

The Fates of Black Americans During the Covid-19 Crisis: Social Protests and Implicit Racism

El destino de los afroamericanos durante la crisis del Covid-19: protestas sociales y racismo implícito

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Abstract

Using data for the period of February through July 2020 to observe 20 states in the U.S. with the highest levels of deaths, this paper finds evidence that after controlling for structural racism, a positive racial differential explains excess deaths among the Non-Hispanic Black population. Moreover, the paper finds evidence that implicit racism declines after May 2020, something that we attribute to the *George Floyd Effect*. The paper also finds evidence that the occurrence of implicit racism is higher in counties with persistent number of deaths, deaths above the sample median, and in red states. Finally, the paper also shows that the number of hospital beds, including ICU beds, is lower in counties with higher shares of the Non-Hispanic Black population. Additional research is needed to identify the medical practices that reduce deaths and the mortality differential not explained by structural racism.

Key words: Structural racism, implicit racism, Non-Hispanic Black, Covid-19 deaths.

Resumen

Se analizan los datos de los veinte estados de la unión americana con los mayores niveles de muerte, durante el periodo de febrero a julio de 2020, y se encuentra que, aun controlando por racismo estructural, existe un diferencial racial positivo que explica el exceso de muertes observadas entre la población Africana Americana no Hispana. Además, el artículo encuentra evidencia de que el racismo implícito se redujo después de mayo de 2020, un evento que atribuimos al *Efecto George Floyd*. El artículo también encuentra evidencia de que el racismo implícito es mayor en condados con un número persistente de muertes, con un número de muertes por encima del promedio de la muestra y en estados republicanos. Finalmente, el artículo muestra que el número de camas de hospital, incluyendo las camas con acceso a unidades de cuidado intensivo, es menor en condados con mayores fracciones de población afroamericana no hispana. Se requiere de mayor investigación para identificar las prácticas médicas que redujeron las muertes y el diferencial de mortalidad no explicado por el racismo estructural.

Palabras clave: racismo estructural, racismo implícito, muertes por Covid-19.

Introduction

Ample research documents how a geographic location determines the socioeconomic life chances and even life expectancies in the US. Poverty, for example, has historically concentrated in red states, or those with the highest shares of households headed by single mothers, low birthweight babies, and industrial pollution, compared to wealthier blue states (Hochschild, 2016). Geographic location has also determined who gets to live or die during the recent Coronavirus health pandemic, as Blacks and Hispanics live on average four to six years less in red than in blue states (Fuentes-Mayorga and Burgos, 2017). Scholars have relied on deprivation indices to study different forms of inequality, including health and other variables, such as diet, work, and household conditions. To track health-related inequality in different communities, counties or geographies, scholars have developed deprivation indices that can correlate physical and mental health with socioeconomic status and other contextual variables (Butler *et al.*, 2013). This paper is an attempt at understanding the role of structural and implicit racism in explaining the higher death rates among Non-Hispanic Black populations in different counties of the US. Unlike other studies, we use a deprivation index that includes measures of structural as well as implicit racism in an attempt to explain how the resources of hospitals and the behavior of doctors and care providers may have been positively impacted by public awareness brought upon by the Black Lives Matter Movement (BLMM). We conduct this analysis to con-

tribute further understanding as to how structural and implicit racism combines to differently affect changes in the death rates of NHB groups within different geographical locations of the US and during the first few months or peak of the coronavirus.

The coronavirus pandemic has exposed the stark inequality that non-white minorities experience in every domain of social life, from disparate health outcomes to new forms of housing and work vulnerabilities, as the case of New York Hispanics reveals (Fuentes-Mayorga and Kuckeva, 2020). A recent study using data from the Center for Disease Control finds a new, troubling pattern of rising deaths among young adults, ages 25 to 44. Among these, Hispanics and Blacks have experienced the highest death rates, respectively, 54% and 33% compared with 12% among Whites young adults (Rabin, 2020). Even more concerning is that a good share of these deaths are indirectly related but not caused by Covid-19, reflecting the pernicious effects of cumulative forms of structural and social inequalities which affect marginalized and racialized minorities in the US. In an attempt to develop new public policies to address intersectional forms of inequalities affecting the U.S.'s non-White population, scholars have noted that public awareness about structural and ideological racism, brought upon by the Black Life Matters Movement (BLMM) may have altered the behavior of hospitals or that of medical providers or that of other institutions during political or health crises (Blackstock & Blackstock, 2021; Blackstock, 2020). Social protests are known to have increased edu-

cation or awareness about the pernicious role of structural and implicit racial discrimination on the deaths of the non-white populations during Covid-19 (Nelson 2011; Fernandez, 2020). Yet, we lack insights as to how the Black Lives Movement impacted the behavior of hospitals or that of healthcare providers in different regions of the U.S. This paper makes a contribution to this scholarship with new insights on the role of racial discrimination during the Covid-19 pandemic and the future prevention of death among vulnerable, Non-Hispanic Black population and other non-White minorities in the U.S.

Emerging research shows that counties with higher proportion of Non-Hispanic Black (NHB) population in the US have higher incidence and intensity of Covid 19 deaths (Millet *et. al.* 2020). Similarly, data disaggregated by race shows that death rates among NHB population are higher compared to those for the Non-Hispanic White (NHW) population (CDC, 2021). In trying to identify the reasons behind these disparities, Millet *et al.* (2020) have analyzed death data by county up to April 2020. The scholars conclude that social conditions (e.g., poverty, access to clean air), structural racism, and other factors explain the death differentials for the NHB population. McLaren (2020) using data from USA facts. org and a 5-year sample from the American Community Survey (ACS) analyzes county data for the months of February through May. He shows that racial disparities for the NHB and the Native American (NA) populations cannot be explained by observable characteristics. Bias for Hispanics and

Asians are not robust to the inclusion of occupation and other socio-economic variables. The author interprets these results as evidence that implicit racism exists in the delivery of services. Finally, Brown and Ravallion (2020) model the epidemiological curve and the behavioral response of Social Distancing. They condition on different socio-economic factors as well as medical factors such as medical infrastructure, prevalence of certain relevant medical conditions, age and other factors affecting the NHB population. They also find a positive and significant death differential for NHBs, which they argue is evidence of implicit racism.

This paper contributes to this literature with an exploration of how the event of May 25th, 2020, linked to the death of George Floyd and of the Black Lives Matter Movement (BLMM) which erupted thereafter, may have impacted the level of implicit bias in the behavior of hospitals and health care providers, and in turn, explain the reduction of Covid-19 deaths among the NHB population. There are many potential consequences of those events on the behavior of health care providers and the effect of implicit racism. First, social protests that followed after May 2020 could have reduced the public's mandate for social distancing and increased Covid-19 infection cases and deaths. However, there is evidence now that increments in deaths did not occur (Dave *et al.*, 2020). Second, social protests have been known to generate positive behavioral responses (Mazumder, 2018; Blackstock & Blackstock, 2021). Social protests linked to the BLM Movement

has been found to reduce implicit racism among the Non-Hispanic White (NHW) population (Mazumder, 2019). There is also evidence that the social protest that followed the death of George Floyd generated behavioral responses (Dave *et al.*, 2020). Third, there is evidence that the death of George Floyd has generated attempts to change the law to reduce police brutality (Jordan, 2020), which could have served as a signal for health care providers to not engage in discriminatory behavior. Fourth, there is evidence that social protests can have long-lasting effects (Mazumder, 2018; Blackstock & Blackstock, 2021), including a reduction in racism against the NHB population among the young NHW younger than 50 years old (Mazumder, 2019) and increases in the resources made available to non-white communities, such as opening of medical health care facilities in Black and poor communities as well as increases in the hiring of non-white health care professionals (Blackstock and Blackstock, 2021; Blackstock, 2020), resources which help these communities to cope with structural discrimination and social trauma (Kelly *et al.*, 2020). Our analysis tries to identify changes in implicit bias due to social protests starts by arguing that rapid changes in the correlation of deaths with the share of NHB population can only come from changes in implicit racism, not only from changes in structural racism.

