Online Appendix for "The Determinants of the Differential Exposure to COVID-19 in New York City and Their Evolution over Time"[∗]

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A Summary statistics

Table [A1](#page-0-0) presents the summary statistics of the variables used in our analysis.

[∗]The views expressed in articles and other content on this website are those of the authors and don't necessarily reflect the position of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

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B Robustness checks

% Non ess. - Service $\begin{array}{|l} \hline 0.013 & 0.000169 & 0.007 \end{array}$

B.1 Quantifying attenuation bias from measurement error

The variance in measurement error can be quantified using the variable "Margin of Error" (MoE) provided by the ACS. The numbers that are reported in Table [A1](#page-0-0) are averages across zip codes. To obtain σ_u^2 , we simply use the following transformation:

$$
\sigma_u^2 = \left(\frac{MoE}{1.645}\right)^2.
$$

Then, using our estimates of Table 1 in the main text and the information provided in Table [A1,](#page-0-0) we can approximate the attenuation bias with the following formula:

$$
Bias(\hat{\beta}) = -\frac{\sigma_u^2}{\sigma_x^2 + \sigma_u^2} \beta
$$

. For simplicity, we approximate the attenuation for those variables that enter linearly and not in logs. The reason is that for these variables, we can directly use the numbers provided by the ACS for MoE and the variance of the variable.^{[1](#page-0-1)} Using the regression results of column 5 from Table 2 in the main text, we obtain the results summarized in the table below.

Variable $\text{S}d_x$ sd_x^2

Share > 20

0.084 0.0070 sd_x^2 MoE sd_u^2
0.007056 0.049 0.00088728 Attenuation Bias $\hat{\beta}$ sd_{β} Corrected $\hat{\beta}$
-0.1117019 0.139 (0.050) 0.155 $\text{Share} \ge 20$ $\begin{array}{|l} 0.084 & 0.007056 & 0.049 & 0.00088728 & -0.1117019 & 0.139 & (0.050) & 0.155 \end{array}$ $\text{Share} \geq 40$ $\bigg| 0.033 \bigg| 0.001089 \bigg| 0.041 \bigg| 0.00062121 \bigg| 0.03632347 \bigg| 0.006 \bigg| 0.043 \bigg| 0.008$ $\text{Share} \geq 60$ $\begin{array}{|l} 0.079 & 0.006241 & 0.042 & 0.00065188 & -0.0945728 & 0.396 & (0.048) & 0.433 \end{array}$ Share Male 0.029 0.000841 0.028 0.00028972 -0.2562287 0.115 (0.052) 0.144 $\%$ Black $\begin{array}{|ccc} 0.24 & 0.0576 & 0.016 & 9.4604E-05 & -0.0016397 & 0.058 & (0.011) & 0.058 \end{array}$ % Hispanic $\begin{array}{|l} 0.195 & 0.038025 & 0.025 & 0.00023097 \end{array}$ -0.0060374 0.129 (0.016) 0.130 $\%$ Asian $\begin{bmatrix} 0.139 & 0.019321 & 0.018 & 0.00011973 & -0.0061589 & 0.003 & (0.015) & 0.003 \end{bmatrix}$ % Asian $\%$ Public Transport $\%$ Public Transport $\%$ Dubic Transport $\%$ Dubic Transport $\%$ Uninsured $\%$ Uninsured $\%$ Uninsured $\%$ Uninsured $\%$ Uninsured $\%$ Dubic Uninsured $\%$ Uninsured $\%$ Uninsured % Uninsured $\begin{bmatrix} 0.043 & 0.001849 & 0.015 & 8.3148E-05 & -0.0430339 & 0.249 & (0.041) & 0.260 \end{bmatrix}$ % Uninsured $\begin{array}{|l}\n\% \text{Uninsert} \begin{array}{|l}\n\% \text{Essential - Professional} \end{array} & 0.043 \quad 0.001849 \quad 0.015 \quad 8.3148E-05 \quad -0.0430339 \quad 0.249 \quad (0.041) \quad 0.260 \\
\% \text{Essential - Professional} & 0.089 \quad 0.007921 \quad 0.021 \quad 0.00016297 \quad -0.0201596 \quad -0.086 \quad (0.054) \quad -0.088\n\end{array$ % Essential - Service 0.033 0.001089 0.015 8.3148E-05 -0.0709363 -0.061 (0.069) -0.065 % Essential - Technical 0.009 0.000081 0.005 9.2386E-06 -0.1023801 -0.698 (0.265) -0.769 % Health practitioners $\begin{bmatrix} 0.018 & 0.000324 & 0.007 & 1.8108E-05 & -0.0529299 & 0.085 & (0.102) & 0.089 \\ 0.024 & 0.000576 & 0.01 & 3.6955E-05 & -0.0602893 & 0.261 & (0.077) & 0.277 \end{bmatrix}$

