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Along party Lines: Examining the gubernatorial party difference in COVID-19 mortality rates in U.S. Counties

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ABSTRACT

Drawing upon the literatures on risk factors for COVID-19 and the roles of political party and political partisanship in COVID-19 policies and outcomes, this study quantifies the extent to which differences in Republican- and Democrat-governed counties' observable characteristics explain the Republican - Democrat gap in COVID-19 mortality rate in the United States. We analyze the county COVID-19 mortality rate between February 1 and December 31, 2020 and employ the Blinder-Oaxaca decomposition method. We estimate the extent to which differences in county characteristics - demographic, socioeconomic, employment, health status, healthcare access, area geography, and Republican vote share, explain the difference in COVID-19 mortality rates in counties governed by Republican vs Democrat governors. Among 3,114 counties, Republican-governed counties had significantly higher COVID-19 mortality than did Democrat-governed counties (127 ± 86 vs 97 ± 80 per 100,000 population, $p < 0.001$). Results are sensitive to which weights are used: of the total gap of 30.3 deaths per 100,000 population, 12.8 to 20.5 deaths, or 42.2–67.7 %, are explained by differences in observable characteristics of Republican- and Democratic-governed counties. Difference in support for President Trump between Republican- and Democrat-governed counties explains 25 % of the additional deaths in Republican counties. Policies aimed at improving population health and lowering racial disparity in COVID-19 outcomes may also be correlated with reducing the partisan gap in COVID-19 mortality.

1. Introduction:

COVID-19 policies like masking, social distancing, and shelter-in-place orders were largely effective (Dave et al., 2021; Fowler et al., 2021), but the choice of policies (Baccini & Brodeur, 2021; Kosnik & Bellas, 2020), timing of implementation (Adolph et al., 2021), and public response to the policies (Grossman et al., 2020) varied by gubernatorial party (Amuedo-Dorantes et al., 2020). Not surprisingly, COVID-19 health outcomes also differ by the state's party affiliation (Gollwitzer et al., 2020; Neelon et al., 2021). Our calculations show that between February 1 and December 31, 2020, Republican-governed counties, on average, had 30.3 more deaths per 100,000 population than did Democrat-governed counties (127.4 vs 97.2).

Understanding the drivers of this difference will explain if there are non-political ways for reducing partisan inequality in public health outcomes. Hence, the question is: if Republican counties had the characteristics that Democrat counties do, to what extent would the COVID-19 mortality rate in Republican counties be lower? Stated differently, how much do partisan differences in county characteristics explain the partisan difference in COVID-19 mortality rates? This will also inform the portion of party differential in COVID-19 mortality attributable to unobserved factors, e.g., unconscious bias of healthcare providers, quality of care, cultural norms, etc.; these factors are hard to measure and harder to alter, at least in the short run.

Counties' political affiliation is based on the gubernatorial party in 2020 for two reasons. First, state governors were crucial and often the first to act against COVID-19 in the U.S. (Gupta et al., 2020; Neelon et al., 2021). Second, there is no consistent way to define the political

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party of county governments in a national study because the makeup and responsibilities of county governments vary across the U.S. – county leadership may be set up as commissions, may not require partisan affiliation, and may vary in their scope (US Census Bureau, 2019). One way in which the COVID-19 literature has defined political affiliation at the county level is to use vote share in the 2016 presidential election (Adolph et al., 2021; Allcott et al., 2020; Gupta et al., 2020; Painter & Qiu, 2021) – counties with majority votes for Hilary Clinton (Donald Trump) were considered Democrat (Republican) counties. The vote share definition has the advantage of capturing electoral sentiment, but the purpose of this paper is to follow where policies are made and how governance is set up below the federal level. We treat Republican vote share as one of the drivers of the difference in COVID-19 mortality rates between Republican- and Democrat-governed counties.

The Blinder-Oaxaca method (Blinder, 1973; Fortin et al., 2011; Jann, 2008; Oaxaca, 1973) that was first used in labor economics to explain the male–female wage gap (Z. Chen et al., 2010; Horrace & Oaxaca, 2001; Oaxaca & Ransom, 1994, 1999), and has since been applied to study inequality in health outcomes and extended to other sources of inequality, e.g., union membership, race, and income (Amin & Lhila, 2016; Averett et al., 2014; Charasse-Pouélé & Fournier, 2006; Kino & Kawachi, 2020; Koh et al., 2020; Krieg & Storer, 2006; Lhila & Long, 2012; Rahimi & Hashemi-Nazari, 2021; Sen, 2014; Spencer et al., 2018). It has recently been used to study whether the change in representation relationships with voters and co– partisans explains the increased polarization in the U.S. senate (Butler, 2021).

While these results cannot be interpreted as causal, this study will provide suggestive evidence about both the choice of pathways and the extent to which partisan health differences can be affected. For instance, if the partisan difference in county characteristics like population density, health status, or access to healthcare were to meaningfully explain the partisan COVID-19 mortality gap, that would suggest that policies aimed at improving these characteristics may be correlated with a smaller partisan mortality gap too.