We conduct the above analysis as follows: First, we explore how the death of George Floyd which occurred on May 2020, affected the estimated mortality differentials for the NHB population. Se-

cond, we then investigate how the intensity of the Covid-19 pandemic, measured by persistent deaths over the months and occurrence of deaths above the sample median, relates to the BLMM effect. Third, we explore the role that certain variables linked to hospital infrastructure play in the estimated racial differences; and fourth, we try to understand if in counties where there is evidence that the costs of discrimination are lower, we would observe higher implicit discrimination. Our analytical model adds additional variables and months to the McLaren (2020) specification to better measure structural racism; second, it also explores the role that certain variables linked to hospital infrastructure play in the estimated racial differences (Diamond, 1971; Li, Lang and Leung, 2018); and third, it explores how other social factors, such as the Black Lives Matter Movement (BLMM), may have mediated a reduction in implicit bias affecting the estimated mortality differentials for the NHB population.

The paper contributes several key findings: first, after controlling for variables linked to structural racism and hospital infrastructure, implicit racism was reduced after May 2020, or by what we have conceptualized as the George Floyd's effect (GFE); second, we find that implicit racism is higher in counties that experienced four or more months with deaths and also if they observed deaths above the sample median; third, we evidence that counties with lower shares of hospital beds and ICU beds, and with higher shares of NHB populations, which usually have the highest levels of poverty in the nation, experien-

ced the most deaths. Fourth, we find that counties in red states experienced higher implicit bias than counties in blue states.

Overall, these findings suggest that in counties where the intensity of the pandemic was severe, implicit racism was probably most intense and may have caused additional deaths among the NHB population. Specifically, the paper identifies that deaths in excess to the share of the population among the NHB population were about 31% in April and May of 2020. Fortunately, these positive mortality rate differentials decline after May 2020.

The rest of the paper is organized as follows: the first part reviews the literature on race and discrimination in the procurement of medical services; the second part presents the empirical strategy followed in this paper; the third part presents the data and results from statistical and econometric analyses; the fourth part presents the conclusions and recommendations.

I. Race and discrimination in the procurement of medical services

There is evidence that a legacy of structural and implicit racism has influenced the delivery and procurement of medical services for the non-white population of the U.S. (Bailey *et al.*, 2017; Blair *et al.*, 2013; Jost *et al.*, 2009). Bailey and collaborators (2017:1457), for example, have shown evidence that structural racism explains partially why, on average, the NHB have lower health indicators than the rest of the population. The authors define structural racism as “the totality of ways in which societies foster racial discrimination through

mutually reinforcing systems of housing, education, employment, earnings, benefits, credit, media, health care, and criminal justice. These patterns and practices in turn reinforce discriminatory beliefs, values, and distribution of resources” (Bailey *et al.*, 2017:1457) A legacy of structural racism put in place by the institution of Slavery and Jim Crow Laws in the US has led to the institutionalization of racist-based practices and ideologies that have advantaged the life chances of whites at the expense of African Americans, Hispanics, and other people of color (Leong, 2013; Nelson, 2011).

There is also evidence that beyond structural or explicit racial discrimination, implicit racism negatively affects the quality of health services provided to NHB populations (Jost *et al.*, 2009). Implicit racism is defined as ethnic or racial bias in the delivery of care which is not “consciously acknowledged and operates through subtle ways” (Blair *et al.*, 2013: 44).

For over half a century, economic theory has explained conditions under which racial bias continues to persist in the delivery of services (Becker, 1957; Li, Lang and Leong, 2018). According to this theory, there are two main conditions: First, discrimination could exist either because the owner of the business, the workers, or the clients of the business may engage in discrimination acts; second, discrimination requires the existence of conditions that allow the persistence of non-competitive behavior, since under perfect competition discrimination is expected to disappear from the market (Becker, 1957).

However, economic theory has also shown that even when conditions are put in place to reduce discrimination in the market they could still fail. For example, in the early 1970s, search models (Diamond, 1971) predicted that the existence of search costs could derail the law of market prices. Recent evidence shows that even when search costs are small, the delivery of services still introduces discrimination (Li, Lang and Leong, 2018). It is important to mention that in search models, there are elements from both supply and demand of services that can contribute to the maintenance or reproduction of discrimination. Elements that increase searching costs for customers will increase discrimination in equilibrium (Diamond, 1971). While elements that increase costs for discrimination for suppliers of services reduce discrimination in equilibrium (Li, Lang and Leong, 2018).

II. The relation between racial inequality, geography and deaths

A complete data set that disaggregates deaths by county and race is not available, which has prompted researchers to look at the correlation between the NHB population and the total number of deaths (Millet *et al.*, 2020; McLaren 2020; Brown and Ravallion 2020).

Therefore, in this paper, we follow the approach of McLaren (2020) that indirectly estimates the differential mortality ratio between NHB and the comparison racial group. The method consists in estimating the partial correlation between total deaths and the NHB share of population, as

shown in Equation (1):

$$(1) D_{it} = \beta_0 + \beta_1 nhb_i + u_{it}$$

Where D_{it} represents deaths at county i at time t ; nhb_i represents the share of NHB population in county i ; nhb_i represents the usual error term; and u_{it} represents the correlation between deaths at county level and the Non-Hispanic Black share of population. Following McLaren (2020), define the weighted average deaths in county i by Equation (2):

$$(2) D_i = nhb_i d_{nhb,i} + (1 - nhb_i) d_{-nhb,i}$$

Where $d_{nhb,i}$ represents deaths among Non-Hispanic Blacks in county i , and $d_{-nhb,i}$ represents deaths among the comparison racial group in county i , which is the Non-Hispanic White population.

Differentiating equation (1) and equation (2) with respect to nhb_i

$$(3) \frac{dD_{it}}{dnhb_i} = \beta_1$$

$$(4) \frac{dD_i}{dnhb_i} = d_{nhb,i} - d_{-nhb,i}$$

Which implies that:

$$(5) \beta_1 = d_{nhb,i} - d_{-nhb,i} = \Delta_{nhb}^*$$

Δ_{nhb}^* is the death mortality differential for the NHB population, if $\beta_1 > 0$, the NHB population have higher mortality ratio than expected. Studies usually introduce variables that can measure structural racism and if the mortality differential does not disappear, the residual differential is said to

be explained by implicit racism (McLaren, 2020; Brown and Ravallion, 2020).

There have been attempts to measure implicit racism in the literature using the Implicit Association Test that asks individuals to make associations between different ideas (Jost *et al.*, 2009). This measure, however, is not available for all US counties (Jost *et al.*, 2009) and consequently cannot be used in the context of this paper.

As explained in the introduction, in this paper we explore how the death of George Floyd and the social protests that erupted thereafter could have changed implicit racism in the US, given that there is evidence that social protests can change attitudes (Mazumder, 2018; Fernandez, 2020), that the BLM movement has reduced implicit racism towards the NHB population (Mazumder, 2019; Blackstock and Blackstock, 2021; Blackstock, 2020) and that the social protests that started in June did not generated an increase in deaths (Dave *et al.*, 2020). Our argument is that rapid changes in the correlation of deaths with the share of NHB population can only come from changes in implicit racism, not only by changes in structural racism. Consequently, if we observe a reduction of β_1 over time implies that the implicit racism towards the NHB population is reducing. To capture the change over time and to include variables that attempt to measure structural racism we estimate the following equation:

(6)

$$D_{it} = \beta_0 + \sum_{j=1}^4 \beta_j \text{race}_{ij} + \beta_5 X_{it} + \sum_{t=1}^6 \theta_t \text{month}_t + \sum_{t=1}^6 \sum_{j=1}^4 \gamma_{tj} \text{month}_t \text{race}_{ij} + \sum_{t=1}^6 \delta_t \text{month}_t X_{it} + \alpha_i + u_{it}$$

Where *race* stands for the share for demographic group *j*, X_t represents a control variable, represents a dummy variable for months March, April, May, June, and July, α_i represents a county level unobserved factor constant over time. With this model, the differential effect for each race is measured along the studied period covering the months between February and July of 2020. Initial work included in the analysis August, however, some of the data is not available after July 2020, which led us to exclude all data after July 2020. Additional rules to select our sample are explained in more detail in the data section of the paper.

As control variables, different measures of Structural Racism are introduced. In our first specification, we follow closely McLaren (2020) and we include as control variables the following variables measured at county level: population, share of population with some college or more education, share of population with high school completed, shares of population working in 23 occupation categories, median household income, share of uninsured population, fraction of households with child poverty, fraction of households with no car, the death rate in the rest of the State, as well as state dummies. Notice that the estimation includes the interactions of all control variables with the month dummies, except for the state dummies.