% Other health $\begin{array}{|l} 0.024 & 0.000576 & 0.01 & 3.6955 \text{E} - 0.5 & -0.0602893 & 0.261 & (0.077) & 0.277 \end{array}$ % Firefighting $\begin{array}{|l} 0.009 & 0.000081 & 0.004 & 5.9127E-06 \end{array}$ -0.0680307 -0.14 (0.176) -0.150 % Firefighting 0.009 0.000081 0.004 5.9127E-06 -0.0680307 -0.14 (0.176) -0.150
% Law enforcement 0.007 0.000049 0.003 3.3259E-06 -0.0635615 -0.681 (0.209) -0.724 % Ind. and Construction $(0.027 \quad 0.000729 \quad 0.017 \quad 0.0001068 \quad -0.1277804 \quad -0.091 \quad (0.085)$ -0.103 % Transportation 0.016 0.000256 0.007 1.8108E-05 -0.0660607 0.351 (0.089) 0.374 % Non ess. - Professional $\begin{array}{|l}$ 0.075 0.005625 0.056 0.0011589 -0.1708304 -0.109 (0.052) -0.128
% Science fields 0.007 0.000049 0.003 3.3259E-06 -0.0635615 -0.785 (0.222) -0.835 % Science fields $\begin{array}{|l} \sim 0.007 & 0.000049 & 0.003 & 3.3259E-06 \end{array}$ -0.0635615 -0.785 (0.222) -0.835 % Law and related $\begin{array}{|l} \n\% \text{ Non ess. - Service} \\
0.013 \quad 0.000169 \quad 0.007 \quad 1.8108 \text{E-05} \\
\text{Non ess. - Service} \\
\end{array}$ -0.13001 -1.042 (0.094) -1.062

Table B1: Summary statistics

¹For occupational shares that are the result of a aggregation of categories provided by the ACS, we have approximated their MoE by summing over the MoE across their individual factors.

What we observe is that in this case, attenuation bias does not seem excessively large. It ranges from 0.1% to 25.6%, with an average of 8.6%. The bias corrected β 's are not statistically different from the estimated $\hat{\beta}$'s. We conclude that even though the presence of measurement errors shrinks our coefficients, this attenuation seems small and does not lead to statistically different results.

B.2 Tests per capita as a proxy for local disease expansion

In the following tables, we present our results including a covariate for the number of performed tests per capita, which we call "tests per capita." The reason to include this variable is as follows. The limited availability of tests in NYC forced health authorities to constrain testing to people showing sufficiently acute symptoms or determined to be at high risk of infection at the beginning of the pandemic. Thus, we expect the daily number of tests administered to be close to the population in that segment, which in turn should be roughly proportional to the number of infected people.[2](#page-0-1) Therefore, we use the number of tests per capita as a proxy for the overall level of the spread of the pandemic within a neighborhood. All of our results are qualitatively robust to the inclusion of this variable (Table [B2\)](#page-3-0). We find that when the number of tests per capita increases, the share of positive tests also increases. This result stems from both variables' co-moving with the true number of infected people within a neighborhood. However, we also find that as testing becomes more widely available and more tests are performed on the asymptomatic population, the magnitude of tests per capita decreases over our analyzed time period.

The tests per capita coefficient is positive and highly significant across all days for specification (3), as shown in columns 3 and 6 in Table [B2.](#page-3-0) As argued above, we interpret this variable as a proxy for the rate of infections within the neighborhood, especially during early stages of the pandemic.^{[3](#page-0-1)} Its magnitude decreases over time as testing becomes more available to the rest of the population.[4](#page-0-1)

One may expect that this relationship is not appropriately captured by a linear term. In Table [B3,](#page-4-0) we also include a quadratic term finding that while a non-linear relationship is plausible, we find no statistical differences for the coefficients of the other variables.

²As a matter of fact, at earlier dates, tests were performed only on those who required hospitalization.

³A concern in potential large differences in the age distribution across NYC zip codes. In the data, we find that the average age ranges from 27.5 to 45.5 across neighborhoods in NYC, with the exception of zip code 11005. It is a fairly small zip code with 1700 residents and an average age of 76. It is mainly composed of retired immigrant women. Given such differences, we have excluded it from our analysis.