This paper draws upon literature from several disciplines and contributes to our understanding of disparities in COVID-19 outcomes. Inequalities in COVID-19 outcomes based on race and socioeconomics have received due attention in the public health literature (Kantamneni, 2020; McLaren, 2021; Patel et al., 2020; Rossen et al., 2020; Wrigley-Field, 2020; Yehia et al., 2020). There is also a rich debate on the causes and nature of political polarization (Castle & Stepp, 2021; Iyengar et al., 2019; Iyengar & Krupenkin, 2018), and as it relates to COVID-19 in the U.S. (Allcott et al., 2020; H.-F. Chen & Karim, 2021; Neelon et al., 2021). However, to our knowledge this is the first study to consider party ideology as a lens through which to study the drivers of inequalities in COVID-19 outcomes.

2. Materials and method

Counties and county equivalents within the 50 states of the United States are the units of analysis. After dropping 28 counties for missing information, the sample size is 3,114 counties, of which 1,758 are in Republican- and 1,356 in Democrat-governed states.

The outcome variable is cumulative COVID-19 deaths between February 1 and December 31, 2020 (USAFacts, 2021). County mortality count is scaled by county population, which yields COVID-19 deaths per 100,000 population. We limit our study to COVID-19 mortality through December 31, 2020, to hold constant the political and public health environments. A new president assumed office in 2021, and the availability of COVID-19 vaccines became more widespread; which together altered COVID-19 outcomes, independent of gubernatorial party affiliations.

Data on explanatory variables are obtained from a variety of sources. Demographics, socioeconomics, and employment and commuting data are from the U.S. Census Bureau's 2014–2018 American Community Survey 5-Year Data Profile (US Census Bureau, 2018). Measures of county health status are from the CDC's 2016–2018 Interactive Atlas of Heart Disease and Stroke (Centers for Disease Control and Prevention, n.d.) and 2017 Diabetes Surveillance System. The 2018–19 Area Health Resource Files yield information on healthcare access, supply, and area geography (HRSA, 2021). County data on 2016 presidential election returns are obtained from the MIT Data Election and Science Lab (MIT Election Data and Science Lab, 2018). These explanatory variables are chosen based on published risk factors for COVID-19 mortality (Gansevoort & Hilbrands, 2020; Goodman et al., 2020; Grasselli et al., 2020; Jordan et al., 2020; Kim et al., 2020; Li et al., 2020; Mikami et al., 2020; Weiss & Murdoch, 2020; Zhou et al., 2020) and the standard correlates in the partisanship and COVID-19 literature. We measure characteristics at pre-COVID levels to avoid potential endogeneity as the characteristics of the counties themselves changed simultaneously with the spread of the pandemic.

The Blinder-Oaxaca decomposition method was initially used to study gender and racial wage discrimination (Blinder, 1973; Oaxaca, 1973). It divides the wage differential between two groups: the portion attributable to differences in the distribution of endowments (e.g., training, education, productivity, experience) and an unexplained portion due to group differences in coefficients or returns to labor market investments; the latter measures discrimination in the labor economics literature.

Briefly, the method first estimates a linear regression where Y_i is the outcome variable, and $X_{1i}, \cdots, X_{ki}$ are k observable explanatory variables. The regression is estimated separately for two groups, A and B, and all explanatory variables represented by X are the same in both equations:

$$Y_i^A = \sum\nolimits_{j=1}^{k} \beta_j^A X_{ji}^A + \mu_i^A \tag{1}$$

$$Y_i^B = \sum\nolimits_{j=1}^{k} \beta_j^B X_{ji}^B + \mu_i^B \tag{2}$$

Assuming that the error term is uncorrelated with the outcome, Y, or is at least the same for both groups, the gap between $\overline{Y}^A$ and $\overline{Y}^B$ is represented as:

$$\overline{Y}^A - \overline{Y}^B = \left(\sum_j \beta_j^A \overline{X}_j^A\right) - \left(\sum_j \beta_j^B \overline{X}_j^B\right) \tag{3}$$

By adding and subtracting $\sum_j \beta_j^A \overline{X}_j^B$, Equation (3) can be re-written:

$$\overline{Y}^A - \overline{Y}^B = \sum_j \beta_j^A \left(\overline{X}_j^A - \overline{X}_j^B\right) + \sum_j \left(\beta_j^A - \beta_j^B\right) \overline{X}_j^B \tag{4}$$

Groups A and B represent Republican and Democrat parties, respectively; and $\overline{Y}$ is the predicted county COVID-19 mortality rate estimated at the means of the explanatory variables.

The first term on the right-hand side represents the portion of the partisan COVID-19 mortality gap attributable to differences in the distribution of X in Republican and Democrat counties. This term is called the composition effect and has been likened to the local average treatment effect, in program evaluation parlance (Fortin et al., 2011). These include the distributions of race/ethnicity, educational attainment, healthcare supply, health status, geographic factors, and Republican vote share. In this case, the explained portion is the difference between (i) the predicted COVID-19 mortality for Republican counties conditional upon the Xs in the model, and (ii) what the predicted COVID-19 mortality rate would be in Democrat counties if the effect of county characteristics on COVID-19 mortality in Democrat counties were the same as they are in Republican counties.