In a second specification, we introduced additional variables, in an attempt to better measure structural racism. Specifically, we introduce some additional variables linked with the Townsend Index (Townsend, Phillimore and Beatie, 1988) which is considered to be a deprivation index and has been found to be correlated with geographic areas with high health problems (Nagaraja, 2015). The variables linked to the Townsend index that we included in the regression are the unemployment rate, the percentage of HH that rent, and the percentage of HH that are overcrowded.

We introduce other measures as an

attempt to measure structural racism, such as Black-White Segregation Index, population density, an index of overall poverty, and an index of inequality. The measures of inequality and poverty are included following Brown and Ravallion (2020).

Equation (7) shows a third specification where we include variables z_{lit} that represents control variables that attempt to measure transaction costs that have been linked to the survival of discrimination (Diamond, 1971; Li, Lang and Leong, 2018) and z_{2it} which are variables that could increase the cost of discrimination to services' suppliers (Li, Lang and Leong, 2018):

$$(7) \quad D_{it} = \beta_0 + \sum_{j=1}^4 \beta_j \text{race}_{ij} + \beta_5 X_{it} + \beta_6 z_{1it} + \beta_7 z_{2it} + \sum_{t=1}^5 \theta_t \text{month}_t + \sum_{t=1}^5 \sum_{j=1}^4 \gamma_{tj} \text{month}_t \text{race}_{ij} + \sum_{t=1}^5 \delta_t \text{month}_t X_{it} + \sum_{t=1}^5 \delta_{1t} \text{month}_t z_{1it} + \sum_{t=1}^5 \delta_{2t} \text{month}_t z_{2it} + \alpha_i + u_{it}$$

As elements linked to transaction costs, we introduce the number of hospital beds per person, which we will assume that as it grows it reduces transaction costs. Similarly, we will use ICU beds per person, which in the case of Covid-19, are beds required to treat patients with acute symptoms of the disease. We expect that a larger number of ICU beds per person will reduce transaction costs. We also introduce the percentage of beds occupied, which will measure exactly the opposite, since as beds become saturated, transactions costs raise.

As elements linked to costs of discrimination for services' suppliers, we introduce the number of social protests in the state, since there have studies documenting that social protests can have behavioral effects on attitudes and that those effects persist (Mazumder- 2018; Blackstock and Blackstock- 2021; Blackstock- 2020). We expect that as protests in the State grow, medical providers will be more aware of implicit racism and be afraid of incurring in such practices, since it may imply the loss of clients or legal consequences.

Exploiting the panel nature of the data has certain advantages over the OLS estimation. First, the fixed effect estimation eliminates idiosyncratic county level fixed effects considering that we are interested in comparing the periods before and after May 2020. Second, the random effect estimation can be a better estimation than OLS and the Fixed effect estimation if the county level effects are random. Considering that the evolution of the pandemic is subject to different random shocks, it would be difficult to justify that unobserved elements at the county level are fixed over time.

Considering that we are interested in the changes over time, we now show how to obtain a measure of such changes that is not subject to potential estimation biases. We start by noting that the coefficient for race i and month t , which measures the death mortality differential Δ^*_{nhb} is given by:

$$(8) \Delta^*_{nhb,t} = \beta_i + \gamma_{it}$$

Notice that in a fixed effect estimation, the coefficient β_i is not identified, since it is absorbed in the fixed effect. In a random effect estimation, β_i may be subject to bias to the extent that there exists correlation between non-observed fixed factors and other variables that do not change over time. To eliminate coefficients that may suffer from bias, we note that the change in time t with respect to the omitted month category, in our case March, is given by:

$$(9) \Delta^*_{nhb,t} - \Delta^*_{nhb,0} = \gamma_{it}$$

Moreover, we can define any of the

available months as the base month and define π_t as the normalized mortality differential, measuring the mortality differential in time t , relative to the mortality differential in the month b :

$$(10) \pi_t = \frac{\Delta^*_{nhb,t} - \Delta^*_{nhb,0}}{\Delta^*_{nhb,b} - \Delta^*_{nhb,0}} = \frac{\gamma_{i,t}}{\gamma_{i,b}}$$

III. Data Sources

County data on mortality comes from USA facts, a website that tracks coronavirus cases and deaths by county (USAFacts-2020). This data is restricted to the months of March through July for the reasons explained in the previous section. Data was restricted to the top 20 states with the highest numbers of deaths by July 2020, listed in alphabetical order: Arizona, California, Colorado, Connecticut, Florida, Georgia, Illinois, Indiana, Louisiana, Maryland, Massachusetts, Michigan, Minnesota, New York, New Jersey, Ohio, Pennsylvania, Texas, Virginia and Washington. This was done to reduce the number of counties with zero deaths and reduce the selection bias in our estimations.

Columns 1 through 4 in Table 1 show the distribution of counties with total number of months with deaths above zero.¹ The variable attempts to measure the

¹ The data set shows the number of cumulative deaths. For some days, the cumulative number of deaths reduces, which would imply a data correction done by the county. Since we use in estimation the change in cumulative deaths, this generates some data points with negative deaths. For all sample statistics, coun-

persistence of the deadly consequences of the pandemic. By July 2020, only 11% of the 1501 counties included in the top 20 states with most deaths showed no deaths, which is the category that has the lowest share in the observed sample. The mode in the sample is four months with positive deaths, since this category is observed in almost 30% of analyzed counties. The second most important category is one month of positive deaths observed in almost 19% of all counties.

Columns 5 and 6 of Table 1 measures whether these counties experience number of deaths above the median*, which we define as the median of total deaths for the March-to-July period for all counties with deaths greater than zero. We attempt to measure with this variable if the health system of the county is under stress, keeping as reference the same median for the entire period for reasons of allowing inter county comparisons. The distribution of months with positive deaths is very different for counties with deaths above median*, since 60% of this type of counties have four or more months with positive deaths; while among counties with deaths below median*, approximately 56% of them have three or less months with positive deaths.

Table 2 analyzes the death rate, defining the death rate as cumulative deaths per month divided by the total county population. Column 1 in Table 2 shows that May presents a death rate of 2.5%, which is the highest average monthly death rate. July

2020 showed an increase in the average monthly death rate.

Columns 2 and 3 in Table 2 present the death rate for counties that showed persistent and counties that did not show persistent deaths. Counties that did not show persistent deaths have a higher death rate than counties that experienced a persistent rate. Moreover, counties that experienced persistent death rates show a decline in June and July. We interpret this result as potential evidence that counties that experience persistent deaths show a learning process in how to deal with the pandemic. Whether this trend persists during the second wave that started in August is beyond the scope of this paper.

Columns 4 and 5 in Table 2 present the death rate in counties that experienced deaths above and below the median*. A clear pattern is that the death rate in counties with deaths below the median* is the lowest in the sample, since it reaches its maximum in April, at 0.3%. on the contrary, counties experiencing deaths above the median*, present the highest death rates in the sample with a maximum of 5.3% observed in March and a minimum of 2.9% observed in June.

Counties that show a persistent pattern in the death rate (i.e. four or more months with positive deaths) show a higher fraction of counties experiencing deaths above the median* than counties which did not experience persistent deaths. During April, May and June more than 60% of counties experienced deaths above the median* in counties showing persistent deaths.

ties included in the sample are those with deaths greater than zero.

Table 1. Distribution of US counties in top 20 states with most deaths (March to July, 2020)

Months with deaths >0	Number of counties	%	Cummulative %	With deaths below median*(%)	With deaths above median*(%)
0	157	10.46	10.46	15.84	0
1	276	18.39	28.85	22.5	10.39
2	175	11.66	40.51	13.12	8.82
3	266	17.72	58.23	20.48	12.35
4	443	29.51	87.74	18.37	51.18
5	184	12.26	100	9.69	17.25
N	1501			991	510

Note: Median* defined as the median of deaths for all counties with deaths greater than zero during the studied period of March through July 2020.

Source: Own calculations with data from USAfacts (2020).