⁴One should bear in mind that the variable tests per capita may be capturing other time-varying unobservables that correlate with the share of positive tests, such as (lagged) daily commuting patterns at the neighborhood level. Thus, the interpretation of its coefficient should not be done lightly. Owing to data limitations, we are not able to test for such hypotheses.

Table B2: Regressions of Rate of Positive Tests on Occupations and Demographics

Spatial HAC (2km) standard errors in parentheses

 $*$ p < 0.10, $**$ p < 0.05, $***$ p < 0.01, $***$ p < 0.01

Table B3: Regressions of Rate of Positive Tests on Occupations and Demographics

Spatial HAC (2km) standard errors in parentheses

 $* p < 0.10, ** p < 0.05, ** p < 0.01, ** p < 0.01$

Finally, one could argue that tests per capita is not an exogenous covariate and thus may yield the coefficients of the regressors correlated with test per capita incosistent. On the other hand, we find very stable coefficients and differences that are not statistically significant when we compare our main regression with and without test per capita as a regressor (column (6) of Tables 1 and [B2,](#page-3-0) respectively). Only the borough dummies for the Bronx and Staten Island present any statistical differences, with smaller coefficients in the regression that includes tests per capita.

Before drawing any conclusions, it is useful to understand the source of the potential bias. In the simplified case of a bivariate regression,

$$
y = \gamma x + \beta tests + \delta z + u,
$$

where x is an exogenous regressor; tests is correlated with unobservable z, and u is an orthogonal error. The bias of OLS is characterized by,

$$
Bias(\begin{bmatrix} \hat{\gamma} \\ \hat{\beta} \end{bmatrix}) = \frac{\delta}{\sigma_x^2 \sigma_t^2 - Cov_{x,t}^2} \begin{bmatrix} -Cov_{t,z}, Cov_{x,t} \\ \sigma_x^2 Cov_{t,z} \end{bmatrix}
$$

,

where σ_x^2 and σ_t^2 are the variances of x and tests, respectively; $Cov_{x,t}$ is their covariance; and $Cov_{t,z}$ is the covariance of tests with the unobservable component z. All of the numbers in the previous equation can be estimated from the data, exceot fir $Cov_{t,z}$ and δ . On the other hand, if in the previous model we also omit tests per capita, the bias for the coefficient γ is given by

$$
Bias(\hat{\gamma}) = \frac{\beta Cov_{x,t}}{\sigma_x^2}.
$$

Again, all of these numbers can be estimated from the data. Moreover, we can approximate the differences in biases from the differences in coefficients. Thus, using the difference in coefficients, we can recover an approximation for $\delta Cov_{t,z}$. In the case of the variable share of Blacks, we recover a value that is of the order 10[−]⁵ , indicating that there is little unobservable variation correlated with tests per capita after controlling for demographics and occupations.[5](#page-0-1) It is worth noting that this number should be taken as a very loose approximation. For example, we do not know the true parameter β and we are building upon a simplified bivariate example, but it is nevertheless informative about the extent of bias arising from tests per capita being endogenous.

Finally, a possible explanation for the statistical difference for the borough dummies for the Bronx and Staten Island is that testing was more selective in those areas of NYC. For example, if very few tests were performed there at the early stage of the pandemic, according to NYC policy those tests were more likely to be performed on people presenting more severe symptoms. Thus, tests per capita is positively correlated with the number of positive tests through this selection mechanism. Once we account for the number of tests that are being performed, we should see a reduction in the coefficient of these boroughs.

⁵The covariance between tests and the share of Black residents for April 30 is 0.3897.

B.3 Map of residuals

To see how much geographical variation is captured by our covariates, we plot the map of residuals for our preferred specification, column 4 of Table 1 (see Figure [B1](#page-6-0) below). First, the picture greatly differs from our starting point of the map of the percentage of patients testing positive across NYC zip codes (Figure 1). For example, we do not see Manhattan being the borough with the lowest percentages or Brooklyn and Queens being the hardest hit. Second, we find no stark spatial patterns in the unexplained variation of our regression. Both of these facts suggest that much of the spatial variation in positive rates of tests can be explained by spatial variation of demographics and occupations.

Figure B1: Map of residuals for April 30 including occupations and demographics as controls

C Daily evolution of coefficients

In this section, we present the evolution of our estimated coefficients for all of our variables. We include the months of April and May and the first week of June. The main conclusions described in the main text when we compare only two days in April are echoed in the daily analysis. Occupations that had a significant correlation with the share of positive tests in the early days of the pandemic see their effect wane over time, consistent with the expected effects of a stay-at-home order. Notable exceptions include share of workers in Industry and Construction, Law Enforcement, and Firefighting. These occupations have remained essential throughout the period and faced lower-than-average job losses. The correlation between the first two categories and positive tests steadily increased in magnitude over the period, which could be explained by increased activity. The opposite occurs with the share of firefighting, for which we observe a fairly steep change from not significant correlation to negative correlation over the course of a few days. At the beginning of the pandemic, the share of firefighters correlated with higher positive test rates. Furthermore, in early May, it was announced that firefighters had the highest share of positive antibody tests among all frontline workers^{[6](#page-0-1)}. It's possible that these two facts led to higher precautions starting in the second week of May among the FDNY.

