Exploring Trends in Severe Maternal Morbidity in the U.S.

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Abstract

The incidence of severe maternal morbidity (SMM) in the U.S. has been rising among mothers over time, and worse so among Black mothers. In this paper, we examine why this might be happening. Previous literature takes a limited-scope approach by focusing on select variables as determinants of SMM. We take a broader approach and evaluate the contributions of a large set of variables over a long time span to let the data inform us a what factors may be most influential in determining SMM. We use inpatient data from 1998-2019 to see how maternal, hospital, and county-level characteristics may be associated with both the rising trends and the racial disparity in SMM. Using three different methods to draw conclusions, we find that observable characteristics explain very little of the overall variation of SMM across and within hospitals, but chronic conditions and C-sections appear to be large drivers of the variation time. We also find that about half of Black-White gap in SMM can be explained by differences in the observable characteristics. These associational results indicate that focusing on patients with co-morbid chronic conditions, who deliver by C-sections, and who deliver in hospitals with large portions of Black patient are promising places for researchers to delve more deeply into the root causes of SMM.

1. Introduction

Against the backdrop of steady improvements in life expectancy and infant mortality over the last century, a discordant new trend has emerged in the US – over the past 20 years, maternal mortality and severe maternal morbidity (SMM) have been rising (Creanga et al. 2012; Callaghan et al., 2012; Creanga et al., 2014; Moadabb et al., 2016). The SMM rate in the US increased from 5.9 per 1,000 in-hospital deliveries in 1998 to 7.97 per 1,000 in-hospital deliveries in 2019 (Authors' own calculations).[1] The maternal mortality rate in the U.S. fell by 68 percent between 1969 and 1998, but then increased from 9.9 deaths per 100,000 live births in 1999 to 17.4 deaths per 100,000 live births in 2018 (Singh, 2021). This striking trend in maternal mortality is unique to the U.S. Few other industrialized countries have experienced increases in maternal mortality in recent years (Creanga et al., 2012), and, as of 2007, the U.S. ranked 27th out of 35 OECD countries in its maternal mortality rate (Moaddab et al., 2016).

Considerable variation exists across racial/ethnic groups in maternal mortality and morbidity. Based on data from 2007-2016, the U.S. maternal mortality rate was 3.2 times higher among non-Hispanic Blacks vs. non-Latino Whites (Petersen et al., 2019), and rates have been rising most rapidly among non-Hispanic Blacks (Campbell et al., 2013; Creanga et al., 2014; Singh, 2021). Notably, all racial/ethnic and nativity groups in the US (excluding foreign-born, White women) are more likely than native-born White women to die from pregnancy-related causes (Campbell et al, 2013; Creanga et al., 2012; Singh, 2021). There is emerging evidence of racial disparities in SMM rates as well (WHO, 2009; Creanga et al., 2014).

[1] These statistics are calculated from the 1998 to 2019 National Inpatient Sample (NIS). We exclude SMM related to blood transfusions in these numbers. In contrast to rising rates of maternal mortality and SMM during this time-period, infant mortality in the US declined from 6.9 per 1,000 live births in 2000 to 5.6 per 1,000 live births in 2019. Between 2003 and 2018, the trend in the percent of infants born at low birthweight (<2500 grams) in the US was essentially flat, but the rate was higher in 2018 (6.6 percent) than in 2003 (6.2 percent) (Pollock et al. 2021).

Why have SMM rates been rising in the US, and why have non-Hispanic Black mothers been disproportionately affected? Researchers hypothesize that increasing rates of SMM and mortality may be due to changes such as increased maternal age, increased body weight, Cesarean delivery, cigarette and illegal drug use during pregnancy, preexisting chronic conditions, low SES, and issues related to providers and medical care (Creanga et al. 2012; Callaghan et al., 2012; Creanga et al., 2014; Moadabb et al., 2016; Leonard et al. 2019; Admon et al. 2017). Structural racism, both inside and outside the health care system, has been linked to Black-White gaps in SMM (Liu et al., 2019), and there is large body of work documenting the connection between SES and maternal health. Of note, a recent study by Kennedy-Moulton et al. (2022) of births in California shows that women at the bottom of the income distribution are three times more likely to die within the first year after childbirth than women at the top of the income distribution.