Table 2. Average Monthly Death Rates for counties in the Top 20 States with more deaths

	All	Counties with positive deaths less than 4 months	Counties with positive deaths more than four months	Counties with deaths greater than median*	Counties with deaths lower than median*
March	0.2%	0.5%	0.1%	5.3%	0.1%
sd	1%	2%	1%	6.2%	0.1%
N	252	38	214	7	245
April	2.1%	2.9%	1.5%	3.7%	0.3%
sd	10%	11%	9%	13.4%	1.0%
N	1,054	427	627	540	514
May	2.5%	3.7%	1.9%	3.9%	0.2%
sd	12%	18%	7%	15.1%	0.3%
N	942	319	623	578	364
June	1.7%	2.8%	1.2%	2.9%	0.2%
sd	7%	9%	5%	8.7%	0.7%
N	912	295	617	525	387
July	2.0%	3.5%	1.1%	3.5%	0.2%
sd	10%	14%	6%	12.9%	0.4%
N	956	345	611	510	446

Note: Monthly death rate defined as cumulative deaths by month over total county population. The Median rate* defined as the median of total deaths for all counties with deaths greater than zero during the period of March through July 2020.

Source: Own calculations with data from USAfacts (2020).

Table 3 presents the share of the Non-Hispanic Black (NHB) population for each of the subsample counties analyzed, this data comes from the 2019 County Health Rankings (CHR, 2020). We do this calculation because in this study we do not count with the actual distributions of deaths by race and by county. Therefore, the race mortality differential will be inferred from the partial correlation that exists between the share of NHB population and total deaths. Table 2 clearly shows that counties experiencing persistent deaths have higher shares of NHB population. Similarly, counties experiencing deaths greater than the median* also have higher shares of NHB population. This may be linked to structural racism and the daily activities than the NHB population performs in jobs with greater exposure or to differences in medical infrastructure between counties with larger NHB populations than the rest of counties.

Table 4 explores the role that the number of hospital beds and ICU hospital beds per ten thousand people have on the persistent death rates and in the occurrence of more deaths than the median*. Data on beds available, ICU beds available and beds occupied per state come from CDC National Healthcare Safety Network (NHSN, 2020) from the Hospital capacity Covid19 data dashboard. It is very clear that counties with less persistent deaths have more hospital beds and ICU hospital beds per ten thousand people than counties with more persistent death rates. In fact, the

number of beds per 10 thousand people is the greatest among counties with less persistent death rates. For almost all months in the sample period, counties with deaths lower than the median* also have more hospital beds and ICU beds than counties with more deaths than the median*.

Together with the results of Table 3, this statistical analysis shows that part of the higher deaths observed among the NHB population is due to the lower hospital infrastructure that exists in the counties where they concentrate.

Table 4A shows data for state-level aggregate number of June 2020 BLM social protests and how this movement affected state the occurrence of persistent deaths or deaths above the median* in specific counties. Data on state level aggregate for BLM crowds for June 2020 comes from the Crowd Counting Consortium (CCC, 2020). In addition, Table 4A shows that counties with greater BLM crowds were more likely to be in the set of counties with deaths below the median*. Moreover, counties with four or more months with persistent positive deaths saw greater crowds than counties where the pandemic had less than four months with positive deaths. These results show that when counties were facing deaths above the median*, individuals were less likely to join the protests. However, in counties that sustained persistent deaths, individuals were more likely to join crowds. Considering the importance of social protests in our study we decided to include this measure as control variable.

Table 3. Non-Hispanic Black Population Share in Top 20 states with more deaths

	All	Counties with less than 4 months	Counties with more than four months	Counties with deaths greater than median*	Counties with deaths lower than median*
March	8	2	9	30	8
sd	11	6	12	27	10
N	252	38	214	7	245
April	12	9	14	14	9
sd	15	14	15	16	12
N	1054	427	627	540	514
May	13	10	14	14	10
sd	15	14	15	15	13
N	942	319	623	578	364
June	13	11	14	15	11
sd	15	14	15	16	13
N	912	295	617	525	387
July	11	7	14	16	7
sd	14	12	15	16	9
N	956	345	611	510	446

Note: The Median death rate* is defined as the median of total deaths for all counties with deaths greater than zero during the period of March through July 2020.

Source: Own calculations with data from USAfacts (2020) and CHR (2020).

Table 5 shows the mean values of the variables used in this paper for the Top 20 states with more deaths from March through July 2020. Socioeconomic characteristics at the county level come from the 2019 County Health Rankings (CHR, 2020). Data obtained from this data at county level include: county population, population density, share of Non-Hispanic Black, share of Hispanic population, share of First Nations Population, share of Asian population, share of population with some college or

more education, with high school completed, median household income, share of uninsured population, fraction of households (HHs) with child poverty; with no car; the unemployment rate; the percentage of HHs that rent; that are overcrowded; and the Black-White Segregation Index; an index of overall poverty, and an index of inequality. The data about death rates in the rest of the States, was calculated from the mortality data from USAfacts (2020), by obtaining the aggregate deaths in the state, excluding county *i*.

Table 4. Hospital Beds and ICU Beds per 10 thousand people, Top 20 states with more deaths

	All		Countries with less than 4 months with deaths greater than zero		Countries with more than four months with deaths greater than zero		Countries greater than median*		Countries with deaths lower than median*	
	Beds per 10 k	ICU Beds per 10 k	Beds per 10 k	ICU Beds per 10 k	Beds per 10 k	ICU Beds per 10 k	Beds per 10 k	ICU Beds per 10 k	Beds per 10 k	ICU Beds per 10 k
March	8.5	1.2	11.2	1.5	8.0	1.1	8.1	0.9	8.5	1.2
sd	3.1	0.4	1.5	0.3	3.1	0.4	2.3	0.3	3.1	0.4
N	252	252	38	38	214	214	7	7	245	245.0
April	8.3	1.1	8.5	1.1	8.2	1.1	8.4	1.1	8.2	1.1
sd	2.4	0.5	2.0	0.5	2.6	0.5	2.5	0.5	2.2	0.5
N	1054	1054	427	427	627	627	540	540	514	514.0
May	7.9	1.1	8	1	7.8	1.1	7.8	1.1	8.0	1.1
sd	2.1	0.6	1.8	0.5	2.2	0.6	2.2	0.6	2.0	0.6
N	942	942	319	319	623	623	578	578	364	364.0
June	7.2	1.1	7.3	1.1	7.1	1.2	7.2	1.2	7.2	1.1
sd	1.8	0.6	1.6	0.6	1.9	0.6	2.0	0.6	1.5	0.5
N	912	912	295	295	617	617	525	525	387	387.0
July	7.1	1.2	7.3	1.2	7.1	1.2	7.0	1.1	7.3	1.2
sd	1.9	0.6	1.6	0.6	2.1	0.6	1.9	0.6	1.9	0.7
N	956	956	345	345	611	611	510	510	446	446.0

Note: The Median* is defined as the median of total deaths for all countries with deaths greater than zero during the period of March through July 2020.

Source: Own calculations with data from CCC (2020) and USAfacts(2020).

Table 4A. Aggregate June Social Protests and the intensity of the Covid 19 pandemic

	Mean	Sd
Deaths above median*	148.8	141.8
Deaths below median*	191.3	176.5
4 or more months with positive deaths	143.5	163.0
Less than 4 months with positive deaths	133.1	92.3

Note: Median* defined as the median of total deaths for all counties with deaths greater than zero during the studied period of March through July 2020.

Source: Own calculations with data from USAfacts (2020) and (NHSN, 2020).

Table 5 also presents the mean values for those same variables for two subsamples: the first one shows counties with deaths above the median of deaths for the sample (median*), and the second subsample shows counties with four or more months with positive deaths. The first difference that stands out is that population and density is larger in counties that experienced deaths above the median* and deaths persistence for four or more months. The segregation index is higher only in counties with four or more months with positive deaths, as well as the average household income. Almost all other variables show similar mean values for the three subsamples.

Table 6 shows the distribution of occupations for the analyzed sample and subsamples. The share of population working in 23 occupation categories was obtained from the 5-year- public use micro data sample of the American Community Survey (ACS, 2020). Table 6 shows very similar distribution of occupations in the three analyzed subsamples. This is of particular interest, since it has been argued that occu-

pations more exposed to Covid-19 could generate higher deaths. These preliminary results would suggest that the role of occupations is limited in explaining differences in deaths.

