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Research Article

Decomposition analysis of disparities in infant mortality rates across 27 US states

Benjamin Sosnaud

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Benjamin Sosnaud[1]

Abstract

BACKGROUND
Infant mortality rates (IMRs) vary dramatically across US states. A potential explanation centers on compositional differences in births from sociodemographic groups with a high risk of infant mortality.

OBJECTIVE
I seek to identify the contribution of key compositional factors to state-level disparities in IMRs using a series of Kitagawa–Blinder–Oaxaca decompositions.

METHODS
Drawing on linked birth–death records for US infants born between 2015 and 2017, I decompose cross-state disparities in IMRs into two components: (1) disparities attributable to differences in the distribution of maternal education, race/ethnicity, and age; and (2) disparities attributable to differences in the association between these sociodemographic characteristics and infant mortality (plus unmeasured compositional differences). I apply this approach to analyze disparities between the US IMR and 27 state IMRs. I then decompose IMR gaps between 630 pairs of states. I use linear regression to explore state-level predictors of variation in the second decomposition component.

RESULTS
In 7 of the 18 sample states with IMRs higher than the rest of the United States, led by Louisiana, South Carolina, and Georgia, more than 50% of this disparity can be attributed to the proportion of births from high-risk sociodemographic groups. In 11 high-IMR states, including Oklahoma, Indiana, and Missouri, more than 50% of the disparity is unexplained by the distribution of observed sociodemographic characteristics. The sample also includes nine states with IMRs lower than the rest of the United States. In Colorado, Oregon, and Minnesota, more than 50% of this advantage can be attributed to sociodemographic composition. Conversely, in six states, including New York, New Jersey, and California, the contribution of sociodemographic factors is outweighed by the

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unexplained decomposition component. Regression analyses show that variation in this component is associated with state differences in contextual predictors.

CONTRIBUTION
Decomposing cross-state differences in IMRs reveals considerable heterogeneity in the contribution of sociodemographic composition. This highlights variability in the social processes that produce disparities in infant mortality across populations.

1. Introduction

A newborn's risk of dying before their first birthday varies dramatically depending on the US state where they live. In Mississippi, 8.4 out of every 1,000 infants born in 2018 died before they turned 1, but in Massachusetts, the infant mortality rate (IMR) was only 4.2 per 1,000 births during this year (Ely and Driscoll 2020). The magnitude of this disparity highlights the importance of identifying the sources of cross-state variation in infant mortality rates.

One explanation centers on differences in sociodemographic composition between states. In Mississippi, births to Black mothers comprise more than 40% of all births, and the mortality rate is 11.7 deaths per 1,000 births among these infants.[2] Moreover, 14% of Mississippi infants are born to mothers who did not complete high school. The mortality rate for this group is 11 deaths per 1,000, more than twice as high as the rate for Mississippi infants born to mothers with at least a college degree. These examples illustrate how greater representation of members of sociodemographic groups with especially high mortality risk can contribute to high rates of infant mortality in some states (Paul et al. 2009). However, evidence suggests that sociodemographic differences cannot fully explain cross-state variation in IMRs (Brown Speights et al. 2017). Even among infants born to White mothers, Mississippi's mortality rate is among the highest in the nation (6.8 per 1,000 live births). This raises the possibility that state-specific factors contribute to cross-state differences in infant mortality rates. For example, spending on social services, medical infrastructure, and social welfare policy varies among states, and these expenditures are established predictors of health outcomes (Montez et al. 2020).

In this paper I seek to identify the contribution of key compositional factors to state-level variation in infant mortality rates. Drawing on US vital statistics records from 2015–2017, I apply the Kitagawa–Blinder–Oaxaca (KBO) decomposition method first to

[2] All quantities in this paragraph are based on the author's calculations using 2015–2017 linked birth and death certificate data (National Center for Health Statistics 2015–2017).

analyze disparities between 27 state infant mortality rates and the US national rate. I then decompose IMR gaps between 630 pairs of states. These analyses produce evidence of considerable heterogeneity in the contribution of sociodemographic composition. For some IMR disparities, the gap is largely attributable to differences in the distribution of key sociodemographic characteristics. For others, large gaps remain even after accounting for these compositional factors. I then present a preliminary exploration of possible state-level predictors of this unexplained variation by analyzing a dataset with information on differences in economic context, social welfare policy, and medical system infrastructure between 630 state pairs.

2. Background

Infant mortality stands out as a key outcome in research on health and health disparities. Not only is it vital to understand why some infants face a greater risk of experiencing this tragic outcome, but the prevalence of infant mortality is widely considered to be an important barometer of the strength of the broader health system (Gonzalez and Gilleskie 2017). A well-developed literature has helped identify individual-level factors that make some infants especially likely to die in their first year of life. For example, research has established maternal health and nutrition before and during pregnancy (Abu-Saad and Fraser 2010; Chen et al. 2009; Ramakrishnan et al. 2012), prenatal exposure to cigarettes and alcohol (Anderson et al. 2019; Popova et al. 2016; Salihu et al. 2003), receipt of prenatal and neonatal care (Conway and Deb 2005; Lasswell et al. 2010; Partridge et al. 2005; Phibbs et al. 2007), sleep position (Hauck 2003), and housing conditions (Reece 2021) as important predictors of infant health outcomes.

However, current scholarship is unable to fully explain why the risk of infant mortality varies so dramatically across US states (Mathews, MacDorman, and Thoma 2015). As the example of Mississippi demonstrates, one source of variation is the characteristics of individuals who comprise a given state population (Ross and Mirowsky 2008). Infants born to mothers who face discrimination and racism based on their race and ethnicity are more likely to experience adverse birth outcomes (Alhusen et al. 2016; Collins et al. 2004; Green and Hamilton 2019; Hauck, Tanabe, and Moon 2011; Mustillo et al. 2004). This can be traced to the negative health effects of a lifelong exposure to structural racism as well as more acute experiences of unequal treatment from medical providers (Greenwood et al. 2020; Williams, Lawrence, and Davis 2019). In addition, a mother's socioeconomic position shapes her diet and health behaviors, housing and neighborhood environment, access to prenatal care, and relationship with medical providers (Aizer and Currie 2014). These factors have been shown to predict infant mortality, and this multiplicity of connections establishes socioeconomic position as a fundamental cause of infant mortality risk (Finch 2003; Link and Phelan 1995; Sosnaud 2019). Maternal age is another relevant sociodemographic characteristic – infant mortality risk is highest for infants born to mothers in the youngest and oldest age groups (Driscoll and Ely 2020). The distribution of maternal race, socioeconomic position, and age is not uniform across states. So if infants from sociodemographic backgrounds that put them at especially high risk of mortality comprise a large proportion of a state population, then the state is likely to have a high rate of infant mortality (Paul et al. 2009).

Another potential explanation for cross-state disparities in infant mortality is that the health consequences of an infant's sociodemographic position can vary in different contexts. This idea is consistent with research that documents an association between health outcomes and state-level variation in policies, infrastructure, and other institutions (Montez et al. 2020; Fenelon and Witko 2021; Shi et al. 2005). Work in this area highlights US states as distinct social and institutional contexts that can influence the relationship between sociodemographic characteristics and health outcomes (Montez, Hayward, and Zajacova 2019; Montez et al. 2019). For example, race may be more salient for health in states with entrenched histories of institutionalized racism (Krieger et al. 2013), and the importance of one's socioeconomic position may be less pronounced in states where social services and medical system resources are widely available (Sosnaud 2019).

Infant mortality stands out as an outcome for which state context is likely to be influential in shaping the extent to which sociodemographic characteristics matter for health. Potential pathways emerge even before birth. As noted, maternal malnutrition before and during pregnancy, restricted access to prenatal care, unsafe housing conditions, and exposure to chronic stress (including stress caused by discrimination) are key determinants of infant birth outcomes (Aizer and Currie 2014; Mustillo et al. 2004). However, state-level variability in policies such as Temporary Assistance for Needy Families (TANF), state earned income tax credits (EITC), and Medicaid means that exposure to these determinants is not constant across states (Bhatt and Beck-Sagué 2018; Leonard and Mas 2008; Strully, Rehkopf, and Xuan 2010). In states where social policies are less generous and more restrictive, women in disadvantaged socioeconomic positions face greater barriers to accessing healthy food, safe housing, self-care resources, medical care, and other resources that matter for infant health. Moreover, an emerging body of research calls attention to cross-state differences in structural and institutionalized racism (Brown, Kamis, and Homan 2022; Hardeman et al. 2022). Variation in the nature of racial inequalities in criminal justice, education, the labor market, and other societal institutions across state contexts supports the idea that the importance of maternal race as a predictor of infant health outcomes may depend in part on the state of residence (Wallace et al. 2017).

The pathways linking state context to mortality risk persist as infants progress through their first year of life. For example, even after a healthy birth process, infants are at risk of death due to sudden infant death syndrome (SIDS), accidental suffocation and strangulation in bed, and other unknown causes – collectively classified as sudden unexpected infant deaths (SUID). Rates of this outcome vary across states, and variation persists even after accounting for individual-level predictors (Mitchell et al. 2020). Prior research has established an important role for primary care physicians in promoting care and sleep practices that can reduce the risk of SIDS (Willinger et al. 2000), and primary care access stands out as an element of state medical systems that predicts infant mortality and is not uniformly distributed (Merritt et al. 2021; Shi et al. 2005). Other aspects of state institutional context likely to be especially salient for older infants include economic policies designed to reduce poverty, public spending on social services, and infrastructure that promotes public safety. Consistent with this idea, Komro and colleagues (2016) identify state-level variation in minimum wage levels as a predictor of mortality risk in the post-neonatal period.