The second term on the right-hand side is the unexplained portion that captures the party differences in regression coefficients or marginal effects of the characteristics, X on COVID-19 mortality rates. Intuitively, the second term in equation (4) is the partisan difference in mortality rates that is due to different returns to health inputs in Republican- and Democrat-governed counties, which may be due to unobserved county characteristics like racial segregation of healthcare services, cultural norms, and quality of healthcare. More explicitly, Republican and Democrat counties with the same level of education, racial composition, insurance rate, and access to healthcare could have different *effects* on COVID-19 mortality due to these unobserved (by the researcher) differences.

One estimation issue is related to self-selection of individuals. Unobservable traits like health consciousness and risk aversion may be correlated with both county characteristics and COVID-19 mortality rate. We use lagged county characteristics to reduce this concern, but admit this is an imperfect solution. Thus, we view this as a descriptive study and caution against making causal inferences.

The results of the decomposition are sensitive to the choice of regression coefficients used to weight the difference in endowments. The explained portion of equation (4) is specified with coefficients obtained from the regression for group A; and the unexplained portion is weighted by the means for group B. Equation (4) can be re-written using regression coefficients from the Democrat regression and mean of explanatory variables from Republican counties. The choice of regression coefficients is based on a judgement about which gubernatorial party has the ideal returns on inputs. Instead of assuming that returns in Democrat-governed counties are preferable because they have lower mortality rates, we follow the literature and estimate the decomposition both ways. We also check the robustness of our results by using regression coefficients from a third regression equation, which employs data pooled from all counties and includes a group indicator as a control in the model (Jann, 2008; Neumark, 1988). This assumes that the associations between county characteristics and COVID-19 mortality are the same in Republican and Democrat counties. The three sets of weighting coefficients are obtained from Ordinary Least Squares regressions where standard errors are clustered at the state level to account for within-state correlation among counties, which is particularly important as we measure the political party of the county at the state level.

3. Results and Discussion:

3.1. Study sample

Table 1 presents descriptive statistics for all characteristics included in this analysis, separately for Republican and Democrat counties. Pairwise comparisons using t-tests show that there are statistically significant differences in the characteristics of Republican- and Democrat-governed counties; however, the magnitude of differences is often small. The percentages reported are the *average* of percentages in Republican and Democrat counties. On average, Republican counties' populations are 73.1 % white, 10.9 % African American, and 5.8 % from other races; compared to Democrat counties that tend to be 76 %, 7.9 %, and 6.7 % white, African American, and other races, respectively.

Families in Republican counties are more likely to be single parent-headed and less likely to consist of non-family members compared to those in Democrat counties. Republican counties have lower educational attainment than do Democrat counties. The average poverty rate in Republican counties is 16.2 % versus 14.8 % in Democrat counties.

Average county unemployment rates are similar in Republican and Democrat counties. On average, 80.7 % of workers drive to work in Republican counties whereas workers in Democrat counties are more likely to take public transportation or commute by walking, biking, etc.

Republican counties have worse average health status than do Democrat counties. The average coronary artery disease mortality rate is 108.2 (96.3) per 100,000 population and the average obesity rate is 34.1 % (32.3 %) in Republican (Democrat) counties.

The average uninsured rate is 11.1 % in Republican counties and 7.4 % in Democrat counties. Republican counties have fewer hospital beds (27.4 vs 31.2), primary care physicians (4.6 vs 5.8), registered nurses (34.2 vs 41.3 fulltime equivalents), and respiratory therapists (2.3 vs 2.6).

Democrat counties are more likely to be urban whereas Republican counties are more likely to be designated suburban and rural. The average population per 10 square miles is 1,482 in Republican counties compared to 4,397 in Democrat counties. On average, 66.5 % of voters chose Trump in 2016 in Republican-governed counties, compared to 59.1 % Republican vote share in Democrat counties.

3.2. Regression results

Table 2 presents results for three samples – Republican, Democrat, and all counties.

Minority race/ethnicity is statistically significantly associated with higher mortality. On average, a 10-percentage point increase in Hispanic and African American populations is related to 6.8 – 10 and 10.7 – 14.4 additional COVID-19 deaths per 100,000 population, respectively, when compared to the same increase in the white population. Counties with higher percentage of elderly have higher COVID-19 mortality but the relationship is statistically significant only in Republican counties. This is consistent with the findings that minority race (Morales & Ali, 2021; Rossen et al., 2020; Yehia et al., 2020) and older age are independent risk factors for COVID-19 mortality (Dowd et al., 2020; Ho et al., 2020; Sasson, 2021).

Living arrangements are not statistically significantly associated with COVID-19 mortality, except in the Democrat model, which shows that living in a single-parent family is associated with higher COVID-19 mortality. The proportion of least educated (less than high school) and the proportion of less educated (high school graduates) are associated with higher rates of COVID mortality in Republican and Democrat counties, respectively. Further, poverty rate is not statistically significantly associated with COVID-19 mortality rate in either model, but higher incomes are associated with lower COVID-19 mortality. We speculate that these results are because populations with lower education and income levels are employed in frontline jobs thereby placing them at greater risk of exposure (Hawkins et al., 2020).