IV. Econometric Models Results

IV.1 Structural racism, implicit racism and the George Floyd's death effect

Figure 1 presents the estimations for the NHB population and the entire sample, comprised of all counties in the top 20 States with more deaths during the months of February through July. The estimated equation is shown in Equation (6). Only the months of April through July are shown. The figure presents the estimations using OLS and the McLaren (2020) specification we propose in this paper, which we call the Cuecuecha, Fuentes & McLeod (CFM) specification. Figure 1 clearly shows that the two specifications are very similar and that the results obtained using the CFM specification has lower coefficients, which is exactly what we expected since this analysis includes additional variables that attempt to measure structural racism.

Table 5. Mean values for selected variables and subsamples, Top 20 states with more Covid 19 deaths from March to July 2020

Variable	All (N=7505)		Death > median* (N=2160)		4 or more months with positive deaths (N=2692)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Population	64417	170269	69452	189113	88093	193965
Density	669	3252	867	3947	886	3723
Non Hispanic Black	12	14	15	16	14	15
Hispanic	11	15	12	15	12	14
First Nations	1	3	1	4	1	4
Asian	3	4	3	4	3	5
Some College	59	12	58	12	60	12
Graduation Rate	87	9	86	10	86	8
Household Income	56278	16516	55655	17120	58843	17818
Uninsured	10	5	11	5	10	5
Child poverty	20	9	22	9	20	9
No car	20%	8%	20%	8%	20%	8%
Unemployment	5%	1%	5%	2%	5%	1%
Renting households	30%	9%	31%	10%	32%	9%
Overcrowded	2%	2%	3%	2%	3%	2%
Segregation Index	40	22	41	22	45	19
Overall poverty	14	6	15	6	14	6
Index inequality	5	1	5	1	5	1
Social protests	169	161	149	142	180	177
Bed available	12625	7514	11537	6910	12619	7761
ICU available	1925	1386	1781	1331	1919	1395
Bed occupied	60	7	61	7	60	8

Note: The Median* is defined as the median of total deaths for all counties with deaths greater than zero during the period of February through July 2020.

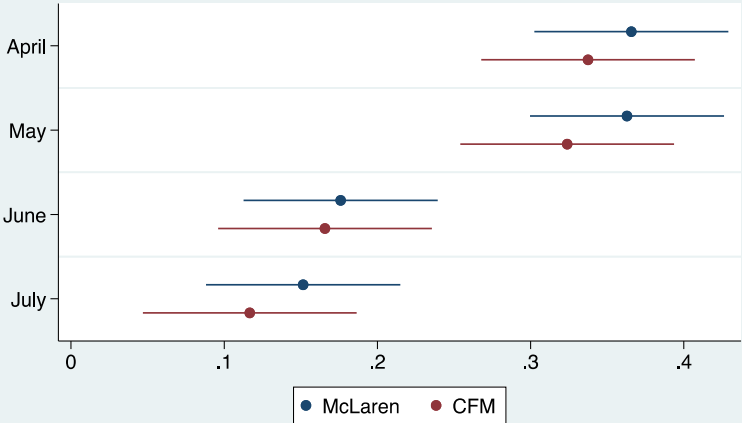
Source: Own calculations with data from CHR (2020), CCC (2020), USAfacts(2020), and NHSN(2020).

Table 6. Mean values for selected variables and subsamples, Top 20 states with more Covid 19 deaths from March to July 2020

Variable	All (N=7505)		Death > median* (N=2160)		4 or more months with positive deaths (N=2692)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Business and Financial Operations	9%	2%	9%	2%	9%	2%
Computer & Math. Operations	4%	2%	4%	2%	4%	2%
Architecture & Engineering	2%	2%	2%	2%	2%	2%
Life, Physical and Soc. Sciences	2%	1%	1%	1%	2%	1%
Community & Soc. Serv.	1%	1%	1%	1%	1%	1%
Legal occupations	1%	1%	1%	1%	1%	1%
Educ., training and library	6%	2%	6%	2%	6%	2%
Arts, design, entertainment, sport	1%	1%	1%	1%	2%	1%
Healthcare practitioners	4%	1%	4%	1%	4%	1%
Healthcare support	2%	1%	2%	1%	2%	1%
Protective service	3%	1%	3%	1%	3%	1%
Food preparation & serving	1%	1%	2%	1%	1%	1%
Building & grounds maintenance	6%	2%	6%	2%	6%	1%
Personal care	4%	1%	4%	1%	4%	1%
Sales	3%	1%	3%	1%	3%	1%
Office & administrative support	10%	2%	10%	2%	10%	2%
Farming, Fishing & Forestry	11%	2%	11%	2%	12%	1%
Construction & extraction	8%	2%	8%	19%	8%	3%
Installation, maintenance	6%	2%	6%	2%	6%	2%
Production	4%	1%	4%	1%	4%	1%
Transportation & Material	8%	4%	8%	4%	7%	4%
Others	4%	1%	4%	1%	4%	1%

Source: ACS (2020).

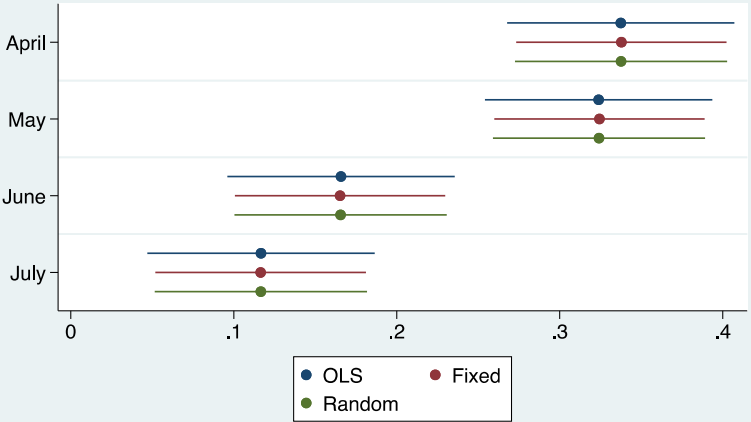
Figure 1. Differential mortality, Non Hispanic Blacks
Top 20 States, 95% confidence intervals, different specifications



CFM: Cuecuecha, Fuentes & McLeod Specification

Source: Own calculations; Usafacts (2020), County Health Rankings (2019)

Figure 2. Differential mortality, Non Hispanic Blacks
Top 20 States, 95% confidence intervals, different methods



Random and Fixed Effects Pannel Estimations

Source: Own calculations; Usafacts (2020), County Health Rankings (2019)

Moreover, all coefficients are statistically different from zero, while the coefficients for June and July are smaller than the coefficients for April and May. These results are similar to those found by McLaren (2020) and by Brown and Ravallion (2020). Our contribution to these previous studies is documenting a clear reduction in the pattern of implicit bias effects after the month of May, which coincides with the death of George Floyd and the subsequent social protests that the Black Live Matter Movement (BLMM) fueled.

Figure 2 compares the results using OLS, Fixed and Random effects, the three methodologies explained before that would be explored and the CFM specification, given that there is evidence that the latter specification controls for additional dimensions in which structural racism may influence death differentials. Figure 2 makes it clear that the OLS estimation has higher variance than the FE and the RE estimations. Moreover, the coefficients are very similar between the FE and the RE estimation. According to the Hausman (1978) test, if the coefficients from Fixed and Random effects are similar, then Random effects are preferred since they control better for heteroskedasticity.

