1.022, 1.064]
Average household size					0.623	[0.490, 0.791]	0.625	[0.488, 0.800]
% Households with limited English proficiency					1.004	[0.992, 1.016]	1.004	[0.992, 1.016]
% Workers traveling an hour or more					0.997	[0.987, 1.007]	0.996	[0.986, 1.006]
% Essential workers					0.993	[0.980, 1.006]	0.994	[0.980, 1.008]
Income inequality					0.998	[0.991, 1.005]	0.999	[0.991, 1.006]
% Uninsured adults					0.977	[0.956, 0.998]	0.978	[0.957, 1.000]
Neighborhood disorganization								
Log of crime rates							0.961	[0.884, 1.045]
Instability							1.002	[0.983, 1.022]
θ (overdispersion hyperparameter)	1.701	[1.562, 1.836]	2.264	[2.039, 2.437]	2.728	[2.285, 3.065]	2.657	[2.183, 3.028]
DIC	1,661.43		1,565.44		1,504.12		1,507.55	

Notes: N = 177. The dependent variable is the number of 311 calls about face masking violations, and the offset variable is the number of all 311 service calls. CR = credible region; DIC = deviance information criterion. The numbers in the table indicate rate ratios.

Appendix D

Sensitivity analysis with other covariates, COVID-19 case rates, and COVID-19 positivity rates

	Model 1		Model 2		Model 3	
	M	95% CR	*M*	95% CR	*M*	95% CR
Intercept	0.461	[0.108, 1.935]	0.478	[0.115, 1.960]	0.530	[0.124, 2.218]
COVID-19-related death rates	1.062	[1.001, 1.125]				
COVID-19 case rates			1.009	[0.999, 1.018]		
COVID-19 positivity rates					1.001	[0.998, 1.004]
Sociodemographic features						
% Population aged 65 and above	0.999	[0.981, 1.017]	1.002	[0.986, 1.019]	1.004	[0.988, 1.021]
% Hispanics	1.005	[1.000, 1.011]	1.005	[0.999, 1.010]	1.006	[1.001, 1.011]
% Non-Hispanic Blacks	1.007	[1.003, 1.011]	1.007	[1.003, 1.011]	1.008	[1.004, 1.012]
% Asians	0.998	[0.993, 1.004]	0.999	[0.993, 1.005]	0.999	[0.993, 1.005]
Log of population density	0.951	[0.882, 1.027]	0.955	[0.887, 1.028]	0.945	[0.879, 1.017]
Disadvantage index	0.984	[0.859, 1.127]	1.024	[0.897, 1.167]	1.015	[0.889, 1.159]
Household and labor force features						
% Household overcrowding	0.987	[0.971, 1.002]	0.986	[0.970, 1.002]	0.988	[0.972, 1.004]
Average household size	1.074	[0.875, 1.317]	1.060	[0.865, 1.299]	1.047	[0.848, 1.293]
% Households with limited English proficiency	1.012	[1.002, 1.022]	1.012	[1.002, 1.022]	1.012	[1.002, 1.023]
% Workers traveling an hour or more	0.991	[0.983, 0.999]	0.991	[0.984, 0.999]	0.991	[0.983, 0.999]
% Essential workers	1.005	[0.994, 1.017]	1.002	[0.990, 1.014]	1.003	[0.990, 1.015]
Income inequality	1.000	[0.994, 1.006]	0.999	[0.993, 1.005]	0.999	[0.993, 1.005]
% Uninsured adults	0.996	[0.979, 1.014]	0.999	[0.981, 1.016]	0.997	[0.980, 1.015]
% Housing units lacking complete plumbing facilities	1.072	[0.979, 1.176]				
% Housing units lacking complete kitchen facilities	0.945	[0.875, 1.019]				
Neighborhood disorganization						
Log of crime rates	0.945	[0.878, 1.016]	0.958	[0.892, 1.030]	0.957	[0.890, 1.029]
Log of other 311 service call rates	0.998	[0.868, 1.148]	0.989	[0.863, 1.135]	0.986	[0.858, 1.132]
Instability	0.999	[0.983, 1.014]	0.998	[0.983, 1.014]	0.999	[0.984, 1.015]
θ (overdispersion hyperparameter)	8.610	[4.912, 10.476]	8.117	[4.752, 9.976]	8.469	[4.877, 10.341]
DIC	1,111.47		1,113.81		1,114.03	

Notes: *N* = 177. Model 1 considers plumbing and kitchen variables. Model 2 replaces COVID-19 death rates with COVID-19 case rates, and Model 3 replaces COVID-19 death rates with COVID-19 positivity rates. The numbers in the table indicate rate ratios. CR = credible region; DIC = deviance information criterion.