As occupations lose importance in explaining variation in positive tests, some demographic variables account for higher shares of the variation. In particular, share of population above age 60 and household size have positive correlations with the share of positives throughout April and May. For example, in mid May, a 10-percentagepoint increase in the share of the population over 60 correlates with around three percentage points more in the percentage of positive tests. The correlation between the share of uninsured and the share of positive tests also follows an interesting trajectory. It was positive from mid-April until the first week of May. As we discuss in the main text, it's possible that uninsured individuals got tested only when showing severe enough symptoms. As testing became more available at city-run centers, uninsured status plays less of a role in testing patterns. The coefficients on shares of Blacks and Hispanics remain positive and significant throughout the period, but at low and economically small values.

 6 See this $link$ for more information.</u>

Figure C1: Regression coefficients of specification (3) and CI at the 95% level over time

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Figure C2: Regression coefficients of specification (3) and CI at the 95% level over time

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Figure C3: Regression coefficients of specification (3) and CI at the 95% level over time
 α

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D Results for May

In this section, we perform our analysis for later days in May and June. We start by running our main specifications for May 14 and May 27, as shown in Table [D1.](#page-12-0) When comparing specifications at the same point in time, some of the main takeaways from the April results still hold. The only commuting pattern that correlates with the disease incidence is commute time. It explains part of the variation in positive test rates even in May, but the correlation is not significant once we include occupations and demographics.

We similarly perform our weekly analysis as shown in Table [D2](#page-13-0) and can discuss more thoroughly some of the results seen in the daily graphs. As explained before, the share of firefighters negatively correlates with the share of positive tests. The effect peaks in late May, after it was announced that FDNY members had the highest rate of positive antibodies among frontline workers. Conversely, as non-essential construction resumed in the city, we document an increase in the correlation between share of construction workers and positive test rates.

Another notable time trend is the positive correlation between the Bronx and Staten Island boroughs with share of positive tests, even after controlling for demographics and occupations. This is a reversal of the results from April, where we found a negative correlation for these two boroughs. This could suggest that the increase in testing in these boroughs happened at slower rate than in the others.

One caveat in analyzing these results is that many jobs losses took place at the end of April and May, and thus the variables measuring occupation shares become less well measured. In light of this trend, we expect these regression coefficients to suffer from attenuation bias.[7](#page-0-1) Moreover, as some sectors were harder hit than others, with the service sector having the largest declines in employment, the share of different occupations will correlate to a different extent with the share of unemployed people across locations. As becoming unemployed changes the risk exposure to COVID, we may expect these shares to correlate with unobservable factors that also affect the rate at which positive cases are detected. Therefore, an important concern is that these regressors are endogenous at later stages of the pandemic, with their likelihood of being endogenous increasing over time.

⁷This attenuation bias may also explain why for some occupations we see a converging pattern toward zero in their estimated coefficients for our daily regressions.