Pre-COVID county employment rate is associated with higher COVID-19 mortality rate. This is consistent with the early findings that approximately-one-third of working adults continued to commute to work (Brynjolfsson et al., 2020) after the national emergency declaration so that higher percentages of employed populations would be associated with greater risk for COVID-19 transmission (Hawkins et al., 2020). Counties with greater proportion of public transportation use had higher COVID-19 mortality rates, although the result in statistically significant only in Democrat counties.

Results suggest that 10 percentage point increase in the coronary heart disease is associated with 1.3 – 1.5 additional COVID-19 deaths, on average. In Republican counties, a percentage point increase in obesity rate is accompanied by a 0.94 percentage point increase in COVID-19 mortality rate, on average. The literature has consistently concluded that patients with a history of coronary artery disease are at greater risk of mortality (Loffi et al., 2020; Szarpak et al., 2022) and that obesity is a risk factor for COVID-19 complications and mortality, although some studies conclude that the relationship is more salient for the elderly and near-elderly (Poly et al., 2021; Popkin et al., 2020; Tartof et al., 2020).

County health insurance coverage rate is associated with higher (lower) COVID-19 mortality rates in Republican (Democrat) counties. Lack of insurance is generally associated with increased overall mortality (Abel & McQueen, 2020; Franks et al., 1993; Wilper et al., 2009). Whereas the supply of healthcare personnel is not statistically significantly associated with COVID-19 mortality in the Republican model; the availability of hospitals, respiratory therapists, and primary care physicians are related to an increase in COVID-19 mortality, and supply of nurses is associated with lower COVID-19 mortality in the Democrat model. We speculate that higher numbers of hospitals and hospital personnel indicate better diagnoses and more accurate reporting of COVID-19 mortality, which would explain the positive correlation

Table 1
Differences in County Charateristics, by Gubernatorial Party. Means and (Standard Deviations in paretheses).