Figure 3 shows different specifications for estimations using RE, the first specification is the CFM specification presented before, while the second specification, which we call the CFM+, incorporates variables measuring search costs for medical services and potential costs for the implicit bias incurred by hospitals and health care

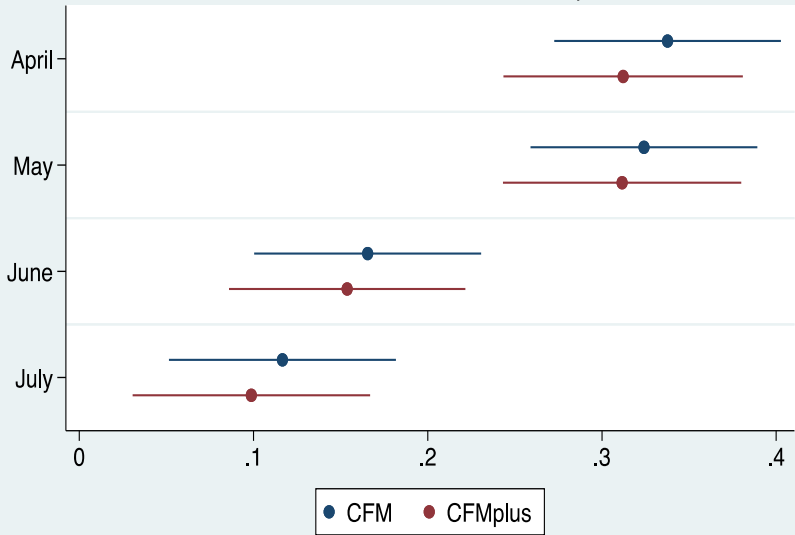
providers while treating or evaluating NHB patients. As proxy measure variables measuring search costs for medical services, we calculate the number of hospital beds available per population, ICU beds per population, and the share of beds occupied. For potential costs arising from the incurring of implicit racism we use social protests. Figure 3 clearly shows that the CFM+ specification obtains very similar estimations as those obtained using CFM, with smaller coefficients. Even though the difference is not statistically significant, we prefer the CFM+ specification because it reduces the implicit racism coefficient in all months. This reduction is in line with Search Theory (Diamond, 1971) since controlling for factors that would influence search costs and the costs of applying racism, we still find an effect from the social protests that followed the death of George Floyd.

Table 7 presents the estimation of Equation (7) using random effects and the CFM+ specification. They show the estimation of the mortality differentials per month for all racial groups, using February as the month of reference. Table 7 shows the coefficient estimated, the standard error and then each coefficient normalized against the April coefficient for the NHB population.

Column 1 shows that the implied mortality differential is .31 points in April and May, while it declines to .154 points in June as low as .09 points in July. Column 1 shows that the observed mortality differential in July was only 32% of that observed in April.

Figure 3. Differential mortality, Non Hispanic Blacks

RE, 95% confidence intervals, different specifications



CFM+:CFM plus Beds, ICU beds, Occupied beds & BLMM Protests

Source: Own calc.,Usafacts(2020), CHR(2019),NY Times(2020),NHSN(2020)

The mortality differential observed show that after George Floyd's death implicit bias by medical providers and hospitals is reduced between 50% and 66%.

Column 2 shows that the Gorge Floyd's effect is not observed for any other racial group. In the case of the NHB population, the estimation shows no bias during April, May and June, while positive bias is observed in July. The first result coincides with that shown by McLaren (2020), which suggests that during April and May, mortali-

ty differentials for the Hispanic population is explained by structural racism. Instead, our results show that after July, implicit bias started to increase also in counties with higher shares of Hispanic population, and at the same level as that observed in July among the NHB population.

Column 3 shows the results for the First Nations group. Implicit racism is shown during May, June and July, although not as the same level that is observed in April among the NHB population.

Table 7. Estimated mortality differentials, N=9006 county-months, for the top 20 states with most deaths up to July 2020 State

		Non Hispanic Blacks	Hispanics	First Nations	Asians
April	Coeff.	0.312***	0.018	-0.002	0.032
	(sd)	(0.035)	(0.031)	(0.054)	(0.030)
	Rel. to April ^b	1	0.058	-0.006	0.102
May	Coeff.	0.312***	0.037	0.126*	0.047
	(sd)	(0.035)	(0.031)	(0.054)	(0.030)
	Rel. to April ^b	.998	0.117	0.405	0.149
June	Coeff.	0.154***	0.026	0.153**	-0.0001
	(sd)	(0.035)	(0.031)	(0.054)	(0.030)
	Rel. to April ^b	.493	0.083	0.490	-0.001
July	Coeff.	0.099**	0.100**	0.161**	-0.004
	(sd)	(0.035)	(0.031)	(0.055)	(0.030)
	Rel. to April ^b	.316	0.319	0.517	-0.013

Notes: The comparison racial group is Non-Hispanic Whites. N=9006 county-months. R²: 40%.^a The comparison month is February. ^b Showing coefficients normalized to NHB April=1. *Significant at 10%, **Significant at 5%, ***Significant at 1%.

Source: Coefficients estimated from equation 9, using CMF+ specification with random effects.

The result for April and May is also obtained by McLaren (2020). It is important to notice that by July the racial group showing the largest differential not explained by structural racism is the First Nations group.

Column 4 shows the results for the Asian group. No coefficient is found to be statistically significant. This result is also like McLaren's (2020).

IV.2 Robustness results

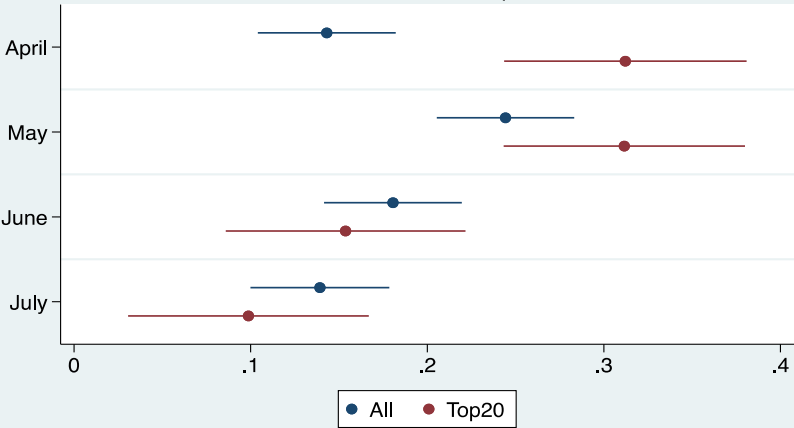
a. Comparing what happened in the 52 States with the top 20 States

As it was shown in section III, the number of deaths in the Top 20 States with more deaths during the months previous to July, was higher than for the rest of states in the US. This would imply that on average, county hospitals in other counties in the US were less pressured to increase

their share of available beds and ventilators, which would have reduced the possibilities of observing discrimination in Covid19 related medical outcomes. This would imply that the GF-BLMM effect would be lower in all US states than in the Top 20 States

experiencing the most deaths. Our analysis finds no significant qualitative differences between the top 20 states and all the US states (as evident in Figure 4), and a quantitatively smaller effect in all the US states, as predicted by theory.

Figure 4. Differential mortality, Non Hispanic Blacks
RE, 95% confidence intervals, Top 20 and All States



CFM+:CFM plus Beds, ICU beds, Occupied beds & BLMM Protests

Source: Own calc., Usafacts(2020), CHR(2019), NY Times(2020), NHSN(2020)

b. Comparing the behavior of medical providers with the GF-BLMM Effect

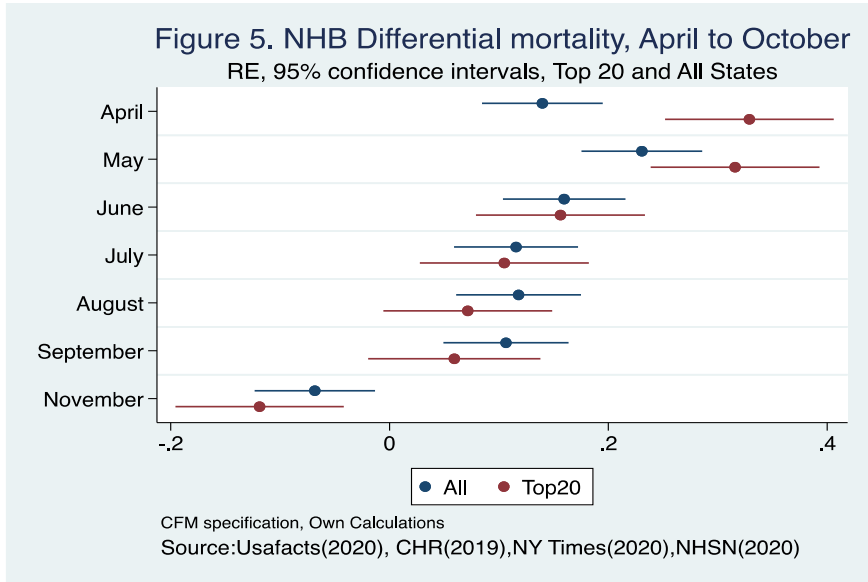
An alternative explanation to the GF-BLMM effect is that counties were gaining an awareness about the cost of racial discrimination brought upon by the BLMM, and probably investment on infrastructure, which probably would imply that by July we were only observing such dynamic adjustment process, and not really a change in

behavior by medical providers. Alternatively, we could have been observing only the effects of the shut-down which reduced the number of infections, and consequently the GF-BLMM is only a temporary decline in the correlation between deaths and the NHB share of population. Consequently, if the GF-BLMM generated a change in behavior we expect that the coefficient of discrimination would remain constant after June or July. It is important to note that due to data limitations, these comparisons are

done using the CFM and not the CFM+ specification because national data from the NHSN (2020) is only available up to July 2020.