Prior research on cross-state disparities in infant mortality has largely focused on controlling for sociodemographic characteristics as a way to analyze the effects of broader contextual factors, such as infrastructure or policy interventions (Ehntholt et al. 2020; Paul et al. 2009). For example, holding constant mother's race and education can help identify aspects of state medical systems associated with cross-state differences in infant mortality (Sosnaud 2019). However, treating the influence of sociodemographic composition as a background factor to be statistically controlled has limitations when it comes to identifying the sources of observed state infant mortality differentials. When analyzing cross-state disparities like the IMR gap between Mississippi and Massachusetts, a key question arises: How much of Mississippi's disadvantage is attributable to the large proportion of infants born in sociodemographic positions that put them at greater risk of mortality and how much is attributable to state-specific factors that shape the extent to which these sociodemographic characteristics matter for infant health?

In this paper, I help address this complex question by measuring the contribution of a set of key sociodemographic factors to observed differences in infant mortality rates across states. I utilize a series of KBO decompositions to analyze disparities between state infant mortality rates and the national infant mortality rate, and disparities between pairs of state IMRs. KBO decomposition is a technique pioneered by Kitagawa (1955) and further extended by Oaxaca (1973) and Blinder (1973). It is used to divide group disparities in a mean outcome into two components: (1) a part that is attributable to group differences in the predictor variables, and (2) a part that is due to differential associations between the predictors and the outcome of interest as well as any unobserved predictors (Rahimi and Hashemi Nazari 2021). For example, Tharp and colleagues (2019) decompose the gender pay gap in a sample of financial planners and find that 91% of the observed disparity can be attributed to gender differences in key individual-level characteristics like experience, productivity, and marital status. They attribute the remaining portion of the disparity to an unequal association between these characteristics and pay between men and women.

KBO decompositions have been used in prior research on infant mortality in the study of mortality differentials between racial groups. For example, Sosnaud (2021) decomposes US Black–White disparities in neonatal mortality into a component attributable to racial differences in the distribution of birth weights and a component attributable to disparities due to differences in birth weight–specific mortality (see also Carmichael and Iyasu 1998; Elder, Goddeeris, and Haider 2011; Schempf et al. 2007). Fan and Luo (2020) present another application of this technique to identify factors contributing to infant mortality disadvantages among White and Black mothers.

In this paper I present a novel application of the KBO methodology to decompose state IMR disparities into two components:

1) Disparities attributable to differences in the distribution of maternal race, education, and age. This component quantifies the extent to which key elements of the sociodemographic composition of state populations contribute to a given IMR gap.
2) Disparities attributable to differences in the association between observed sociodemographic characteristics and infant mortality. This component captures both state-specific factors that influence the extent to which sociodemographic characteristics matter for infant health as well as any unmeasured compositional differences.

The distinction between these components has important implications. If an observed disparity between states is largely attributable to sociodemographic composition (represented by an outsize contribution of Component 1), then the IMR gap can be interpreted with a focus on the processes that contribute to the fundamental link between sociodemographic characteristics and health outcomes throughout the United States (Phelan and Link 2015). In contrast, evidence of large IMR disparities, conditional on the distribution of observed sociodemographic characteristics (measured by Component 2), raises the possibility that state-specific factors, such as policies or other institutions, influence the extent to which sociodemographic characteristics matter for infant health. Although the KBO methodology cannot explicitly identify the extent to which this second component corresponds to differences in state context, I seek to inform future research on this issue by using the results from a series of decompositions to create a dataset with information on the contribution of each component to 630 state-versus-state IMR disparities. I then use linear regression models to analyze the association between the magnitude of the IMR gap attributable to Component 2 and variables measuring state differences in economic context, social welfare policy, and medical system infrastructure. Based on research that highlights variation in institutional context across states (Montez et al. 2020), I hypothesize that differences in these state-level variables will be important predictors of the magnitude of the Component 2 contribution.

3. Methods

3.1 Data

Infant mortality data for this project come from infant birth and death records collected through the US National Vital Statistics System (NVSS). The NVSS links birth and death certificates for all infants born in the United States. (Approximately 99.5% of all deaths are successfully linked each year.) Through an agreement with the National Center for Health Statistics (NCHS), I utilize a restricted-access version of the linked birth–death data that includes the state of residence for all infants born between 2015 and 2017 (NCHS 2015–2017). This results in a sample of 11,779,872 infants born to US residents. The most recent year of available data is 2017, and pooling data from the three years is necessary to expand the sample and ensure that the number of infant deaths is sufficient to enable the state- and subgroup-specific analyses discussed below. When specifying the regression models used in the decomposition analyses, I adjust the standard errors to account for the clustering of observations within birth years.

Each linked birth record includes information on a range of infant and maternal attributes. Here I focus on three key measures of sociodemographic position: maternal age, educational attainment, and race.[3] Maternal age is broken into four categories: 19 or younger, 20–24, 25–34, and 35 and older.[4] Maternal educational attainment is divided into four levels of education: less than a high school degree, high school degree (or GED), some college or an associate degree, and bachelor's degree or more. I use the available information on maternal race and ethnicity to distinguish infants born to five groups of mothers: non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, Hispanic/Latina, and other non-Hispanic races.[5]

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[3] Overall, 2.27% of the observations are missing information on either maternal education or race/ethnicity. These observations are excluded from the decomposition analysis.

[4] These categories provide a parsimonious way to categorize mothers with similar age-related infant mortality risk (Driscoll and Ely 2020). In analyses available upon request, I evaluate alternative specifications, and the results are robust to the use of three-year age groups and an alternative set of five-year age groups with a sixth category to differentiate mothers age 40-plus from those 35-plus.

[5] The other race category includes infants born to non-Hispanic mothers identified as Native Hawaiian and other Pacific Islander, American Indian and Alaska Native, and those reporting more than one race. The sample sizes required for state-specific analyses are not sufficient to allow for a more detailed analysis of these

These variables were selected because they are strongly associated with an infant's risk of mortality and vary in their distribution across states. Although other measures of sociodemographic composition in the linked birth–death records are associated with infant health outcomes (e.g., infant sex and plurality of birth), variation in the distribution of these characteristics across states is not sufficient to suggest that they are plausible predictors of cross-state differences in infant mortality.[6] Thus a focus on maternal age, educational attainment, and race/ethnicity ensures that the analysis accounts for leading compositional predictors of differences in infant mortality across states.

Due to differences in population size and the distribution of maternal age, education, and race across states, the number of deaths among infants from these subgroups in some states is not sufficient to generate reliable estimates when analyzing the distribution and effects of these sociodemographic characteristics.[7] According to NCHS guidelines (2020), infant mortality rates can reliably be calculated for populations with at least 20 infant deaths during the period of interest (see also Buescher 1997). Thus, when decomposing state-level IMR disparities, I include only states with sufficient infant deaths to meet this threshold in each sociodemographic category.[8] This results in the exclusion of 14 states (Alaska, Delaware, Idaho, Maine, Montana, New Hampshire, New Mexico, North Dakota, Rhode Island, South Dakota, Utah, Vermont, West Virginia, and Wyoming) plus the District of Columbia, which comprises 5.9% of all US births during the study period.[9] I begin the analysis by comparing the infant mortality rate in each of

categories. However, infants from all three groups are aligned in having mortality rates that exceed the national average IMR.

[6] Maternal marital status is another sociodemographic variable that both matters for infant health and varies across states. However, data on this variable is not available in the linked birth–death records for infants born to residents of California. Since these infants represent more than 12% of births during the study period, I elect not to include maternal marital status in the analysis.

[7] Although, the number of infant births and deaths in the linked data files represents essentially the full population of these events, a common interpretation when analyzing infant mortality using vital statistics data is that the observed outcomes represent one occurrence of a range of possible outcomes (NCHS 2020). For example, only one of the 163 Black infants born to Black mothers in Wyoming from 2015 to 2017 died in the first year of life. This low observed frequency is not sufficient to conclude that Wyoming's Black infant mortality rate is among the lowest in the nation. (If just one more infant had died during this period, the rate would be twice as high.)

[8] The sample also includes nine states (Iowa, Louisiana, Kansas, Alabama, South Carolina, Kentucky, Arkansas, Nebraska, and Mississippi) in which the number of deaths to infants of non-Hispanic Asian mothers is below this threshold (ranging from 9 to 19 deaths). Supplemental analyses confirm that the non-Hispanic Asian IMRs observed in these states are consistent with IMRs calculated after pooling data from a sufficiently long period to meet the recommended 20-death threshold (2012–2017).

[9] An examination of these excluded states reveals that the percentage of births to White mothers tends to be high and the percentage of births to Black, Hispanic, and Asian mothers tends to be low. In 5 of the 14 states (Idaho, Rhode Island, Wyoming, Vermont, and New Hampshire), the IMR is substantively lower than the national IMR. Further, in three states (Delaware, West Virginia, and South Dakota) the IMR is substantively higher than the national IMR. Also worth noting is that data from these 14 states are included when calculating the national IMR, used as the comparison group in Figures 1 and 2.

the remaining 36 states in the sample to the national infant mortality rate. In 27 of these 36 states, the 95% confidence intervals for the state and national estimates do not overlap. These 27 states are used in the state-versus-national IMR decomposition analysis described in section 3.2. I use the full sample of 36 states for the state-versus-state decompositions described in section 3.3.