	Republican		Democratic		Difference		All Counties	
No. of counties in sample	1,758		1,356				3,114	
COVID deaths per 100,000 population	127.4	(85.7)	97.2	(80.1)	30.3	***	114.2	(84.6)
Demographic								
Sex ratio	100.7	(11.4)	100.8	(12.4)	−0.1		100.8	(11.9)
Pct population Hispanic	10.2	(14.8)	9.4	(12.2)	0.8		9.8	(13.7)
Pct population non-Hispanic White (alone)	73.1	(20.4)	76.0	(18.3)	−2.9	***	74.4	(19.6)
Pct population non-Hispanic Black (alone or in combination)	10.9	(15.9)	7.9	(11.9)	3.0	***	9.6	(14.4)
Pct population non-Hispanic other race	5.8	(8.0)	6.7	(7.4)	−0.9		6.2	(7.7)
Pct population < 5 years old	6.0	(1.2)	5.6	(1.1)	0.4	***	5.8	(1.2)
Pct population 5–19 years old	19.5	(2.8)	18.5	(2.6)	1.0	***	19.1	(2.7)
Pct population 20–24 years old	6.2	(2.3)	6.2	(2.5)	0.0		6.2	(2.4)
Pct population 25–34 years old	11.8	(2.2)	11.7	(2.3)	0.0		11.8	(2.2)
Pct population 35–54 years old	24.4	(2.4)	24.6	(2.5)	−0.2	**	24.5	(2.4)
Pct population 55–64 years old	13.9	(2.1)	14.6	(2.3)	−0.7	***	14.2	(2.2)
Pct population 65 + years old	18.2	(4.5)	18.7	(4.6)	−0.5	***	18.4	(4.5)
Pct population U.S. citizens	95.7	(5.2)	94.9	(6.2)	0.8	***	95.3	(5.7)
Pct population foreign-born	4.3	(5.2)	5.1	(6.2)	−0.8	***	4.7	(5.7)
Socioeconomic Status								
Pct population living in married/couple families	61.9	(8.4)	61.4	(7.3)	0.5		61.7	(7.9)
Pct population living in single parent families	21.2	(7.6)	19.8	(6.1)	1.4	***	20.6	(7.0)
Pct population living in non-family households	16.9	(4.8)	18.8	(5.3)	−2.0	***	17.7	(5.2)
Pct population 25 + with < HS diploma	14.4	(6.6)	12.2	(5.8)	2.3	***	13.4	(6.3)
Pct population 25 + with HS diploma	35.3	(6.9)	32.9	(7.4)	2.4	***	34.3	(7.2)
Pct population 25 + with some college	30.2	(5.1)	31.4	(5.3)	−1.2	***	30.7	(5.2)
Pct population 25 + with college or higher	20.1	(8.4)	23.5	(10.3)	−3.4	***	21.6	(9.4)
Pct population with famiy income < 100 % FPL	16.2	(6.7)	14.8	(6.0)	1.4	***	15.6	(6.4)
Pct population with with famiy income 100–200 % FPL	21.5	(5.0)	19.9	(4.8)	1.7	***	20.8	(5.0)
Pct population with with famiy income 200–300 % FPL	18.8	(3.2)	18.1	(3.2)	0.7	***	18.5	(3.2)
Pct population with with famiy income 300–400 % FPL	14.5	(3.0)	14.7	(2.6)	−0.1	*	14.6	(2.8)
Pct population with with famiy income 400–500 % FPL	9.9	(2.6)	10.6	(2.4)	−0.6	***	10.2	(2.5)
Pct population with with famiy income > 500 % FPL	19.0	(7.6)	22.0	(9.1)	−3.0	***	20.3	(8.4)
Employment & Commuting								
Pct population 19–64 year employed	71.4	(7.9)	72.3	(7.6)	−0.8	***	71.8	(7.8)
Pct population 19–64 year unemployed	3.6	(1.9)	3.7	(1.5)	−0.1		3.7	(1.7)
Pct population 19–64 year not in labor force	24.9	(7.0)	24.0	(6.9)	0.9	***	24.5	(7.0)
Pct workers 16 + who commute = drive	80.7	(6.0)	78.9	(7.5)	1.9	***	79.9	(6.8)
Pct workers 16 + who commute = carpool	9.9	(3.2)	9.5	(2.5)	0.4	***	9.7	(2.9)
Pct workers 16 + who commute = other (walk, bike, etc.)	4.6	(3.6)	6.4	(6.3)	−1.8	***	5.4	(5.0)
Pct workers 16 + who commute = public transportation	0.5	(1.4)	1.4	(4.4)	−0.9	***	0.9	(3.1)
Pct workers 16 + who commute = none (work from home)	4.8	(3.4)	5.2	(3.0)	−0.5	***	5.0	(3.2)
Health Status								
Mean mortatlity due to coronary artery disease per 100,000 population	108.2	(33.3)	96.3	(28.7)	11.8	***	103.0	(31.9)
Mean obesity rate, age 20+	34.1	(5.8)	32.3	(5.9)	1.7	***	33.3	(5.9)
Healthcare Access								
Pct population no health insurance coverage	11.1	(5.5)	7.4	(3.3)	3.6	***	9.5	(5.0)
Pct population with private HI coverage alone	48.5	(10.0)	49.5	(9.9)	−1.0	***	49.0	(9.9)
Pct population with public HI coverage alone	21.2	(6.8)	22.6	(7.6)	−1.4	***	21.8	(7.2)
Pct population with private and public HI	19.3	(4.3)	20.4	(4.4)	−1.2	***	19.8	(4.4)
Mean no. of hospitals per 10,000 population	0.5	(0.8)	0.6	(1.0)	0.0		0.6	(0.9)
Mean no. of hospital beds per 10,000 population	27.4	(53.2)	31.2	(50.3)	−3.8	**	29.1	(52.0)
Mean no. of primary care physicians per 10,000 population	4.6	(3.3)	5.8	(4.0)	−1.2	***	5.2	(3.7)
Mean no. of respiratory therapist per 10,000 population	2.3	(2.8)	2.6	(3.3)	−0.3	***	2.4	(3.0)
Mean no. full-time equivalent registered nurses per 10,000 population	34.2	(50.2)	41.3	(51.3)	−7.1	***	37.3	(50.8)
Area Geography								
Pct in metropolitan areas with population > 250,000	34.5	(47.5)	41.1	(49.2)	−6.6	***	37.3	(48.4)
Pct non-metro counties with population > 2,500, adjacent to metro area (suburban)	27.9	(44.8)	23.3	(42.3)	4.6	***	25.9	(43.8)
Pct non-metro counties with population > 2,500, not adjacent to metro area (small city)	16.4	(37.1)	16.7	(37.3)	−0.3		16.6	(37.2)
Pct counties completely rural or population < 2,500, not adjacent to metro area (rural)	21.2	(40.9)	18.9	(39.1)	2.3	*	20.2	(40.2)
Mean population (in 100′s) per 10 square miles	14.8	(49.7)	44.0	(265.0)	−29.2	***	27.5	(179.4)
Partisan Support								
Pct voters who voted for Donald Trump, 2016	66.5	(15.1)	59.1	(15.4)	7.3	***	63.3	(15.7)

Notes:
Unless otherwise specified, all data are civilian non-institutionalized population from 2014 to 18 American Community Survey 5-year Data Profile.

COVID-19 mortality betweem February 1 and December 31, 2020 obtained from USAFacts 2021.
Race and ethnicity data obtained from 2020 Decennial Census.
Health status from Center for Disease Control and Prevention, 2017 Diabetes Surveillance System.
Voter return data obtained from MIT Election Data and Science Lab, 2018.
*(**)(***) indicate statistical significance at 0.1(0.05)(0.01) levels of significance, respectively.

between healthcare supply and COVID-19 mortality.

Area geographic characteristics are not statistically significantly associated with COVID-19 mortality in any of the models. Although Republican vote share is not statistically significantly associated with COVID-19 mortality in Republican-governed counties, greater fraction of Trump voters is associated with higher COVID-19 mortality in counties with Democrat governors. The explanation is likely that governors with higher percentages of Trump supporters were sluggish in their COVID-19 response, and social distancing policies were followed less stringently in those areas (Adolph et al., 2021; Allcott et al., 2020; Gupta et al., 2020).