Worsening trends and racial disparities in SMM and mortality are hard to explain because some trends and risk factors are advantageous to outcomes in disadvantaged groups. For example, advanced age and rurality are risk factors for poor outcomes, but non-Hispanic Black mothers tend to be younger and are less likely to live in rural areas than non-Latino Whites. Moreover, rates of un-insurance and Cesarean delivery have fallen over time, and adherence to treatments for chronic conditions which are risk factors for poor maternal outcomes, such as diabetes and cardiovascular disease (CVD), have improved over time.

As solutions to the worsening trends in SMM are sought, answers are still elusive. Much of the existing public health literature examining the factors associated with SMM does so in a piecemeal way, focusing on only a particular contributor or a small set at a time. For example, Linsonkova et al. (2017) study the effect of older maternal age on SMM. Howell et al. (2016)

look at rates of SMM in hospitals serving predominantly non-Hispanic blacks and identify certain hospitals for targeted quality improvements. Jarlenski et al. (2017) examine the effects of state coverage of medically necessary abortions on SMM. Studies that focus on the relative contributions of larger sets of variables tend to focus on small or specific populations including births in university-based hospitals (Grobman et al. 2014) and patients within New York (Howland et al. 2018 and Guglielminotti et al. 2019). There have been no systematic nationwide analyses of the determinants of SMM. This paper fills the gap.

In this paper we use national hospital discharge data over a twenty-two year time period (1998-2019) to examine the relative contributions of maternal characteristics, hospital characteristics, and the community socioeconomic environment in determining rates of severe maternal morbidity across and within hospitals and over time. We also examine racial disparities. While the methods we use will highlight the main associative determinates and the results are not necessarily causal, however, the methods employed are useful in quantifying the roles of the different factors that affect maternal health outcomes, statistically explaining racial differences, and empirically assessing the reasons for the worsening trends. This information is crucial to take the next step, which is to identify and test whether and what kinds of policy interventions may be beneficial in reducing SMM.

We use three different analyses to draw conclusions. We first assess the model fit to see which variables may contribute the most to explaining the overall variation in SMM. Second, we calculate the contribution to the total prediction accounted for by each set of variables over time. Third, we decompose the Black-White gap in SMM rates using mean and distributional techniques. Our results indicate that chronic conditions and C-sections appear to be the largest drivers of SMM over time, however, the racial gap in SMM is reflected by existing disparities in

the hospital. These results suggest that researchers may need to look at patient conditions before the time of delivery and within hospitals at the time of delivery for solutions to the SMM problem.

2. Background

Severe Maternal Morbidity (SMM) is the term used to describe severe complications of pregnancy and represents near-death misses (CDC, 2018; MacDorman et al., 2016). The most common medical causes of SMM include hemorrhage, hypertensive disorders of pregnancy, infection, embolisms, anesthesia complications, cardiovascular conditions, cardiomyopathy, cerebrovascular accident, and non-cardiovascular medical conditions (Grobman et al, 2014; Singh, 2021). The full list of conditions and procedures used to define SMM is described below.

To date, few studies have systematically identified and assessed the relative importance of plausible causes of SMM. Grobman et al. (2014) use a sample of women giving birth in 25 university-based hospitals to examine the amount of variation in five specific maternal morbidities. They measure the amount of variation in the outcomes that can be attributed to patient characteristics, provider and hospital characteristics, and obstetric care characteristics, and find that while patient and provider/hospital characteristics can explain part of the variation in some of their outcomes, 50-100% of inter-hospital variation remains unexplained. Howland et al. (2018) and Guglielminotti et al. (2019) both examine the issue within New York City and state, respectively, and while both find patient characteristics matter, they differ on the conclusions with regard to neighborhood-level characteristics.

Adams et al. (2023) and Adams et al. (2025) conduct Oaxaca-Blinder decompositions of the Black-White gap in rates of SMM in Georgia. These authors focus on a variety of correlates

including sociodemographic factors, medical conditions, obstetrical factors, access to care, hospital characteristics, and local area characteristics. They find that these factors combined can explain up to about half of the gap, with hospital fixed effects constituting the largest proportion. Access to care and sociodemographic factors are also major contributors.

The results of these papers complement within-hospital assessments of individual SMM cases. For example, researchers in Maryland found that about two-thirds of SMM events were preventable with changes to either clinician, system, or patient factors. Changes in clinician level factors had the largest effects and were deemed relevant in almost all of the cases deemed preventable (Wolfson et al. 2022). There are also a few papers that ask whether specific policies can help reduced rates of SMM. Examples of this include work by Hawkins et al. (2019) who find that state-level policies limiting access to family planning and reproductive health services increase maternal mortality. Chatterji et al. (2023) test if Medicaid expansions affect maternal morbidity as measured by specific adverse events. However, these authors find no association with expanded insurance and maternal health outcomes.