3.2 Decomposition of state-versus-national differences in IMR

For the 27 states where the 95% confidence intervals for the state and national IMR estimates do not overlap, I decompose this disparity into two components using the KBO approach (Kitagawa 1955; Blinder 1973; Oaxaca 1973). Following Jann (2005, 2008), I use a linear probability model[10] to regress infant mortality (Y) on sociodemographic characteristics (X) for infants from two groups (j = 1, 2): $Y_j = X_j B_j + \epsilon_j$.

For this set of decompositions, j = 1 represents the population of infants born to residents of one of the focal states, and j = 2 represents the population of all other infants born to US residents (excluding the infants represented in j = 1).

The mean difference in the probability of infant mortality (R) between infants from these two groups can be expressed as:

$$R = \bar{Y}_1 - \bar{Y}_2 = \bar{X}_1'\hat{\beta}_1 - \bar{X}_2'\hat{\beta}_2 \quad (1)$$

Further, R can be decomposed as:

$$R = (\bar{X}_1 - \bar{X}_2)'\beta^* + \left[\bar{X}_1'\left(\hat{\beta}_1 - \beta^*\right) + \bar{X}_2'\left(\beta^* - \hat{\beta}_2\right)\right], \quad (2)$$

where $\beta^* = 0.5\hat{\beta}_1 + 0.5\hat{\beta}_2$ (Kitagawa 1955; Reimers 1983). In this type of two-component decomposition, the first term refers to the component of the gap in infant mortality attributable to state differences in the distribution of the observed sociodemographic characteristics. The second term refers to the component of the gap attributable to differences in infant mortality conditional on the observed sociodemographic characteristics (often referred to as the unexplained part of the gap) (Jann 2005). I use these decompositions to quantify the contribution of each of these components to observed differences between 27 state IMRs and the national IMR. It is important to note that the results of this type of demographic decomposition are descriptive and cannot be interpreted as causal effects.

[10] Using a logit model for this portion of the decomposition produces substantively similar results.

3.3 Decomposition of state-versus-state differences in IMR

In the second part of the analysis, I use the same two-component approach to decompose disparities in rates of infant mortality between all state pairings from among the full sample of 36 states for which sufficient data are available. In this formulation, j = 1 represents the population of infants born to residents of one of these states, and j = 2 represents the population of infants born to residents of one of the other states. With 36 states, there are 630 unique combinations of state pairs, resulting in 630 total decompositions. As above, Component 1 is the gap in infant mortality attributable to differences between the two states in the distribution of the observed sociodemographic variables. Component 2 includes factors that matter for infant mortality, conditional on the distribution of these sociodemographic variables. Component 2 may include aspects of state context that influence the association between sociodemographic characteristics and infant mortality as well as differences in unmeasured compositional variables.

I use the results of these 630 decompositions in a preliminary exploration of the hypothesis that the magnitude of the Component 2 contribution to state disparities in infant mortality rates is associated with state differences in economic context, social welfare policy, and medical system infrastructure. In this analysis, I treat the results of the state-versus-state decompositions as data points in a dataset where each observation is one of 630 state–state pairs. In addition to variables representing the total IMR gap between each state pair, the Component 1 contribution, and the Component 2 contribution, I incorporate a set of variables capturing state differences in relevant contextual factors. Appendix A provides details, descriptive statistics, and data sources for all state-level variables.

3.4 Variables measuring differences in state context

US states vary dramatically in the scope and generosity of their social welfare policies, and these institutional interventions have the potential to influence the extent to which sociodemographic position matters for infant health (Fenelon and Witko 2021; Montez et al. 2019). I account for the generosity of social welfare provision with variables measuring state differences in the dollar values of the minimum wage, state EITC, and maximum monthly TANF benefit for a family of three. I capture the scope of TANF coverage with a measure of the number of TANF recipients divided by the total number of people in poverty (TANF/poverty ratio). Data on these policies come from national welfare data compiled and maintained by the University of Kentucky’s Center for Poverty Research (CPR) (2021).

States (including local governments within states) also differ in the economic resources they devote to social and medical services. I distinguish between two categories of state and local[11] spending. Social service spending includes a range of services that have been shown to matter for health and well-being (Bradley et al. 2016; Dunn, Burgess, and Ross 2005; Goldstein et al. 2020). These include state and local expenditures on cash assistance welfare, education, housing and community development, highways and mass transit, police and fire protection, natural resources, parks and recreation, and sanitation. Health and medical spending includes state and local expenditures on community and public health programs, government-owned hospitals, payments to privately owned hospitals, and payments to physicians and other service providers under Medicaid. Data on these measures are collected by the US Census Bureau's Annual Survey of State and Local Government Finances and are compiled by the State and Local Finance Initiative, an Urban Institute project in the Urban-Brookings Tax Policy Center. Both spending variables are measured in real 2019 dollars per capita.

I also include measures of state differences in the availability of medical resources and health care access. Based on research highlighting the association between infant mortality and the availability of primary care physicians (Shi et al. 2005), I include a measure of state differences in the number of primary care physicians involved in patient care per capita. Access to care also depends on health insurance, and states vary widely in efforts to ensure that their residents have health insurance coverage (Conway and Branch 2023). This includes disparate expansion of Medicaid under the Affordable Care Act (Sommers 2020), which has been found to predict cross-state differences in infant mortality rates (Bhatt and Beck-Sagué 2018). I include a measure of state differences in the percentage of residents age 0–64 who have private or public health insurance to account for this aspect of institutional context.

Finally, I account for broader differences in state political ideology using data from Berry and colleagues' (2010) state ideology database. This resource includes a measure of the political ideology of state legislators derived using their roll call voting records. The measure of state government ideology ranges from 0 to 100; higher values represent states with more liberal ideologies. It is designed to predict policy outcomes and provides a more holistic measure of the sociopolitical context in each state (Berry et al. 1998; Fenelon and Witko 2021).

In addition to these institutional measures, I include a set of control variables measuring gaps in state gross domestic product (GDP) per capita (from the Bureau of Economic Analysis), unemployment and poverty rates (UKCPR 2021), and income

[11] Consistent with the recommendation of the State and Local Finance Initiative (Urban-Brookings Tax Policy Center 2022), both state spending measures include state expenditures and all expenditures by local governments within states (e.g., counties, municipalities, towns). There are cross-state differences in the level of government that provides social and medical services, so aggregating state and local expenditures is necessary when making comparisons across states.

inequality (measured by the gini coefficient using American Community Survey [ACS] data) between states. This ensures that the analysis accounts for differences in economic context that have the potential to contribute to cross-state disparities in infant mortality (Siddiqi, Jones, and Erwin 2015).

As noted, the unit of analysis in this dataset is state–state pairs. For every pairing, I designate the state with the higher infant mortality rate as State 1 and the state with the lower rate as State 2. This ensures that all the observed disparities in infant mortality are expressed as positive values. Each state context variable measures the difference between State 1 and State 2 (calculated as the value for State 1 minus the value for State 2). For example, a large positive value for the difference in TANF benefits variable for a given pairing indicates that State 1 provides more generous benefits than State 2. A large negative value means that State 2 is more generous than State 1.

3.5 Regression analysis of Component 2 contribution on differences in state context

Based on existing evidence that state institutional context can influence the extent to which sociodemographic composition matters for infant health, I hypothesize that where IMR differences between states are observed, the relative contribution of decomposition Component 2 will be greater when the state with higher infant mortality devotes fewer resources and less attention to policies and initiatives that benefit health and well-being. I present a preliminary test of this hypothesis using a series of linear regression models. The dependent variable in these models is the magnitude of the Component 2 contribution to the disparity in infant mortality between pairs of states. The independent variables are the measures of differences in state context. Critically, these models control for the total magnitude of the disparity in infant mortality rates between each pairing. With the size of this gap held constant, a larger contribution of Component 2 implies a smaller contribution of Component 1 (and vice versa). Thus the models capture the effect of the independent variables on differences in the relative contribution of Component 2.