Figure 5 presents what happens if we include in the estimation additional months, and the estimation for the Top 20 States and All States. The levels of discrimination remain almost constant during June, July, August and September, since the observed differences are not statistically significant,

as the 95% confidence intervals demonstrate. On the other hand, the October coefficient is not estimated due to multicorrelation, and the November coefficient shows a reversal in the death differential. This behavior is consistent with a change in behavior, which probably remained during the first and second waves. The evidence also shows that things changed during the third Covid-19 death wave that started in October. Exactly what occurred is left for future research.



c. Estimating death differentials for counties with deaths above and below the median

As the descriptive analysis showed earlier, counties that experienced deaths above the sample median are different from counties that experienced deaths below

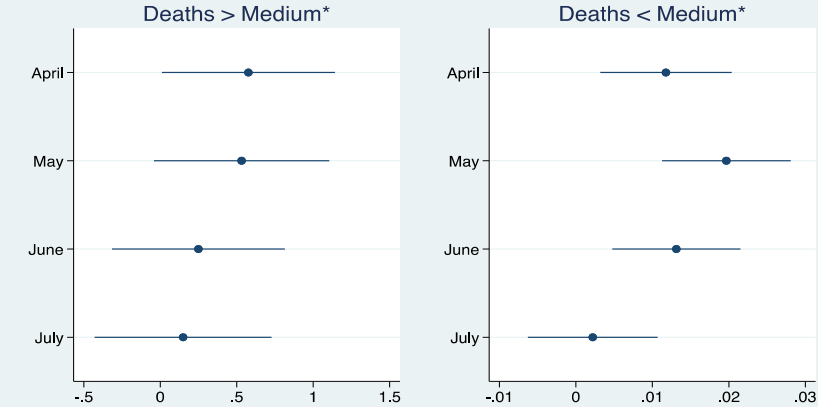
the sample median.² Theory predicts that in counties experiencing more deaths (Li, Lang and Leong, 2018), within the Top 20 States, we should observe more discrimi-

² Remember that the median considered in the analysis is estimated for all the sample with deaths greater than zero.

nation since individuals have less options to avoid discrimination. As Figure 6 clearly

shows, the GF-BLMM effect occurs regardless of whether the counties were experiencing a death crisis or not.

Figure 6. Differential Mortality Ratio
RE, 95% confidence intervals



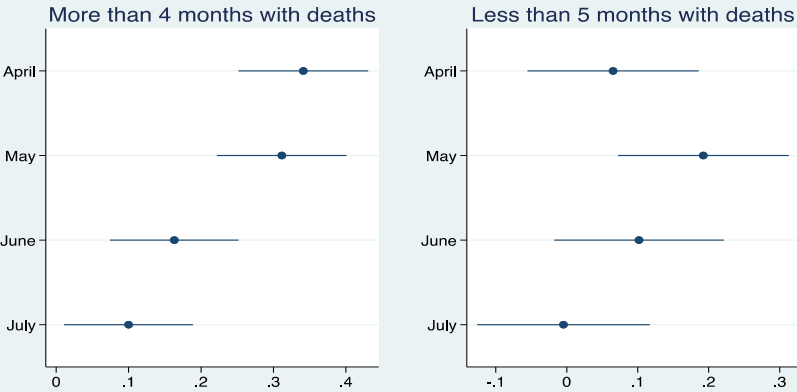
CFM plus specification, Own Calculations, Median* is median for sample with deaths
Source:Usafacts(2020), CHR(2019),NY Times(2020),NHSN(2020)

d. Analyzing the effect of persistent deaths

Another conclusion from the descriptive analysis presented earlier is that counties that experienced persistent deaths are different from those not experiencing persistent deaths. Theory predicts that oppor-

tunities for discriminatory behavior were probably higher in counties with persistent deaths, since there were probably less options to avoid discrimination for patients, and that coefficients should be smaller. Figure 7 clearly shows that the GF-BLMM effect is more present in counties with highly persistent deaths.

Figure 7. Differential Mortality Ratio, NHB, Top 20 States
RE, 95% confidence intervals



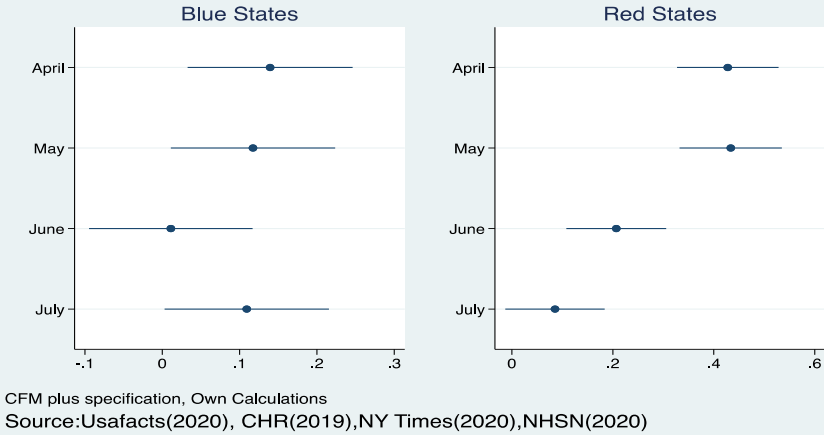
CFM plus specification, Own Calculations
Source:Usafacts(2020), CHR(2019),NY Times(2020),NHSN(2020)

e. Interactions with geographic location: Red versus Blue States

Another corollary from the Theory (Li, Lang and Leung, 2018) is that in places with lower costs for employers to discriminate, more discrimination should be observed. We use as proxy for perceived costs of discrimination the results for the 2016 presidential campaign, defining blue states those who voted for Hillary Clinton, and red states those who voted for Donald Trump.

The hypothesis is that in red states, the perceived cost of discrimination is lower and consequently higher levels of implicit racism should be observed there. Blue states in our sample are California, Colorado, Connecticut, Illinois, New York, New Jersey, Maryland, Massachusetts, Minnesota, Virginia and Washington. Red states are Arizona, Florida, Georgia, Indiana, Louisiana, Michigan, Ohio, Pennsylvania, and Texas. As Figure 8 clearly shows, red states have higher implicit discrimination than blue states.

Figure 8. Differential Mortality Ratio, NHB, Top 20 States
RE, 95% confidence intervals



Conclusions

This paper studies the structural and ideological factors that have altered a pattern of implicit racism in the behavior of hospital and medical practitioners affecting excess deaths among the Non-Hispanic Black (NHB) population living within the top 20 states experiencing the most deaths between the months of March and July 2020.

This paper's findings are the following: first, after controlling for variables linked to structural racism and hospital infrastructure, the paper finds evidence of excess deaths (31%) among the NHB population in April and in May. Such excess deaths reduce in the months of June (15%) and July (9%), something we attribute to the *George Floyd Effect*; second, the paper finds evidence that implicit bias is more likely to occur in counties that experienced four or more

months with deaths, as well as if they experienced deaths above the sample median. Third, the paper finds evidence that counties with lower hospital beds and ICU beds have higher shares of NHB population and experienced more deaths. Fourth, the paper identifies that in counties in Red states implicit racism is higher than in Blue states causing more deaths in excess among the NHB population, extending an earlier literature indicating the higher mortality rates of poor populations, mostly NHB in red states (Hochschild, 2018). In general, we believe that our results may indicate that when medical personnel are not under extreme stress is less likely to incur in subjective decision making, which may be biased by implicit racism.