Other literature, methodologically relevant to the present study, focuses on estimating and trying to statistically explain disparities and trends in infant mortality. Elder et al. (2011, 2014) use birth certificate records from the mid-1980s to the early 2000s, decomposing gaps in infant mortality rates between Blacks and Whites. In these papers, they find that about 90 percent of the mortality gap can be explained by racial differences in "fitness at birth" (birthweight and gestation), and, over time, the explained portion of the Black-White gap has been declining (Elder et al., 2011, 2014). In later work, Elder et al. (2016) decompose gaps in infant mortality between racial/ethnic groups using linked birth and infant death records from 2000-2004. They report striking racial disparities in rates of infant mortality; among Blacks, for example, the death

rate for infants was 12.35 per 1,000 live births vs. 5.35 per 1,000 live births among Whites. Using re-weighting methods, they estimate that of this Black-White gap of about 7 infant deaths, about 2.54 can be explained by differences in the background characteristics of the mothers, particularly maternal age, education, and marital status; the remainder of the gap is unexplained by observable factors.

Our paper uses a similar approach but focuses on maternal health at the time of delivery. Maternal outcomes generally have not been studied by economists and are important outcomes in their own right. Maternal health also is inextricably linked to infant health. Elder et al. (2011, 2014), for example, demonstrate the importance of fitness at birth for infant mortality, which is likely to be closely related to maternal health at the time of the delivery. As a route to improving infant mortality, maternal pre-conception health perhaps may be more important, and more amendable to policy interventions, than health behaviors during pregnancy. Thus, one contribution of our study we focus on maternal health, an important and under-studied outcome in economics.

An additional contribution is our use of hospital discharge data, which has important advantages, including detailed information on the mother's stock of health at the time of the delivery, information which is lacking in the birth certificates data that has been used in prior studies. The richness of these data allows us to separate predictors of SMM and related racial gaps in outcomes into those that are health-related and those that are not health-related. In addition, using hospital discharge data allows us to estimate the contribution of hospital characteristics to trends and gaps in maternal health at the individual level.

3. Methods and Data

Our analyses accomplish the following goals: 1) evaluate the contribution of the different variables and variable groups to the overall variation in SMM across and within hospitals; 2) evaluate the contribution of the different variables and variable groups to the overall variation in SMM over time; 3) decompose the SMM gap between Black and White mothers. We focus on this gap since it is the largest of the racial/ethnic groups. We first describe the data used and then the methods since the particularities of the data inform the empirical estimation strategy.

DATA

Data come from the Agency for Healthcare Research and Quality's Nationwide Inpatient Sample (NIS). The NIS is the largest publicly available all-payor database of inpatient claims available in the US (AHRQ, 2021). The data are nationally representative of all U.S. short-term community hospitals and include public and private hospitals, academic medical centers, and hospitals that provide specialty care. There is extensive information on each hospital stay, including diagnosis codes, patient demographics (sex, race/ethnicity, age, median household income in patient's zip code), patient co-morbidities, and hospital characteristics.

Our analysis sample includes pooled data from the 1998 to the 2019 NIS. There were two important changes in the NIS during our analysis period. The first change is a sample redesign in 2012. From 1998-2011, the NIS includes the universe of hospital discharges from a sample of Healthcare Cost and Utilization Project (HCUP) hospitals. In 2012, however, the NIS became a sample of discharge records from all HCUP-participating hospitals, rather than a sample of hospitals from which all discharges were included. This led to a large increase in the number of participating hospitals in 2012. In addition, from 1998-2011, state and hospital IDs

are available for all discharges in the dataset, and county identifiers are available for a subset of these hospitals. For the years 2012-2019, however the only identifying information available is the Census division in which the hospital is located, and the publicly available data for 2012-2019 do not contain hospital identifiers that can be linked across time. For these reasons, we run all analyses using the full sample (1998-2019), as well as sub-samples for 1998-2011 and 2012-2019 so we can use the geographic information that is available in the earlier 1998-2011 time period only.