When interpreting the results of these models, an independent variable with a negative regression coefficient indicates that negative values (pairings in which the state with a higher infant mortality rate has a lower level of the state predictor) are associated with a greater contribution of Component 2 to the observed disparities (and thus a smaller role of Component 1). I adjust all standard errors in these models to account for correlation between observations because states can occupy the State 1 and State 2 positions multiple times.[12]

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[12] I adjust all standard errors presented here for correlation on the State 1 variable. I also replicate these analyses with adjustments for correlation on the State 2 variable. All results are unchanged except that the standard error

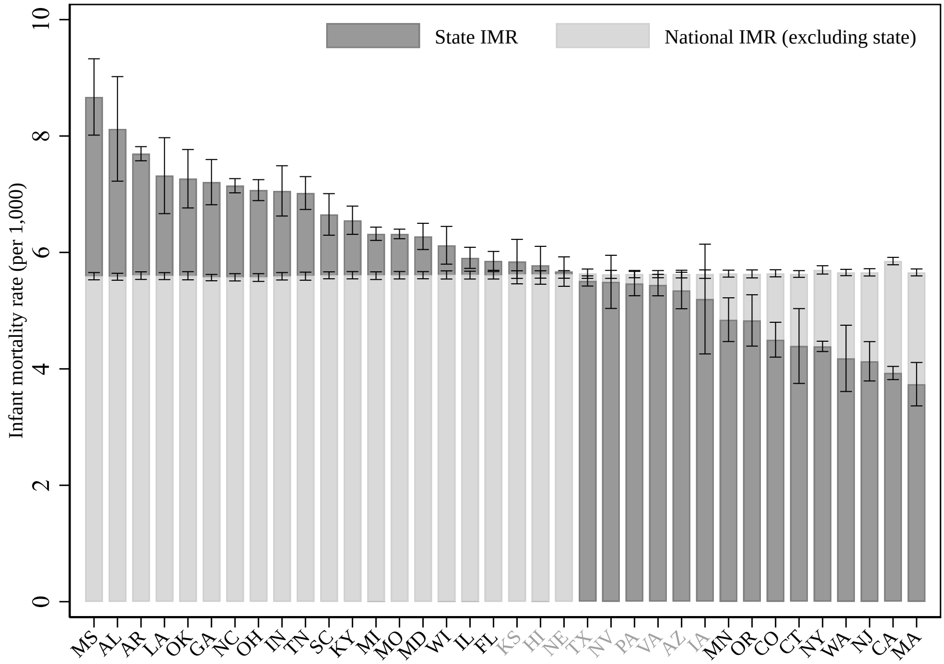
4. Results

From 2015 to 2017, US residents gave birth to 11,779,872 infants. Of these infants, 68,387 died in their first year of life, which represents an infant mortality rate of 5.8 deaths per 1,000 live births. Yet, as shown by the dark gray bars in Figure 1, the infant mortality rate varied widely across the 36 states in the sample during this period, from a high of 8.7 deaths per 1,000 in Mississippi to a low of 3.7 per 1,000 in Massachusetts. The light gray bars in this figure depict the infant mortality rate in the other 49 US states. (The height of the light gray bar differs slightly for each state because the national comparison group changes marginally depending on which focal state is excluded.) This comparison highlights the extent to which state infant mortality rates vary in comparison to the national rate. In 27 of the 36 states, the 95% confidence interval for the state IMR estimate does not overlap with the interval for the national estimate.

For each of these 27 state–national disparities in infant mortality rates, I decompose the disparity into two components. Figure 2 presents the results of these decompositions. The total state–national IMR disparity (per 1,000 live births) is represented by the sum of the solid and dashed bars. The solid bars depict the number of infant deaths per 1,000 attributable to differences in the distribution of key sociodemographic characteristics (Component 1). The dashed bars show the number of deaths that cannot be attributed to the observed measures of sociodemographic composition. This unexplained second component includes deaths attributable to differing associations between sociodemographic factors and infant mortality as well as the levels and effects of unmeasured variables. For example, Mississippi's infant mortality rate is 3.1 deaths per 1,000 live births greater than the rate in all other states. Of these 3.1 deaths, just less than 2.0 can be attributed to the fact that distribution of infants born to mothers with sociodemographic characteristics that put them at high risk of infant mortality is less favorable in Mississippi. The remaining 1.1 deaths reflect factors that cause infant mortality rates to be especially high in Mississippi, even after accounting for the distribution of infants based on maternal age, education, and race.

for the primary care physicians per capita variable increases to the point that the 95% confidence interval for this variable's coefficient includes zero.

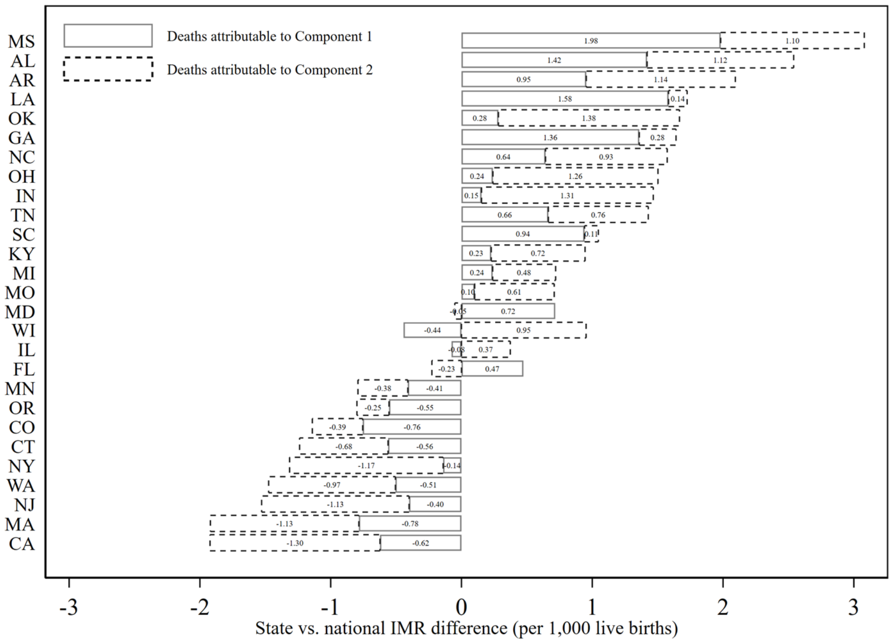
Figure 1: Comparison of state and national infant mortality rates in 36 states, 2015–2017



Notes: Bars depict 95% confidence intervals for each estimate. State labels in black indicate that the state and national intervals do not overlap.

As Figure 2 illustrates, the contribution of these two components varies widely across states. The striking contrast between Louisiana and Oklahoma underscores this distinction. Both states have comparable infant mortality rates of 7.3 deaths per 1,000 live births, roughly 1.7 deaths more than the US rate. In Louisiana, 1.58 of these excess deaths (91%) are attributable to the observed measures of sociodemographic composition. Conversely, in Oklahoma, the state's infant mortality disadvantage compared to the US rate is almost entirely due to the 1.38 deaths due to unexplained factors that matter for infant mortality, conditional on the distribution of the observed sociodemographic characteristics (83% of the total).

Figure 2: Decomposition of differences in state-versus-national infant mortality rates in 27 states, 2015–2017



In four states, the values of Components 1 and 2 have different signs. In Wisconsin, the infant mortality rate is 6.1 deaths per 1,000, 0.51 deaths greater than in the national rate. However, the magnitude of the Component 1 contribution is –0.44, which means that the distribution of sociodemographic characteristics in Wisconsin is actually more favorable for birth outcomes than in the rest of the United States. This advantage is offset by the 0.95 additional deaths in Wisconsin that can be attributed to factors that increase the rate of infant mortality even after accounting for key measures of sociodemographic composition. Illinois joins Wisconsin as a state where the observed state–national disparity in infant mortality can be entirely attributed to Component 2. In contrast, in Maryland and Florida, the higher rate of infant mortality compared to the rate in the rest of the United States is entirely attributable to Component 1.

In addition to decomposing variation in state-versus-national IMR disparities, I extend the analysis to disparities in infant mortality between pairs of states. With 36 states in the full sample, there are 630 unique state–state combinations to decompose. In these 630 pairings, the average state–state disparity in infant mortality is 1.43 deaths per 1,000 live births. Of this gap, an average of 0.64 deaths can be attributed to Component 1 (45% of the average state–state disparity). This leaves 0.79 average deaths attributable to Component 2 (55% of the average state–state disparity). Appendices B and C present matrices that display the number of deaths per 1,000 live births that can be attributed to Component 1 and Component 2, respectively, for each state pair. As with the state-versus-national decompositions, there is considerable heterogeneity in the contribution of these two components across state–state pairs.

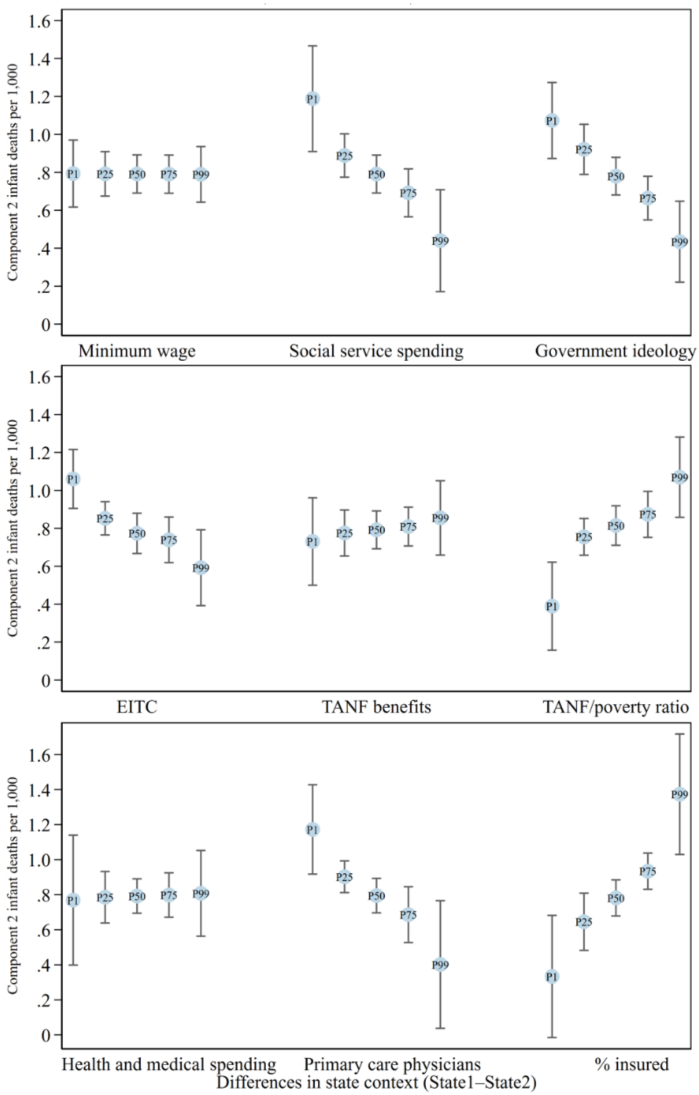
In 267 of the 630 pairings (42%), the distribution of key sociodemographic variables contributes at least 50% to the observed IMR disparity. This includes 94 pairings where the Component 1 contribution is greater than 100% (meaning that the disparity is entirely attributable to differences in the distribution of sociodemographic characteristics). However, a key takeaway from the state–state analysis is the large portion of the disparity between many state pairs that can be attributed to the second decomposition component. There are 363 state pairs (58% of the total number of pairs) for which Component 2 contributes a majority of the gap. Of these, 111 are pairings in which the Component 1 contribution is actually negative, meaning that the observed disparity can be attributed entirely to the second component.