We believe that our results substantiate an emerging literature on the impact of Covid-19 on non-white populations. An

interdisciplinary scholarship which by now has found that the reduced access to medical services and the unprecedented high death rates among the Non-Hispanic Black Population is directly linked to the practice of implicit racism by hospitals and medical providers (Jost et al., 2009). We corroborate existing evidence that social protests can impact behavioral change (Mazumder, 2018), as the BLM protests has been found to reduce the use of implicit racism against the NHB population (Mazumder, 2019). In addition, we find that when search costs increase, especially during the onset of a health crisis and when resources, like hospital beds, mostly ICBs are limited for Covid-19 infected patients, implicit racism appears to take a more prominent and negative role in the delivery of medical services (Li, Lang and Leung, 2018). The emerging literature document that public,

educational awareness, like that brought upon by different levels of social protest in the US can reduce bias as well as increase the level of care and institutional resources local governments make available to historically excluded racial and class minorities and their communities (Blacklock, 2020; Fernandez, 2020). The findings from this paper corroborate this literature by documenting that the Black Life Movement, following the death of George Floyd, increase public awareness and reduced implicit bias even in the states and counties with the highest deaths and with largest Non-Hispanic Black population. However, our results also reveal that further research is needed to better identify how to improve medical services during the onset of health crises, in order to ascertain that medical personnel follows medical protocols and not be influenced by subjective bias.

Bibliography

American Community Survey (ACS, 2020). *Public use five year micro data sample*. <https://www.census.gov/programs-surveys/acs/microdata.html>

Bailey, Z.D., Krieger, N., Agenor, M., Graves, J., Linos, N. and Basset, M.T. (2017). "Structural Racism and Health Inequities in the USA: evidence and interventions". *The Lancet* 389 (10077):1453-1463.

Becker, G. (1971). *The Economics of Discrimination*. 2nd Edition. Chicago: University of Chicago Press.

Blair, I.V., Steiner, F.J., Fairclough, D.L., Hanratty, R. Price, D.W., Hirsch, H.K., Wright, L.A., Bronsert, M., Karimkhani, E., Magid, D.J., and Havranek, E.P. (2013). "Clinicians' Implicit Ethnic/Racial Bias and Perceptions of Care Among Black and Latino Patients". *Annals of Family Medicine* 11 (1): 43-52.

Blackstock, U.A., & Blackstock, O.J. (2021, January). "Serving the People Body and Soul"—Centering Black Communities to Achieve Health Justice. In *JAMA Health Forum*. Vol. 2, No. 1, pp. e201523-e201523. American Medical Association.

- Blackstock OJ. 2020. *How did we get here? Historical perspectives. Conf on Addressing Medical Mistrust in Black Communities: Implications for COVID-19, HIV, Hepatitis, STIs and Other Conditions*, Aug 29.
- Brown, C.S. and Ravallion, M. (2020). *Inequality and the Coronavirus: Socioeconomic covariates of behavioral responses and viral outcomes across US counties*. National Bureau of Economic Research. Working Paper 27549.
- Butler, Danielle C. Stephen Petterson, Robert L. Phillips, and Andrew W. Bazemore (2012). "Measures of Social Deprivation that Predict Health Care Access and Need within a Rational Area of Primary Care Service Delivery". *Health Services Research* 48 (2): 539-59.
- Center for Disease Control (CDC, 2021). *Risk for Covid 19 infection, hospitalization and death by Race/Ethnicity*. Available at: <https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-race-ethnicity.html>
- County Health Rankings (CHR, 2020). *2019 County Health Rankings*. Available at: <https://www.countyhealthrankings.org>
- Crowd Counting Consortium (CCC, 2020). *June 2020 Crowds*. Available at: <https://sites.google.com/view/crowdcountingconsortium/home>
- Dave, D., Friedson, A., Matsuzawa, K., Sabia, J., & Safford, S. (2020). *Black Lives Matter protests, social distancing and Covid19*. National bureau of economic research. Working paper 27408.
- Diamond, P.A. (1971). "A model of price adjustment". *Journal of Economic Theory* 3 (2): 156-168.
- Fernández, J. (2020). "The Young Lords' Public Health Revolution: Fifty years ago, the Young Lords occupied Lincoln Hospital in the Bronx and won concrete advances in services and patients' rights. Their legacy of radical health activism illuminates the inhumanity of for-profit medicine and the urgency of winning free healthcare for all". *NACLA Report on the Americas*, 52(3), 339-347.
- Fuentes-Mayorga, N. & Kucheva, Y. (preliminary findings) s/f. *Revisiting the Hispanic Health Paradox: The Housing and Work Experiences of Immigrants in New York City during the COVID-19 Pandemic*. Funded by the Social Sciences Research Council. Available at: <https://covid19research.ssrc.org/rapid-response-grants-on-covid-19-and-the-social-sciences/grantees/>
- Fuentes-Mayorga, Norma and Giovanni Burgos (2016). "Generation X and the Future Health of Latinos". *Generations* 41 (3): 58-67.
- Hausman, Jerry A. (1978). "Specification Tests in Econometrics". *Econometrica* 46 (6): 1251-71.
- Hochschild, A. R. (2018). *Strangers in their own land: Anger and mourning on the American right*. The New Press.
- Jordan, J. (2020). "Should Congress pass the George Floyd Justice in Policing Act to reform U.S. policing practices and increase accountability?" *Congressional Digest*: 19-23. September.
- Jost, J.T., Rudman, L.A., Blair, I.V., Carney,

- D.R., Dasgupta, N., Glaser, J. and Hardin, C.D. (2009). "The existence of implicit bias is beyond reasonable doubt: A refutation of ideological and methodological objections and executive summary of ten studies that no manager should ignore". *Research in organizational behavior* 29: 39-69.
- Kelly, S., Jeremie-Brink, G., Chambers, A. & Smith-Bynum, M. (2020). "The Black Lives Matter movement: A call to action for couples and family therapists". *Family Process* 59: 1374-1388.
- Li, H., Lang, K., and Leong, K. (2018). "Does competition eliminate discrimination? Evidence from the commercial sex market in Singapore". *The Economic Journal* 128 (111): 1570-1608.
- Mazumder, Soumayit (2018). "The persistent effect of U.S. Civil Rights Protests on political attitudes". *American Journal of Political Science* 62 (4): 922-935.
- Leong, N. (2012). "Racial Capitalism". *Harvard Law Review*, 126, 2151.
- Mazumder, Soumayit (2019). *Black Lives Matter for White's Racial Prejudice: Assessing the role of social movements in shaping racial attitudes in the United States*. SocArXiv. May 6. doi:10.31235/osf.io/ap46d.
- McLaren, J. (2020). *Racial Disparity in COVID 19 Deaths: Seeking economic roots with Census data*. Working Paper. University of Virginia. June 12, 2020.
- Millet, G., Jones, A., Benkeser, D., Baral, S., Mercer, L., Beyrer, C., Honerman, B., Lankiewicz, E., Mena, L., Crowley, J., Sherwood, J., & Sullivan, P. (2020). *Annals of Epidemiology* 47: 37-44.
- Nagaraja, C. (2015). *Deprivation Indices for Census Tracts in Bronx and New York Counties*. Working Paper. Gabelli School of Business. Fordham University.
- National Healthcare Safety Network (NHSN, 2020). *Hospital capacity Covid 19 data dashboard*. Center for Disease Control and Prevention. Available at: <https://www.cdc.gov/nhsn/covid19/report-overview.html>
- National Lawyers Guild (NLG, 2020). *NLG in solidarity with Minneapolis following police killing of George Floyd*. Posted May 28, 2020. Available at: <https://www.nlg.org/nlg-in-solidarity-with-minneapolis-following-police-killing-of-george-floyd/>
- Nelson, A. (2011). *Body and soul: The Black Panther Party and the fight against medical discrimination*. U of Minnesota Press.
- Project Implicit (2021). *How the IAT is scored*. Available at: <https://www.projectimplicit.net/resources/about-the-iat/>
- Ravin, R.C. (2000). "The pandemic's toll closer to 300,000, researchers say, not all from Covid". *The New York Times*, October 25, 2020.
- Townsend, P., Phillimore, P. and Beattie, A. (1988). *Health and deprivation: inequalities and the north*. Croom Helm: London.
- USA facts (USAFacts, 2020). *US Coronavirus cases and deaths. Deaths by County*. Available at: <https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/>

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