The second major change in the NIS during 1998-2019 is a change in diagnosis coding. After the third quarter of 2015, the diagnosis coding changed from ICD-9 to ICD-10. This did not pose a problem for our dependent variable (SMM) because the CDC provides code to map ICD-9 to ICD-10 codes for SMM. For preexisting chronic conditions (which are covariates in this study), however, this mapping was not available, so we mapped health conditions recorded using the ICD-10 back to the ICD-9 for the last quarter of 2015 to 2019. This was straight-forward in some cases, but involved some judgment calls in other cases since the ICD-10 more detailed than the ICD-9 and includes a range of new conditions. We relied on definitions used in the literature to make these judgments (details available upon request).

In each year of our sample, the NIS contains information on 6.8 to 8.0 million discharges from 984 to 1,049 hospitals located in 22 to 46 states. The unit of analysis in our study is an individual mother who delivered an infant in an NIS hospital between 1998 and 2019. We identify deliveries in the NIS using established methods, which involve including ICD-CM diagnosis and procedure codes for normal deliveries and procedures used during deliveries, while excluding codes for procedures such as abortions. The total number of deliveries between 1998 and 2019 is 17,648,783. The number of deliveries between 1998-2011 with hospital

identifiers and with county identifiers are 11,683,664 and 8,393,985, respectively. In addition, not all hospitals provided data on race and ethnicity. Our race-specific samples include 7,767,180 non-Hispanic White mothers and 2,049,259 non-Hispanic Black mothers from 1998-2019.

The dependent variable in this study an indicator of whether the mother experienced an SMM during delivery. SMM events are identified based on 21 ICD-9/ICD-10 diagnosis and procedure codes as described by CDC (2019), with SAS coding provided by Rankin (2018).[2] Blood transfusion in included in the list of procedures, although some have pointed out that blood transfusion may not reflect a dire maternal health situation, we therefore also show results for SMM that excludes this procedure (Snowden 2021).

Our goal is to examine the relative contributions of observable characteristics in explaining variation in SMM. We broadly group the potential predictors into the following groups: (1) maternal characteristics; (2) hospital characteristics; (3) county-level measures of access to care and socioeconomic status. Table 1 list all of the variables within each group along with the definition, source and available years. Individual maternal characteristics include patient age, race, payer, zip code income, comorbid chronic conditions, and delivery type. Hospital characteristics include hospital size, ownership, and urban/rural/teaching status and two measures of disparities (described below). County-level variables include per capita numbers of physicians and obstetricians/gynecologists, an indicator for medically underserved county, and variables reflecting county population, poverty, income, and unemployment. These county-level variables are only available for 1998-2011 and only among select states that report county.

[2] SMM includes the following diagnoses and procedures: Acute myocardial infarction, aneurysm, acute renal failure, acute respiratory distress syndrome, amniotic fluid embolism, cardiac arrest / ventricular fibrillation, conversion of cardiac rhythm, disseminated intravascular coagulation, blood transfusion, eclampsia, heart failure / arrest during surgery or procedure, puerperal cerebrovascular disorders, pulmonary edema / acute heart failure, severe anesthesia complications, sepsis, shock, sickle cell disease with crisis, air and thrombotic embolism, hysterectomy, temporary tracheostomy, and ventilation.

We generate two measures of health disparities within hospitals to help proxy for the hospital quality and the local population health of the hospital catchment area. Prior research indicates that hospitals serving high proportions of Black patients fare worse in terms of patient outcomes and other quality measures so to account for this, we generate and include the annual percent of deliveries by Black mothers in each hospital (Ly et al., 2010). Next, we create hospital-year-level measures of disparity based on the idea that race-based or ethnicity-based differences in preventable hospitalizations among males aged 18-64 years old may reflect unmeasured health differences within the local health care system.[3] We compute the rate of privately insured admissions in the hospital in that year for preventable conditions for Blacks, Hispanics and Whites. The Black/White and Hispanic/White ratios are considered to be capturing structural inequalities in the local health care system, with higher ratios indicating higher degrees of inequality. We do the same for publicly insured admissions. Given that some

[3] Conceptually, we follow Liu et al. who use Black-White ratios of educational attainment, unemployment, and incarceration to capture structural racism. We create these rates based on males only so we can avoid including conditions related to pregnancy and childbirth, which are captured by the dependent variable. The drawback of this approach is women, and pregnant women in particular, may face different conditions than males. However, we think it is reasonable to assume that inequalities in the health care system affecting males is likely to be highly correlated with inequalities in the healthcare system affecting females of childbearing age. The list of preventable hospitalizations includes 10 quality of care indicators developed by AHRQ (https://qualityindicators.ahrq.gov/Modules/PQI_TechSpec_ICD10_v2021.aspx):