Although it is not possible to directly measure the extent to which Component 2 contributions represent state-level factors, I present a preliminary exploration this hypothesis by analyzing the association between Component 2 mortality and variables measuring differences in state-level policies and other institutions. With a dataset of 630 state–state pairings, I model the association between the magnitude of the Component 2 contribution to the IMR gap and state-level differences in key measures of state institutional context using a series of linear regression models. This culminates in a model that includes variables capturing state–state differences in nine contextual variables. This model also includes a variable measuring the total gap in infant mortality for each state–state pairing (as well as control variables capturing state differences in GDP per capita, poverty rate, unemployment rate, and income inequality). Appendix D displays coefficients and confidence intervals for the full series of models.

To facilitate interpretation of the regression results, Figure 3 shows how the magnitude of the predicted Component 2 contribution to the IMR disparity varies across the observed distribution of state–state differences in each independent variable. These predictions are generated by holding values of all other variables in the model constant at their means. Of the state-level measures analyzed, four display a relationship that is fully consistent with the hypothesized association between the Component 2 contribution and the IMR disparity. One of the strongest relationships is observed for per capita state spending on social services. For state pairings in the 1st percentile of the distribution of observed differences in social service spending (where the state with a higher infant mortality rate spends much *less* on social services), 1.2 infant deaths out of the total gap in IMR per 1,000 between State 1 and State 2 are attributable to Component 2. This contribution grows smaller at successively larger percentiles of the distribution, and by the 99th percentile (where the state with higher infant mortality spends more on social services), the contribution of Component 2 to the observed IMR gap is only 0.4 deaths. In other words, among pairs of states with similar IMR disparities, the portion of the disparity unexplained by the distribution of the observed sociodemographic factors (decomposition Component 2) is greater where the state with a higher infant mortality rate spends less on social services per person. If the state with a higher IMR spends more, any observed disparity in infant mortality is more likely to be attributable to differences in the distribution of sociodemographic characteristics. Similar patterns are observed for state differences in EITC payments, primary care physicians per capita, and liberal government ideology.

Three of the variables show no evidence of an association between differences in state context and the magnitude of the Component 2 contribution. Across the distribution of state differences in minimum wage thresholds, TANF benefit generosity, and health and medical spending, the predicted disparity in infant deaths attributable to Component 2 remains similar. Finally, although Figure 3 shows substantive associations between the Component 2 contribution and measures of state differences in the TANF/poverty ratio and the percentage of residents who have health insurance, the direction of these relationships is the opposite of what is hypothesized. For these variables, the contribution of decomposition Component 2 is larger at greater values of the predictors.

Figure 3: Predicted disparity in infant deaths attributable to Component 2 across percentiles of state-level difference variables (State 1–State 2) in 630 pairs of states, 2015–2017



Notes: Bars depict 95% confidence intervals for each estimate; % insured indicates percentage of those age 0–64 with health insurance.

5. Discussion

In this paper, I measure the contribution of the distribution of key sociodemographic characteristics to disparities between 27 state infant mortality rates and the US national rate using a series of KBO decompositions. As shown in Figure 2, four sets of states emerge from this analysis. The first set comprises states where high rates of infant mortality can be largely attributed to the proportion of infants from sociodemographic backgrounds that put them at high risk of mortality. For example, decomposing the disparity between Louisiana's infant mortality rate and the rate in the remaining states shows that more than 90% of the observed gap can be attributed to compositional differences in the distribution of maternal age, education, and race. Compared to the rest of the United States, an especially high proportion of Louisiana infants are born to Black mothers and thus face greater health risks due the effects of racism and discrimination (Alhusen et al. 2016; Mustillo et al. 2004). Louisiana infants are also more likely to be born to mothers with a high school degree or less and mothers who give birth before the age of 20. This suggests that efforts to reduce Louisiana's IMR disparity should focus on expanding access to higher education (and other socioeconomic resources) and addressing processes that produce the fundamental link between race and health outcomes in the United States (Green and Hamilton 2019; Phelan and Link 2015). Mississippi, Alabama, Georgia, South Carolina, Maryland, and Florida also stand out as states where a majority of the IMR disadvantage compared to the rest of the United States can be attributed to key sociodemographic factors. Notably, all of these states are located in the US Census Bureau's South region (see Appendix E).

However, sociodemographic composition is not the dominant contributor in all states where the IMR exceeds the US rate. As Figure 2 shows, in 11 states the observed compositional factors are not the leading contributors to IMRs that exceed the national rate. Oklahoma provides a revealing example. It has the same high infant mortality rate as Louisiana, but decomposing Oklahoma's disparity relative to all other states reveals that differences in sociodemographic distribution contribute only 17% of the gap. The remaining 83% of the disparity can be attributed to factors that produce high rates of infant mortality, conditional on the distribution of sociodemographic characteristics. This component can include both unmeasured compositional factors as well as aspects of Oklahoma's institutional context that influence the association between sociodemographic characteristics and infant health. In other words, there may be something about the state context in Oklahoma that leads to a high rate of infant mortality, even among a population of infants with sociodemographic characteristics similar to those of the United States as a whole. The midwestern states Ohio, Indiana, Michigan, Missouri, Wisconsin, and Illinois and the southern states Arkansas, North Carolina, Tennessee, and Kentucky join Oklahoma as states where compositional factors contribute less than 50% of the observed IMR disparity compared to the rest of the United States. This finding makes it clear that the magnitude of the association between sociodemographic position and infant health is not fixed (Montez et al. 2019; Sosnaud 2019) and underscores the need for research that explores the extent to which state context might influence this association. Also worth noting is that the presence of Arkansas, North Carolina, Kentucky, Tennessee, and Oklahoma in this second set of states indicates that the distribution of sociodemographic characteristics is not the sole contributor to the high rates of infant mortality observed across the South census region.

Finally, the results in Figure 2 highlight two sets of states in which rates of infant mortality are notably lower than in the rest of the US population. In Colorado, Oregon, and Minnesota, more than 50% of the observed IMR advantage can be attributed to the sociodemographic distribution of the population of mothers who give birth. This affirms the importance of maternal education, race, and age as key compositional factors. However, in six states the distribution of observed sociodemographic characteristics is not a leading contributor to an IMR below the national advantage. (A majority of the IMR advantage can be attributed to decomposition Component 2 in Connecticut, New York, Washington, New Jersey, Massachusetts, and California.) In all these states, clustered in the West and Northeast regions, the distribution of maternal race, education, and age does contribute to the low observed IMRs. However, the contribution of these factors is outweighed by the unexplained decomposition component. This highlights the value of identifying state-level institutions with the potential to reduce the extent to which maternal sociodemographic background can put some infants at a greater risk of mortality.

In the second part of the analysis, I apply the KBO methodology to decompose disparities in infant mortality rates between 630 state–state pairings using data from the full sample of 36 states for which sufficient data are available. This approach provides further evidence of variability in the contribution of sociodemographic characteristics. Of the 630 disparities, 267 are pairings in which more than 50% of the disparity can be attributed to differences in the distribution of maternal age, race, and education between pairs of states. In contrast, Component 2 contributes more than 50% of the IMR disparity in 363 of the state–state comparisons. This unexplained decomposition component includes factors that influence the association between the included sociodemographic predictors and infant mortality. Although this component may represent the effects of unmeasured compositional factors, I hypothesize that it also reflects the influence of differences in state economic, political, and institutional context across states (Montez et al. 2020).

While a direct test of this hypothesis is beyond the scope of the current paper, I exploit the observed variation in the magnitude of the decomposition components across state pairs and conduct a multivariate analysis of the association between Component 2 mortality and variables measuring differences in state-level policies and institutions. The results of this analysis provide preliminary support for the idea that variation in the second decomposition component corresponds to state differences in key contextual predictors. As shown in Figure 3, after controlling for the size of the total IMR disparity, state-level differences in social service spending, state EITC generosity, government political ideology, and availability of primary care physicians are negatively associated with the magnitude of the Component 2 contribution. These four measures capture multiple ways in which the political and institutional context can differ between states.

State budgets include funding for a range of initiatives with the capacity to improve health outcomes, and states vary widely in how this money is spent. Research on this topic emphasizes that spending on essential social services like education, housing, public safety, and transportation may play an especially important role in explaining cross-state variation in health outcomes (Bradley et al. 2016; Goldstein et al. 2020). Consistent with this idea, I find that state spending on social services is a strong predictor of the Component 2 contribution but that a similar relationship does not exist for health and medical spending. This result is in line with recent efforts to account for the social determinants of health differences across populations (Thornton et al. 2016). It may also be a sign that state spending on health and medical care is not targeted in ways that can influence the fundamental relationship between sociodemographic position and health (Goldstein et al. 2020).