3.3. Decomposition results

Table 3 presents the results of the Blinder-Oaxaca decomposition. The three horizontal panels present results using weights from the Republican, Democrat, and pooled models respectively. The first column presents the number of deaths explained by differences in county characteristics and the second presents the same as percentages of the overall difference. The total percent explained is the sum of the percent explained by the sets of inputs in the model, which themselves may be positive or negative. The positive results explain why Republican counties have higher mortality and the negative results reveal the traits that protect against COVID-19 mortality in Republican counties.

Using coefficients from the Republican, Democrat, and pooled regressions show that 12.8, 20.5, and 14.8 deaths per 100,000 population or 42.2 %, 67.7 %, and 47.9 % of the mortality differential is explained by the variables included in the models, respectively. The overall result using Republican weights is not statistically significant at conventional levels, but results are statistically significant in the Democrat and pooled models.

Of the seven set of characteristics included in the decomposition model,– Republican-Democrat difference in demographic characteristics statistically significantly explains the overall partisan gap in mortality rates, in the Republican and pooled models. Using Republican coefficients, 9.22 deaths per 100,000 population or 30 % of the partisan gap in COVID-19 mortality is explained by partisan demographic differences; the corresponding results are 7.7 deaths (25 %) and 10.3 deaths (34 %) when coefficients are drawn from the Democrat and pooled models, respectively.

County demographics consist of race, ethnicity, age, and nativity. Table 1 shows that the differences in means of the race and ethnicity variables were the largest relative to partisan differences in other demographic characteristics. A study that included very similar explanatory variables found that fraction of the county population that is African American shares one of the strongest associations with risk adjusted COVID-19 case count and fatality rate (Hawkins et al., 2020). Another study concluded that African Americans were less likely to be diagnosed in an ambulatory care setting but 2.7 times more likely to be hospitalized than their white counterparts (Azar et al., 2020); they speculate that African Americans have higher mortality rates because they delay care, partly because of past negative experiences in healthcare settings, and arrive at the emergency room when their health condition is considerably worsened.

Difference in county health status statistically significantly explains another 11 % of the mortality difference using weights from the Republican regression, but not when coefficients are obtained from the Democrat or pooled regressions. It suggests that 3.3 of the 30.25 excess deaths per 100,000 population in Republican counties are explained by partisan difference in county health status. This is not surprising because the coefficients for coronary artery disease and obesity were statistically significant only in the Republican model. This result is consistent with evidence that patients with coronary artery disease (CAD) are at greater risk for COVID-19 mortality (Loffi et al., 2020; Szarpak et al., 2022).

Using Democrat weights shows that the partisan difference in Republican vote share explains 25 % of the difference in COVID-19 mortality rates in Republican- and Democrat-governed counties. These results indicate that an additional 7.6 COVID-19 deaths per 100,000 population in Republican-governed counties may be attributable to higher support for President Trump, on average, in those counties.

Partisan differences in the remaining sets of characteristics do not statistically significantly explain the partisan gap in COVID-19 mortality rate. The sign of the employment and commuting characteristics result is negative across all models suggesting that these characteristics may have a protective effect on COVID-19 mortality rates in Republican-governed counties.

4. Conclusions

This paper examines the drivers of the partisan divide in county COVID-19 mortality. Governors shape public health policy below the federal level and were crucial in COVID-19 control in the U.S. Thus, we define counties as Republican or Democrat based on the governor's party affiliation. We draw upon existing literature to shed light on the extent to which partisan differences in county characteristics associated with COVID-19 explain the difference in COVID-19 mortality rate between Republican and Democrat-governed counties. Doing so provides insight into non-political avenues of public policy intervention that can potentially be used to reduce the party-based gap in mortality, and hence lower COVID-19 itself.

Republican-governed counties had 30.3 more deaths per 100,000 population than did Democrat-governed counties. Our analysis shows that partisan differences in demographics, socioeconomics, employment and commuting, health status, healthcare access, area geographic characteristics, and electoral support for President Trump explain 12.8–20.47 deaths per 100,000 population, depending on the weights used in the estimation model. This is equivalent to 42.2 – 67.7 % of the overall partisan mortality gap. Depending on the model, demographic differences between Republican and Democrat counties explain 25 – 34 % of the overall partisan gap in COVID-19 mortality. Partisan difference in county health status explains another 11 % of the partisan mortality gap, but the result is statistically significant only in the Republican model. An additional 7.6 COVID-19 deaths per 100,000 population in Republican-governed counties is attributable to higher percentages of Trump supporters in these counties.

The unexplained portion of the partisan difference in COVID-19 mortality is due to partisan differences in the *effects* of these characteristics on county mortality. Republican and Democrat counties with the same fraction of African American population, insurance rate, and supply of hospitals could have different effects on COVID-19 mortality because Republican and Democrat counties are different in ways not captured in our model, such as unconscious bias of healthcare providers, quality of care, and health behaviors related to and compliance with COVID-19 policies.