PQI #1 Diabetes Short-Term Complications Admission Rate
PQI #3 Diabetes Long-Term Complications Admission Rate
PQI #5 Chronic Obstructive Pulmonary Disease (COPD) or Asthma in Older Adults Admission Rate
PQI #7 Hypertension Admission Rate
PQI #8 Heart Failure Admission Rate
PQI #11 Community-Acquired Pneumonia Admission Rate
PQI #12 Urinary Tract Infection Admission Rate
PQI #14 Uncontrolled Diabetes Admission Rate
PQI #15 Asthma in Younger Adults Admission Rate
PQI #16 Lower-Extremity Amputation among Patients with Diabetes Rate

hospitals are rather small, a non-trivial number of hospital-years have zeros in the numerator or denominator. In these cases, we include an indicator variable for a true zero. We also include an indicator variable for when the calculated rate is missing.

Empirical Methods:

The change in the NIS data collection over time and suppression of hospital and state identifiers beginning in 2012 necessitates different models based on years. Our main estimating equations are therefore as follows:

1998-2011: $SMM_{ihct} = \beta_1 Maternal_{ihct} + \beta_2 Hospital_{hct} + \beta_3 County_{ct} + \gamma_t + \delta_h + \varepsilon_{jt}$

1998-2019: $SMM_{ihct} = \alpha_1 Maternal_{ihct} + \alpha_2 Hospital_{hct} + \gamma_t + \Gamma_d + \varepsilon_{jt}$

In the equations above, the indicator for SMM for individual (i) in hospital (h) in county (c) in year (t) are a function of the three vectors of covariates described in Table 1 for the individual maternal and hospital-level characteristics. Both equations also include dummy indicators for year (γ_t) to capture secular trends in the outcomes. In 1998-2011 we add a set of hospital fixed effects (δ_h) and count-level characteristics when possible. In 1998-2019 we include a set of census division indicators (Γ_d) to reflect broad geographic characteristics since other geographic identifiers are not available after 2011.

Using these equations, we first estimate basic linear probability models to identify the variables associated with SMM. This approach is useful because we can explore which determinants and sets of determinants are potentially important and merit further study. We emphasize that we do not attribute causation to the correlations that we uncover. Using these

results, we then estimate the contribution of the different variables and variable groups to the overall variation in SMM across or within hospitals, and over time. For example, we examine the relative contribution of the hospital characteristics and determine how much of the variation in the SMM rates are captured by these hospital-specific indicators. This will help us to gauge whether policy changes should focus on within hospital characteristics or whether the other factors deserve more attention.

In order to examine variation in SMM across or within hospitals, we compare parsimonious to inclusive models and compare the mean squared error (MSE) and adjusted-R^2 values. The MSE of the regression shows how the residual variance changes as sets of independent variables are added to the model. The MSE indicates how close the predicted values are to the actual values, with smaller values indicative of a smaller residual variance and a better model fit. The adjusted-R^2 shows the proportion of the variance in SMM explained by the included right hand side variables. Specifically, we will calculate the MSE and adjusted R-squared first for a parsimonious model that only includes observed maternal factors of age, race, payer, and zip code income, census division indicators, and year indicators. We will then progressively add in different groups of variables and observe how the metrics change.

The progression for years 1998-2019 is as follows:

Model 1: Maternal age, race, payer, and zip code income, year and census division indicators.
Model 2: Model 1 + delivery type + chronic conditions
Model 3: Model 2 + hospital size + hospital location/teaching + hospital ownership
Model 4: Model 3 + hospital percent Black + hospital preventable condition ratios

The progression for years 1998-2011 is as follows:

Model 1: Maternal age, race, payer, zip code income, and year indicators.
Model 2: Model 1+ delivery type + chronic conditions
Model 3: Model 2 + hospital size + + hospital location/teaching + hospital ownership
Model 4: Model 3 + hospital percent Black + hospital preventable condition ratios

Model 5: Model 4 + hospital fixed effects

The progression for years 1998-2011 when county is known is as follows:

Model 1: Maternal age, race, payer, zip code income, and year indicators.
Model 2: Model 1+ delivery type + chronic conditions
Model 3: Model 2 + hospital size + + hospital location/teaching + hospital ownership
Model 4: Model 3 + hospital percent Black + hospital preventable condition ratios
Model 5: Model 4 + county variables
Model 6: Model 5 + hospital fixed effects

There are limitations to these methods. First, order of including variables matters so we will check for the results for different orderings and will focus on identifying the groups that generate the biggest percent change in the metrics. Second, our outcome is binary and these methods ignore the binary nature of the dependent variable.