The relative magnitude of the unexplained decomposition component is also higher in state pairs where the state with higher infant mortality has fewer primary care physicians per capita. This supports research that identifies primary care supply as a key element of state medical infrastructure relevant to infant health (Shi et al. 2005; Sosnaud 2019).

While not all states offer an earned income tax credit that augments the federal EITC, this type of program represents a powerful tool through which states can redistribute economic benefits to low-income workers. Prior research has established that state EITC programs can have a beneficial effect on infant health outcomes (Strully, Rehkopf, and Xuan 2010). The results presented here build on this work by highlighting state EITCs as the type of policy intervention with the potential to reduce the extent to which a mother’s sociodemographic position shapes her infant’s risk of mortality.

State efforts to distribute resources and services that matter for health and well-being are the product of contested political processes. Recent research has established that the political party that controls US government institutions is an important predictor of infant and population health outcomes (Rodriguez 2019; Rodriguez, Bound, and Geronimus 2013; Torche and Rauf 2021). In line with this work, I find that the contribution of Component 2 is larger in state pairings where the state with the larger infant mortality rate has a more conservative government ideology. This measure is especially valuable given the complexity of state social welfare systems. Faced with the challenges of accounting for the full scope of these efforts, the ideological orientation of a state government can serve as a more holistic predictor of a state's broader legislative priorities (Berry et al. 2010; Fenelon and Witko 2021).

Although the vital statistics linked birth–death data represent the best available resource for studying cross-state differences in infant mortality rates, these data are subject to some limitations. Even after pooling data from the 2015–2017 period, there are 14 states in which there are not enough births to mothers from some sociodemographic backgrounds to conduct the decomposition analysis. This incomplete sample of states coupled with the high rates of infant mortality in Delaware, West Virginia, and South Dakota and low rates of infant mortality in Idaho, Rhode Island, Wyoming, Vermont, and New Hampshire means that the analyses do not account for all cross-state disparities in infant mortality in the United States.

Another limitation is that these records may not include all sociodemographic characteristics relevant to infant health outcomes. Based on the available information, I rely on maternal education as a measure of socioeconomic position. Education is a valuable measure in health research because it is related to a mother's economic resources as well as knowledge and cognitive skills that can benefit infant health (Currie and Moretti 2003; Baker et al. 2011). However, the inability to account for other socioeconomic factors in the decomposition analyses, such as income or occupation, means that the estimates of the Component 1 contribution to cross-state disparities in infant mortality rates may underestimate the magnitude of this component. If so, then the contribution of these unmeasured compositional variables will be included in the estimates of Component 2.

Despite this limitation, the results presented in Figure 3 provide preliminary support for the hypothesis that the magnitude of the Component 2 contribution is related to state-level differences in contextual predictors. However, this analysis is descriptive and is only able to identify associations. Thus there is an important role for additional research that builds on the results presented here by isolating the causal effects of variation in specific state-level policies and interventions on infant health outcomes (e.g., Komro et al. 2016; Strully, Rehkopf, and Xuan 2010). A key consideration for future work on this topic is the fact that a state's racial makeup and other compositional factors may influence the policies implemented in that state (Soss et al. 2001). Research that seeks to identify causal effects of state institutions on disparities in infant mortality should also account for the possibility that these effects may span a mother's full life course. Since the state-level variables cover the same three years as the infant mortality data, the current analysis is unable to account for the potential effects of long-term maternal exposure to state institutional contexts that may exacerbate the consequences of prolonged socioeconomic deprivation and cumulative wear on the body's allostatic systems (Lu and Halfon 2003).

Another valuable opportunity for future research concerns the possibility of temporal changes in the contribution of compositional and contextual explanations for IMR differences across states. The use of data from 2015–2017 means that the results presented here cannot be assumed to pertain to prior eras or be extrapolated to future trends. Thus there is a valuable role for research that applies the decomposition framework introduced in this paper to examine cross-state disparities in infant mortality in periods with a different sociodemographic distribution across states. (The leading contribution of sociodemographic factors to many cross-state disparities in infant mortality also highlights compositional transformations as a possible explanation for changes in disparities over time.) It will also be interesting to see how the patterns presented here shift due to events in the post-2017 period. Differences in state responses during and after the COVID-19 pandemic (Zhang and Warner 2020) provide a revealing example of how the importance of state institutional context for health outcomes might increase in future years.

Interestingly, the signs of the coefficients for the variables measuring state differences in the percentage insured and the TANF/poverty ratio are the opposite of what is expected. The contribution of Component 2 is *smaller* in state pairings where the state with the larger infant mortality rate has a lower percentage of insured residents and a lower proportion of poor residents receiving TANF support. Although this may provide meaningful evidence of a counterintuitive effect of these state-level predictors, it could also be a sign of limitations in the ability to measure the underlying aspects of state context. For example, I use the variable measuring the percentage of insured residents age 0–64 as a summary measure of state efforts to ensure that residents have health insurance coverage through initiatives like Medicaid expansion and health insurance marketplaces. However, since health insurance coverage is also related to individual socioeconomic position, this variable may instead be a stronger indictor of compositional differences across states. If so, it would help to explain why this variable is associated with a larger relative contribution of decomposition Component 1. This provides further evidence of the value of research designed to assess the importance of specific state-level variables. As research on this topic continues, one promising avenue for future investigation is to use information on an infant's age of death to help isolate the mechanisms through which state contextual variables are linked to infant mortality (e.g., Sosnaud 2021).

6. Conclusion

US infants face striking disparities in their risk of mortality depending on the state where they live. In some states, high rates of infant mortality can be attributed to the large proportion of infants from sociodemographic backgrounds that put them at high risk of mortality. The importance of these key compositional factors underscores the need to better understand and address the reasons that infants from these groups face such heightened risk. However, other states stand out for high rates of infant mortality even after taking into account the distribution of key sociodemographic characteristics. This suggests that state-specific factors may increase the risk of adverse birth outcomes. Finally, several states achieve infant mortality rates that are even lower than what would be expected based on the composition of their populations. This raises the possibility that large-scale social and medical interventions can help reduce the extent to which an infant's sociodemographic background matters for their life chances.

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Appendices

Appendix A: Details, descriptive statistics, and data sources for state-versus-state difference variables (630 total pairs)

State-versus-state difference variable	Mean	Standard deviation	Years	Source
IMR gap (per 1,000 live births)	1.429	1.007	2015–2017	NCHS linked infant birth–death records
GPD per capita (in tens of thousands of 2012 dollars)	–0.760	1.001	2015–2017 average	Bureau of Economic Analysis
Unemployment rate (%)	0.191	1.081	2015–2017 average	University of Kentucky CPR national welfare data
Poverty rate (%)	2.127	3.388	2015–2017 average	University of Kentucky CPR national welfare data
Gini coefficient (range from 0 to 1)	–0.000	0.023	2013–2017	ACS five-year estimates
Political ideology score (range from 0 to 100)	–14.228	19.502	2015–2017 average	State ideology database (Berry et al.)
Minimum wage ($)	–0.779	1.057	2015–2017 average	University of Kentucky CPR national welfare data
State EITC ($)	–0.092	0.164	2015–2017 average	University of Kentucky CPR national welfare data
Maximum family of three TANF benefit ($)	–133.668	189.142	2015–2017 average	University of Kentucky CPR national welfare data
TANF/poverty ratio	–0.050	0.091	2015–2017 average	University of Kentucky CPR national welfare data
Social service spending per capita (in thousands of 2019 dollars)	–0.729	1.083	2015–2017 average	Urban Institute State and Local Finance Initiative
Health and medical spending per capita (in thousands of 2019 dollars)	–0.099	0.912	2015–2017 average	Urban Institute State and Local Finance Initiative
Primary care physicians per capita (per 100,000 state population)	–8.280	12.861	2015–2017 average	HRSA area resource file
Percentage of residents age 0–64 with health insurance (%)	–1.913	4.786	2015–2017 average	US Census SAHIE program

Note: HRSA – Health Resources and Services Administration
SAHIE – Small Area Health Insurance Estimates

Appendix B: Deaths per 1,000 live births attributable to decomposition Component 1 for each state–state pair (630 total pairs)