This study has several limitations inherent to the Blinder-Oaxaca decomposition method. First, it only highlights variables that are quantitatively significant and does not shed light on the mechanisms underlying the relationship between political parties and COVID-19 mortality. Second, although we have included a wide array of explanatory variables, it is possible that significant predictors of COVID-19

Table 2
Regression Results for Number of COVID-19 Deaths Per 100,000 Population, Pooled and By Governor's Party Coefficient and Standard Error in Parentheses.

	Republican Counties			Democratic counties			All counties		
Demographic									
Sex ratio	0.48	(0.23)	**	0.17	(0.21)		0.41	(0.15)	***
Pct population Hispanic	0.68	(0.27)	**	1.00	(0.31)	***	0.84	(0.20)	***
Pct population non-Hispanic Black (alone or in combination)	1.07	(0.24)	***	1.44	(0.28)	***	1.36	(0.18)	***
Pct population non-Hispanic other race	0.94	(0.35)	***	1.44	(0.40)	***	1.21	(0.26)	***
Pct population 5–19 years old	1.33	(2.71)		−4.94	(3.98)		−2.29	(2.22)	
Pct population 20–24 years old	−3.10	(2.52)		−3.63	(3.29)		−4.73	(1.96)	**
Pct population 25–34 years old	−3.56	(3.05)		−9.87	(4.15)	**	−7.75	(2.41)	***
Pct population 35–54 years old	−4.44	(2.19)	**	−5.25	(3.12)	*	−6.70	(1.75)	***
Pct population 55–64 years old	−6.58	(2.79)	**	−9.20	(3.55)	**	−8.77	(2.16)	***
Pct population 65 + years old	4.50	(2.29)	*	−1.98	(3.20)		0.39	(1.83)	
Pct population citizens	2.07	(0.62)	***	0.62	(0.72)		2.03	(0.46)	***
Socioeconomic Status									
Pct population living in single parent families	0.38	(0.55)		1.17	(0.66)	*	0.34	(0.42)	
Pct population living in non-family households	0.32	(0.65)		0.19	(0.70)		0.24	(0.47)	
Pct population 25 + with < HS diploma	5.32	(0.73)	***	−1.12	(0.82)		3.31	(0.52)	***
Pct population 25 + with HS diploma	1.13	(0.58)	*	3.33	(0.56)	***	2.04	(0.40)	***
Pct population 25 + with some college	1.72	(0.67)	**	−0.16	(0.62)		0.69	(0.46)	
Pct population with income < 100 % FPL	0.72	(0.74)		0.56	(0.90)		0.43	(0.56)	
Pct population with income 100–200 % FPL	−0.60	(0.66)		−2.60	(0.78)	***	−1.52	(0.50)	***
Pct population with income 200–300 % FPL	−2.23	(0.74)	***	−1.32	(0.85)		−2.16	(0.55)	***
Pct population with income 300–400 % FPL	0.69	(0.89)		−1.73	(1.03)	*	−0.82	(0.67)	
Pct population with income 400–500 % FPL	−1.77	(1.15)		−4.37	(1.23)	***	−2.56	(0.84)	***
Employment & Commuting									
Pct population 19–64 year employed	3.05	(0.46)	***	3.44	(0.55)	***	3.56	(0.35)	***
Pct population commute = drive	1.58	(0.71)	**	1.73	(0.91)	*	1.51	(0.55)	***
Pct population commute = carpool	1.52	(0.91)	*	−1.35	(1.24)		0.51	(0.73)	
Pct population commute = other (walk, bike, etc.)	2.58	(1.06)	**	0.88	(1.26)		1.79	(0.81)	**
Pct population commute = public transportation	3.62	(2.35)		4.19	(1.28)	***	4.11	(1.04)	***
Health Status									
Mean coronary artery disease per 100,000 population	0.15	(0.06)	**	0.13	(0.09)		0.09	(0.05)	*
Mean obesity rate, age 20+	0.94	(0.39)	**	−0.53	(0.43)		0.14	(0.29)	
Healthcare Access									
Pct population with private HI coverage alone	2.07	(0.62)	***	−2.19	(0.85)	**	0.63	(0.49)	
Pct population with public HI coverage alone	1.43	(0.67)	**	−0.26	(0.81)		1.13	(0.47)	**
Pct population with private and public HI	0.45	(0.83)		−2.83	(1.01)	***	−0.36	(0.62)	
Mean no. of hospitals per 10,000 population	8.50	(3.00)	***	13.15	(3.13)	***	11.26	(2.14)	***
Mean no. of hospital beds per 10,000 population	0.09	(0.07)		0.05	(0.06)		0.06	(0.05)	
Mean no. of respiratory therapist per 10,000 population	0.28	(1.29)		5.41	(1.20)	***	2.41	(0.88)	***
Mean no. full-time equivalent registered nurses per 10,000 population	−0.04	(0.10)		−0.36	(0.09)	***	−0.13	(0.07)	*
Mean no. of primary care physicians per 10,000 population	0.12	(0.77)		1.85	(0.72)	**	0.30	(0.52)	
Area Geography									
Pct non-metro counties with population > 2,500, adjacent to metro area (suburban)	−0.02	(0.05)		0.08	(0.06)		0.02	(0.04)	
Pct non-metro counties with population > 2,500, not adjacent to metro area (small city)	0.06	(0.06)		−0.02	(0.07)		0.05	(0.05)	
Pct counties completely rural or population < 2,500, not adjacent to metro area (rural)	0.06	(0.07)		−0.01	(0.08)		0.02	(0.05)	
Mean population (in 100′s) per 10 square miles	−0.05	(0.06)		0.004	(0.01)		−0.01	(0.01)	
Partisan Support									
Pct voters who voted for Donald Trump, 2016	−0.19	(0.22)		1.04	(0.27)	***	0.27	(0.17)	
Governor's Party, Democrat	–			–			−15.77	(3.17)	***
Sample Size	1,758			1,356			3,114		
Adjusted R-squared	0.23			0.27			0.24		