Spatial HAC (2km) standard errors in parentheses

 $* p < 0.10, ** p < 0.05, ** p < 0.01, ** p < 0.01$

Dependent Variable:	Daily Cumulative Rate of Positive Tests up to Date									
	(1)		(2)		(3)		(4)		(5)	
	May $6-12$		May 13 - 19		May 20 - 26		May 27 - June 2		June 3 - June 9	
Log Density	0.004	(0.004)	0.006	(0.004)	0.003	(0.004)	0.005	(0.004)	$0.005*$	(0.003)
% Public Transport	-0.006	(0.031)	-0.019	(0.030)	-0.008	(0.029)	-0.010	(0.027)	-0.016	(0.026)
Log Commuting Time	0.005	(0.023)	-0.011	(0.021)	0.006	(0.018)	0.009	(0.016)	0.009	(0.016)
% Uninsured	$0.238***$	(0.086)	0.112	(0.087)	0.059	(0.088)	0.023	(0.083)	-0.035	(0.079)
% Essential - Professional	-0.150	(0.116)	-0.143	(0.116)	-0.139	(0.105)	0.021	(0.088)	0.022	(0.083)
% Non ess. - Professional	$-0.164*$	(0.094)	$-0.188**$	(0.088)	-0.120	(0.077)	$-0.188**$	(0.080)	$-0.178**$	(0.076)
% Science fields	-0.574	(0.584)	-0.158	(0.565)	0.291	(0.484)	0.498	(0.417)	0.456	(0.405)
% Law and related	$-0.907***$	(0.282)	$-0.733***$	(0.271)	-0.055	(0.231)	$-0.720***$	(0.223)	$-0.670***$	(0.215)
% Health practitioners	0.133	(0.248)	0.106	(0.251)	-0.271	(0.191)	-0.223	(0.187)	-0.142	(0.180)
% Other health	0.253	(0.173)	$0.413**$	(0.176)	$0.408**$	(0.177)	0.208	(0.182)	0.183	(0.167)
$%$ Firefighting	-0.119	(0.325)	$-0.867**$	(0.414)	$-1.592***$	(0.424)	$-1.511***$	(0.460)	$-1.363***$	(0.486)
$%$ Law enforcement	-0.594	(0.384)	-0.074	(0.384)	0.176	(0.371)	0.532	(0.350)	$0.551*$	(0.332)
% Essential - Service	-0.194	(0.168)	$-0.307*$	(0.162)	-0.173	(0.155)	$-0.265*$	(0.142)	$-0.265**$	(0.130)
% Non ess. - Service	-0.351	(0.262)	-0.284	(0.259)	-0.054	(0.241)	0.039	(0.224)	0.064	(0.210)
% Ind. and Construction	-0.005	(0.175)	0.083	(0.174)	0.236	(0.179)	0.266	(0.167)	$0.302*$	(0.157)
% Essential - Technical	$-0.808*$	(0.420)	-0.630	(0.424)	-0.197	(0.355)	-0.398	(0.364)	-0.228	(0.347)
% Transportation	0.272	(0.228)	0.211	(0.227)	0.230	(0.230)	0.216	(0.235)	0.277	(0.228)
Log Income	0.021	(0.018)	0.012	(0.017)	-0.001	(0.015)	-0.001	(0.014)	-0.004	(0.013)
Share $> 20, < 40$	$0.191**$	(0.078)	$0.238***$	(0.075)	$0.142**$	(0.065)	0.098	(0.066)	0.060	(0.064)
Share $\geq 40, \leq 60$	0.100	(0.102)	$0.243**$	(0.102)	0.148	(0.092)	$0.206**$	(0.088)	$0.144*$	(0.082)
Share ≥ 60	$0.407***$	(0.081)	$0.406***$	(0.080)	$0.377***$	(0.079)	$0.274***$	(0.076)	$0.218***$	(0.073)
Share Male	0.045	(0.101)	-0.026	(0.097)	0.016	(0.095)	-0.052	(0.088)	-0.009	(0.081)
Log Household Size	$0.080***$	(0.029)	$0.074**$	(0.030)	$0.062**$	(0.029)	$0.067**$	(0.027)	$0.065***$	(0.025)
$%$ Black	$0.059***$	(0.018)	$0.077***$	(0.020)	$0.100***$	(0.019)	$0.099***$	(0.022)	$0.094***$	(0.021)
$\%$ Hispanic	$0.118***$	(0.028)	$0.158***$	(0.028)	$0.136***$	(0.025)	$0.131***$	(0.024)	$0.107***$	(0.023)
% Asian	0.018	(0.028)	0.042	(0.028)	$0.046*$	(0.026)	0.038	(0.026)	0.034	(0.026)
Bronx	0.001	(0.011)	0.016	(0.011)	$0.021*$	(0.011)	$0.028***$	(0.009)	$0.030***$	(0.008)
Brooklyn	$0.032***$	(0.011)	$0.043***$	(0.010)	$0.031***$	(0.010)	$0.030***$	(0.009)	$0.021***$	(0.008)
Queens	$0.043***$	(0.011)	$0.058***$	(0.011)	$0.050***$	(0.011)	$0.049***$	(0.010)	$0.042***$	(0.009)
Staten Island	0.001	(0.013)	$0.036***$	(0.013)	$0.055***$	(0.013)	$0.057***$	(0.013)	$0.055^{\ast\ast\ast}$	(0.011)
Observations	1218		1218		1045		1218		1044	
\mathbb{R}^2 $=$	0.850		0.851		0.876		0.866		0.889	

Table D2: Regressions of Rate of Positive Tests on Occupations and Demographics (days pooled in ^given week)

Spatial HAC (2km) standard errors in parentheses

 $*$ p < 0.10, $**$ p < 0.05, $***$ p < 0.01, $***$ p < 0.01