State 2

State 1	MA	CA	NJ	WA	NY	CT	CO	OR	MN	IA	AZ	VA	PA	NV	TX	NE	HI	KS	FL	IL	WI	MD	MO	MI	KY	SC	TN	IN	OH	NC	GA	OK	LA	AR	AL
MS	2.4	2.4	2.3	2.1	1.9	2.7	2.6	2.2	1.8	2.0	2.0	1.6	1.7	1.6	2.1	2.4	2.5	2.3	1.5	2.3	2.5	1.3	1.7	1.6	1.4	0.8	1.2	1.6	1.8	1.5	0.7	1.7	0.3	1.0	0.7
AL	1.9	1.9	1.7	1.8	1.3	1.9	2.1	1.8	1.4	1.8	1.5	1.1	1.3	1.1	1.5	2.0	1.7	1.9	0.9	1.5	1.9	0.5	1.3	1.1	1.1	0.3	0.8	1.2	1.2	0.8	0.0	1.2	-0.4	0.6	
AR	1.6	1.6	1.3	1.3	1.0	1.5	1.7	1.3	1.1	1.1	1.2	0.7	0.8	0.7	1.2	1.4	1.2	1.3	0.5	1.0	1.1	0.3	0.6	0.4	0.5	-0.1	0.2	0.5	0.5	0.4	-0.4	0.7	-0.8		
LA	1.9	1.8	1.8	1.8	1.4	2.1	2.1	1.9	1.6	1.9	1.6	1.3	1.5	1.2	1.5	2.1	2.4	2.0	1.0	1.8	2.2	0.8	1.6	1.4	1.3	0.6	1.0	1.5	1.6	1.1	0.3	1.7			
OK	1.0	0.9	0.6	1.0	0.4	0.7	1.1	0.9	0.8	0.8	0.6	-0.1	0.5	0.1	0.4	1.0	0.3	1.0	-0.3	0.3	0.7	-0.5	0.1	-0.1	0.1	-0.8	-0.4	-0.1	-0.2	-0.4	-1.3				
GA	1.9	1.7	1.7	1.7	1.3	2.0	2.0	1.7	1.5	1.7	1.4	1.0	1.3	1.1	1.3	1.8	2.4	1.7	0.8	1.5	2.0	0.6	1.3	1.1	0.9	0.3	0.6	1.2	1.3	0.8					
NC	1.3	1.2	1.0	1.1	0.7	1.2	1.4	1.1	0.9	1.1	0.9	0.4	0.7	0.4	0.8	1.2	1.1	1.1	0.2	0.7	1.1	-0.2	0.5	0.3	0.3	-0.5	-0.1	0.4	0.4						
OH	0.9	0.7	0.5	0.9	0.3	0.7	1.0	0.9	0.7	0.8	0.4	0.1	0.3	-0.1	0.2	1.0	0.8	0.8	-0.4	0.3	0.7	-0.6	0.2	-0.1	0.2	-0.8	-0.3	0.1							
IN	0.8	0.6	0.4	0.8	0.1	0.6	0.9	0.7	0.5	0.6	0.3	0.0	0.2	-0.1	0.2	0.8	0.8	0.7	-0.4	0.1	0.4	-0.6	0.0	-0.2	0.1	-0.8	-0.4								
TN	1.3	1.2	1.0	1.1	0.7	1.2	1.4	1.1	0.9	0.9	0.8	0.5	0.6	0.4	0.8	1.2	1.0	1.1	0.2	0.8	0.9	0.0	0.4	0.2	0.3	-0.3									
SC	1.4	1.3	1.1	1.3	0.9	1.5	1.5	1.3	1.1	1.3	1.0	0.7	0.9	0.6	0.9	1.5	1.5	1.4	0.5	1.1	1.5	0.2	0.9	0.7	0.6										
KY	0.9	0.7	0.6	0.7	0.3	0.7	0.9	0.7	0.6	0.5	0.2	0.2	0.2	-0.1	0.3	0.8	0.2	0.6	-0.2	0.3	0.3	-0.3	0.0	-0.2											
MI	0.8	0.5	0.5	0.8	0.2	0.7	0.9	0.8	0.6	0.8	0.3	0.1	0.3	-0.1	0.1	0.9	0.6	0.8	-0.3	0.3	0.7	-0.6	0.3												
MO	0.7	0.5	0.3	0.7	0.1	0.5	0.8	0.7	0.5	0.6	0.2	-0.1	0.1	-0.2	0.1	0.8	0.5	0.6	-0.5	0.1	0.4	-0.7													
MD	1.3	1.1	1.1	1.0	0.7	1.4	1.4	1.1	0.9	1.2	1.0	0.4	0.8	0.5	0.8	1.2	1.5	1.1	0.3	0.9	1.4														
WI	0.3	0.0	-0.2	0.2	-0.4	0.0	0.4	0.4	0.1	0.3	-0.2	-0.6	-0.3	-0.7	-0.4	0.4	-0.7	0.3	-1.0	-0.4															
IL	0.7	0.5	0.3	0.5	0.1	0.5	0.8	0.6	0.4	0.5	0.2	-0.3	0.1	-0.3	0.0	0.5	0.6	0.4	-0.6																
FL	1.2	0.9	0.8	0.8	0.5	1.0	1.2	1.0	0.7	1.0	0.7	0.2	0.6	0.2	0.5	1.0	0.9	0.9																	
KS	0.4	0.3	0.0	0.1	-0.2	0.1	0.4	0.1	0.0	0.0	-0.2	-0.5	-0.3	-0.6	-0.2	0.1	-0.6																		
HI	0.1	0.2	-0.2	0.5	-0.2	-0.1	0.4	0.4	0.5	0.6	0.5	-0.8	0.1	0.0	-0.4	0.2																			
NE	0.2	0.2	-0.2	0.1	-0.3	-0.1	0.2	0.0	-0.1	-0.1	-0.3	-0.7	-0.5	-0.7	-0.4																				
TX	0.9	0.4	0.3	0.3	0.1	0.5	0.7	0.4	0.4	0.5	0.2	-0.4	0.2	-0.3																					
NV	0.9	0.6	0.5	0.6	0.3	0.6	0.9	0.7	0.6	0.8	0.4	-0.1	0.5																						
PA	0.5	0.2	0.2	0.3	-0.1	0.3	0.5	0.4	0.3	0.4	-0.1	-0.2																							
VA	0.8	0.7	0.5	0.6	0.2	0.8	0.9	0.7	0.4	0.6	0.5																								
AZ	0.6	0.2	0.0	0.2	-0.1	0.1	0.5	0.3	0.3	0.4																									
IA	0.1	-0.1	-0.3	0.1	-0.4	-0.1	0.2	0.1	-0.1																										
MN	0.1	-0.1	-0.1	0.0	-0.3	0.1	0.2	0.0																											
OR	0.1	0.0	-0.3	0.0	-0.3	-0.2	0.1																												
CO	0.1	-0.2	-0.4	-0.2	-0.5	-0.3																													
CT	0.3	0.0	-0.2	0.0	-0.5																														
NY	0.6	0.3	0.3	0.3																															
WA	0.2	0.1	-0.1																																
NJ	0.4	0.1																																	
CA	0.4																																		

< 0 deaths per 1,000 (111 pairings)

0–0.999 deaths per 1,000 (342 pairings)

1–1.999 deaths per 1,000 (154 pairings)

2–2.999 (23 pairings)

Appendix C: Deaths per 1,000 live births attributable to decomposition Component 2 for each state–state pair (630 total pairs)