Notes:
Coefficients and associated standard errors obtained from Ordinary Least Squares estimation that includes a constant (not reported) and standard errors clustered at the state level.
Gubernatorial party determines if county is democratic or republican.
Sex ratio = Percent male/Percent female in population.
Race/ethnicity based on up to 5 races identified.
Omitted categories: White (alone, not in combination with another race); age < 5 years; married/cohabiting households; college or higher education; income > 500 % FPL; unemployed or not in labor force; work from home; uninsured; and metropolitan counties.
*(**)(***) indicate statistical significance at 0.1(0.05)(0.01) levels of significance, respectively.

Table 3
Decomposition Results – Percent Explained of the COVID Mortality Difference Between Republican and Democratic Counties, Using Regression Coefficients from Three Different Estimations as Alternate Weights. Blinder-Oxaca Estimation Results with Standard Errors.

COVID deaths per 100,000 population				
Counties with Republican Governor	127.41		n = 1,758	
Counties with Democratic Governor	97.15		n = 1,356	
Total Difference	30.25	***		
	Difference Explained (1)	**SE**		**Percent Explained** (2)
I. Weights from Republican Counties				
Demographics	9.22	(4.37)	**	30 %
Socioeconomic Status	11.94	(8.09)		39 %
Employment & Commuting	−6.73	(6.41)		-22 %
Health Status	3.39	(1.97)	*	11 %
Healthcare Access	−0.38	(1.70)		−1%
Area Geography	−3.29	(4.57)		−11 %
Percent Votes for Donald Trump	−1.37	(3.26)		−5%
Total	12.78	(7.85)		42.2 %
II. Weights from Democratic Counties				
Demographics	7.65	(5.56)		25 %
Socioeconomic Status	5.56	(6.02)		18 %
Employment & Commuting	−5.44	(5.99)		−18 %
Health Status	0.66	(2.06)		2 %
Healthcare Access	4.18	(6.09)		14 %
Area Geography	0.22	(0.48)		1 %
Percent Votes for Donald Trump	7.63	(3.73)	**	25 %
Total	20.47	(7.48)	***	67.7 %
III. Weights from All Counties				
Demographics	10.25	(4.69)	**	34 %
Socioeconomic Status	9.83	(6.34)		33 %
Employment & Commuting	−6.72	(6.18)		-22 %
Health Status	1.35	(1.52)		4 %
Healthcare Access	−2.55	(3.28)		−8%
Area Geography	0.32	(0.56)		1 %
Percent Votes for Donald Trump	2.00	(2.47)		7 %
Total	14.48	(7.12)	**	47.9 %

Notes:
Standard errors clustered at the state level.
Gubernatorial party determines if county is Democrat or Republican.
Demographics includes sexratio, racial & ethnic distribution, age categories, and US nativity.
Socioeconomics incluse living arrangements, educational attainment, and categories for income as proprtion of federal poverty level.
Employment & commuting includes employment rate and mode of commute.
Health status includes coronary artery disease and obesity rate.
Healthcare access includes insurance rate and hospitals, hospital beds, respiratory therapists, primary care physicians, and registered nurses per 10,000 population.
Area geography includes urbanicity and population density.
*(**)(***) indicate statistical significance at 0.1(0.05)(0.01) levels of significance, respectively.

mortality (e.g., social policies, administrative structure) have been omitted. Third, potential self-selection bias in the empirical results may be mitigated with the use of lagged explanatory variables, but we cannot rule out estimation bias. Fourth, the results of this ecological study may not hold at the individual level. The main takeaways of this study are that higher COVID-19 mortality rate in counties with Republican governors is partly explained by the higher support for President Trump in Republican-governed counties, relative to counties with Democrat governors. Further, policies aimed at improving population health and reducing racial disparities in COVID-19 outcomes may also be associated with lower partisan gap in COVID-19 mortality.

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CRediT authorship contribution statement

Aparna Lhila: Conceptualization, Software, Validation, Formal analysis, Data curation, Writing – review & editing, Visualization, Supervision, Project administration. **Fares Alghanem:** Conceptualization, Methodology, Investigation, Data curation, Software, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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