State 2

State 1	MA	CA	NJ	WA	NY	CT	CO	OR	MN	IA	AZ	VA	PA	NV	TX	NE	HI	KS	FL	IL	WI	MD	MO	MI	KY	SC	TN	IN	OH	NC	GA	OK	LA	AR	AL
MS	2.5	2.3	2.3	2.4	2.4	1.6	1.6	1.7	2.0	1.4	1.3	1.6	1.5	1.6	1.1	0.6	0.4	0.6	1.3	0.5	0.0	1.1	0.6	0.8	0.8	1.2	0.5	0.0	-0.2	0.0	0.8	-0.3	1.1	0.0	-0.1
AL	2.5	2.3	2.3	2.2	2.4	1.8	1.5	1.5	1.8	1.2	1.3	1.6	1.3	1.5	1.1	0.5	0.7	0.4	1.4	0.7	0.1	1.4	0.5	0.7	0.4	1.2	0.3	-0.2	-0.2	0.2	1.0	-0.4	1.2	-0.2	
AR	2.4	2.2	2.3	2.2	2.3	1.8	1.5	1.6	1.8	1.4	1.2	1.6	1.4	1.5	1.0	0.6	0.7	0.6	1.3	0.7	0.5	1.2	0.8	1.0	0.7	1.2	0.5	0.1	0.1	0.2	0.9	-0.3	1.2		
LA	1.6	1.6	1.4	1.3	1.5	0.8	0.7	0.6	0.9	0.2	0.4	0.6	0.3	0.6	0.3	-0.5	-0.9	-0.6	0.4	-0.3	-1.0	0.2	-0.6	-0.4	-0.5	0.1	-0.7	-1.2	-1.3	-0.9	-0.2	-1.6			
OK	2.5	2.5	2.6	2.1	2.4	2.2	1.7	1.5	1.6	1.2	1.3	1.9	1.3	1.6	1.4	0.6	1.2	0.5	1.7	1.1	0.4	1.5	0.9	1.1	0.6	1.4	0.7	0.3	0.4	0.5	1.4				
GA	1.6	1.6	1.4	1.3	1.6	0.9	0.8	0.6	0.9	0.3	0.4	0.7	0.4	0.7	0.4	-0.3	-1.0	-0.4	0.5	-0.2	-1.0	0.3	-0.4	-0.3	-0.3	0.3	-0.5	-1.0	-1.1	-0.7					
NC	2.1	2.0	2.0	1.9	2.1	1.5	1.2	1.2	1.4	0.9	0.9	1.3	1.0	1.2	0.9	0.3	0.2	0.2	1.1	0.5	-0.1	1.0	0.3	0.5	0.3	0.9	0.2	-0.3	-0.3						
OH	2.4	2.5	2.4	2.0	2.4	1.9	1.6	1.3	1.6	1.1	1.4	1.6	1.3	1.7	1.4	0.4	0.5	0.4	1.6	0.9	0.3	1.4	0.6	0.8	0.3	1.2	0.4	-0.1							
IN	2.6	2.5	2.6	2.1	2.5	2.1	1.7	1.5	1.7	1.2	1.4	1.6	1.4	1.7	1.4	0.6	0.5	0.5	1.6	1.0	0.5	1.4	0.7	0.9	0.4	1.2	0.4								
TN	2.0	1.9	1.9	1.8	2.0	1.4	1.2	1.1	1.3	0.9	0.9	1.1	1.0	1.2	0.7	0.2	0.2	0.1	1.0	0.3	0.0	0.8	0.3	0.5	0.2	0.7									
SC	1.5	1.5	1.4	1.2	1.4	0.8	0.6	0.5	0.7	0.2	0.3	0.5	0.3	0.6	0.2	-0.5	-0.7	-0.6	0.3	-0.3	-0.9	0.2	-0.5	-0.4	-0.5										
KY	1.9	1.9	1.9	1.6	1.8	1.5	1.2	1.1	1.1	0.8	1.0	0.9	0.9	1.2	0.8	0.1	0.5	0.1	0.9	0.4	0.1	0.6	0.2	0.5											
MI	1.8	1.8	1.7	1.3	1.7	1.2	0.9	0.6	0.8	0.3	0.7	0.8	0.5	1.0	0.7	-0.3	-0.1	-0.3	0.8	0.1	-0.5	0.6	-0.3												
MO	1.9	1.9	1.9	1.4	1.8	1.4	1.0	0.8	1.0	0.5	0.7	1.0	0.7	1.0	0.7	-0.1	0.1	-0.2	0.9	0.3	-0.2	0.7													
MD	1.3	1.2	1.1	1.1	1.2	0.5	0.4	0.3	0.5	-0.1	0.0	0.4	0.1	0.3	-0.1	-0.6	-1.0	-0.7	0.2	-0.5	-1.3														
WI	2.1	2.2	2.2	1.7	2.1	1.7	1.2	0.9	1.2	0.6	1.0	1.3	0.9	1.3	1.0	0.1	1.1	0.0	1.3	0.7															
IL	1.4	1.5	1.5	1.2	1.5	1.0	0.7	0.5	0.7	0.2	0.3	0.8	0.4	0.7	0.4	-0.3	-0.5	-0.3	0.7																
FL	0.9	1.0	0.9	0.9	1.0	0.4	0.2	0.1	0.3	-0.3	-0.1	0.2	-0.2	0.2	-0.2	-0.8	-0.8	-0.9																	
KS	1.7	1.7	1.7	1.5	1.7	1.4	1.0	0.9	1.0	0.6	0.7	0.9	0.7	1.0	0.6	0.1	0.7																		
HI	2.0	1.6	1.9	1.1	1.6	1.5	0.9	0.5	0.4	0.0	-0.1	1.2	0.2	0.3	0.6	-0.1																			
NE	1.7	1.6	1.7	1.4	1.6	1.3	1.0	0.8	1.0	0.6	0.6	0.9	0.7	0.9	0.5																				
TX	0.9	1.1	1.1	1.0	1.0	0.7	0.3	0.3	0.3	-0.2	0.0	0.4	-0.2	0.3																					
NV	0.8	1.0	0.9	0.7	0.8	0.5	0.1	0.0	0.0	-0.5	-0.3	0.1	-0.4																						
PA	1.2	1.4	1.2	0.9	1.2	0.7	0.5	0.2	0.3	-0.1	0.2	0.2																							
VA	0.9	0.8	0.8	0.7	0.8	0.3	0.1	-0.1	0.2	-0.3	-0.4																								
AZ	1.0	1.3	1.2	1.0	1.0	0.8	0.4	0.2	0.2	-0.3																									
IA	1.3	1.4	1.3	1.0	1.2	0.9	0.5	0.3	0.4																										
MN	1.0	1.0	0.9	0.7	0.8	0.4	0.1	0.0																											
OR	1.0	0.9	1.0	0.6	0.8	0.6	0.3																												
CO	0.6	0.8	0.8	0.5	0.6	0.4																													
CT	0.4	0.5	0.5	0.2	0.5																														
NY	0.1	0.2	0.0	-0.1																															
WA	0.2	0.2	0.2																																
NJ	0.0	0.1																																	
CA	-0.2																																		

< 0 deaths per 1,000 (94 pairings)

0–0.999 deaths per 1,000 (297 pairings)

1–1.999 deaths per 1,000 (199 pairings)

2–2.999 (40 pairings)

Appendix D: Linear regression of the IMR gap attributable to decomposition Component 2 on variables measuring state–state differences in contextual variables (n = 630 pairs of states)

Models 1–5

State-versus-state difference variable	Model 1	Model 2	Model 3	Model 4	Model 5
IMR gap	0.58 [0.49, 0.66]	0.56 [0.47, 0.65]	0.56 [0.45, 0.67]	0.57 [0.48, 0.66]	0.59 [0.49, 0.69]
GDP per capita	–0.00 [–0.15, 0.14]	0.01 [–0.13, 0.15]	–0.00 [–0.14, 0.14]	0.02 [–0.12, 0.16]	0.01 [–0.15, 0.17]
Unemployment rate	–0.18 [–0.27, –0.09]	–0.17 [–0.26, –0.09]	–0.18 [–0.26, –0.10]	–0.18 [–0.26, –0.10]	–0.18 [–0.26, –0.09]
Poverty rate	–0.00 [–0.07, 0.06]	–0.01 [–0.07, 0.05]	–0.01 [–0.07, 0.06]	–0.01 [–0.07, 0.05]	–0.01 [–0.07, 0.05]
Gini coefficient	–7.88 [–12.41, –3.35]	–7.31 [–11.92, –2.69]	–7.87 [–12.41, –3.33]	–7.23 [–12.08, –2.39]	–7.93 [–12.43, –3.43]
Political ideology score		–0.00 [–0.01, 0.00]			
Minimum wage			–0.03 [–0.09, 0.04]		
State EITC				–0.42 [–0.82, –0.02]	
Maximum TANF benefit					–0.00 [–0.00, 0.00]
TANF/poverty ratio					0.42 [–0.14, 0.98]
Constant	0.01 [–0.14, 0.15]	0.00 [–0.14, 0.14]	0.01 [–0.13, 0.15]	0.00 [–0.14, 0.15]	0.01 [–0.13, 0.15]
R2	.7299	.7353	.7307	.7355	.7313

Note: Table displays coefficients and [95% confidence intervals].

Appendix D: (Continued)

Models 6–9

State-versus-state difference variable	Model 6	Model 7	Model 8	Model 9
IMR gap	0.59 [0.51, 0.67]	0.57 [0.48, 0.66]	0.58 [0.49, 0.66]	0.58 [0.48, 0.67]
GDP per capita	0.12 [–0.01, 0.25]	–0.00 [–0.14, 0.13]	–0.01 [–0.16, 0.13]	0.13 [0.00, 0.26]
Unemployment rate	–0.16 [–0.24, -0.08]	–0.18 [–0.28, –0.09]	–0.18 [–0.27, –0.09]	–0.18 [–0.25, –0.11]
Poverty rate	–0.03 [–0.09, 0.04]	–0.01 [-0.07, 0.06]	–0.00 [–0.07, 0.07]	–0.04 [–0.11, 0.03]
Gini coefficient	–7.17 [–11.46, –2.89]	–7.58 [–12.67, –2.49]	–7.55 [–12.06, –3.05]	–1.34 [–6.87, 4.18]
Political ideology score				–0.01 [–0.01, –0.00]
Minimum wage				–0.00 [–0.06, 0.06]
State EITC				–0.57 [–0.94, –0.19]
Maximum TANF benefit				0.00 [–0.00, 0.00]
TANF/poverty ratio				1.53 [0.63, 2.43]
Social service spending	–0.18 [–0.28, –0.09]			–0.13 [–0.22, –0.04]
Health and medical spending	0.10 [0.02, 0.19]			0.01 [–0.13, 0.15]
Primary care physicians per capita		–0.00 [–0.01, 0.01]		–0.01 [–0.02, -0.00]
Percentage 0–64 with health insurance			0.01 [–0.01, 0.03]	0.04 [0.02, 0.07]
Constant	–0.00 [–0.14, 0.14]	0.01 [–0.13, 0.15]	0.01 [–0.13, 0.15]	–0.00 [–0.13, 0.12]
R2	.7469	.7304	.7335	.7846

Note: Table displays coefficients and [95% confidence intervals].

Appendix E: Map of US states and list of two-letter state abbreviations

State		State	
Alaska	AK	Montana	MT
Alabama	AL	North Carolina	NC
Arkansas	AR	North Dakota	ND
Arizona	AZ	Nebraska	NE
California	CA	New Hampshire	NH
Colorado	CO	New Jersey	NJ
Connecticut	CT	New Mexico	NM
Delaware	DE	Nevada	NV
Florida	FL	New York	NY
Georgia	GA	Ohio	OH
Hawaii	HI	Oklahoma	OK
Iowa	IA	Oregon	OR
Idaho	ID	Pennsylvania	PA
Illinois	IL	Rhode Island	RI
Indiana	IN	South Carolina	SC
Kansas	KS	South Dakota	SD
Kentucky	KY	Tennessee	TN
Louisiana	LA	Texas	TX
Massachusetts	MA	Utah	UT
Maryland	MD	Virginia	VA
Maine	ME	Vermont	VT
Michigan	MI	Washington	WA
Minnesota	MN	Wisconsin	WI
Missouri	MO	West Virginia	WV
Mississippi	MS	Wyoming	WY