In order to examine variation in SMM over time, we will use the model coefficients to calculate how much of the change in the outcomes over time can be explained by the change in included variables. To do this, we multiply the change in each variable between the initial year (1998) and the last year (2019) by the estimated coefficient on the variable. This effectively scales-up the coefficient values to match the changes in the variables over our sample period. By summing these values over the included variables, we generate a total predicted change. This is then compared to the actual observed change in SMM over the sample time period. We also calculate the percentage of the observed change that is attributed to each group of variables. This method was successfully used by Chou et al. (2004) in explaining the determinants of rising obesity rates over time. We again caution that these will not necessarily be causal relationships.

Black/White SMM Gap Decomposition: We also analyze the SMM gap between non-Hispanic Black mothers and non-Hispanic White mothers, measured at the time of delivery. As a baseline, we first estimate a standard Oaxaca-Blinder decomposition between Blacks and Whites. This technique uses the estimated coefficients and the mean levels of the predictor variables for each group to break down the difference in the mean SMM rate between Black and White mothers into: (1) an "explained portion" which can be attributed to differences in the averages of the predictor variables across the groups; and (2) an "unexplained portion" that is due to differences in the coefficient estimates across the groups. Identifying the explained portion is useful because we can quantify the degree to which the racial difference in SMM would decrease if White mothers had the same mean characteristics as Black mothers. The unexplained portion may capture differences in the influences of variables on outcomes across racial/ethnic groups, as well as omitted variables bias and measurement error that systematically differs between groups.

The standard Oaxaca-Blinder decomposition focuses on changes in mean values, so we supplement this with a reweighting procedure described by Elder et al. (2015) that matches the distribution of characteristics. The procedure is implemented as follows: Let $t \in \{W, B\}$ denote White mothers and Black mothers. Let x denote the observed characteristics of a mother. To reweight the samples of White mothers so that the distribution of x for White mothers matches the distribution of x for Black mothers, we use propensity score reweighting (e.g. see DiNardo et al., 1996) applied to the White mothers. That is, we estimate the following sample weights for the White mothers:

$$\psi^{x}_{W \to B}(x) = \frac{P(t = B|x)}{1 - P(t = B|x)}, \quad (1)$$

which is just the odds ratio of a mother being Black conditional on her characteristics x.

In the paper, we generate these weights above using standard probit models. Once we generate the weights, reweighting using $\psi^{x}_{W\to B}(x)$ matches the distributions of all variables in x between the two groups. In practice, however, we often would like to isolate one variable or a set of variables in x and examine their effects while holding other variables "constant." For example, in our context, we may want to only match the age distribution of the White mothers that of the Black mothers, while holding the distributions of the other characteristics of White mothers constant, and then examine how this change would affect the White mothers' SMM rate. Suppose that we divide x into x_1 and z, where z contains those variables for which we want to match distributions between the two groups, and x_1 consists of those variables we would like to keep "constant". Elder et al. (2015) proposes a reweighting method which fulfills such a task and at the same time preserves the dependence structure between x_1 and z (see the Appendix for details regarding how we implement this method). The Elder et al. (2015) method requires that all covariates are discrete, so we discretize the continuous measures (details in the Appendix). We apply this method in the paper to assess the contributions of individual factors and sets of factors to the Black-White gap in SMM.

4. Results

Table 2 show sample means for the full sample in years 1998-2019, the sample with hospital identifiers in 1998-2011, the sample with hospital and county identifiers in 1998-2011, and samples of Whites and Blacks for 1998-2019. SMM is rare for all mothers, with about 1.4 percent of mothers experiencing an SMM during delivery including blood transfusion and 0.6 percent experiencing an SMM without blood transfusion. SMM is more than twice as common among Black mothers (2.3 percent) compared to White mothers (1.2 percent). Figure 1 show

trendss in SMM and SMM excluding blood loss during delivery for all mothers, clearly showing the increase over time. Figure 2 shows corresponding trends among Blacks and Whites. The gap between the races is prominent and growing larger over time.

Appendix Table 1 shows standard linear probability models for SMM and SMM excluding blood transfusion as the dependent variables. These models are the basis of the analyses below. Our results are in line with what many others have found. Older and very young mothers, mothers with chronic health conditions, and mothers having C-sections have elevated risk of adverse outcomes. Having public insurance, and delivering in a large, urban, teaching, and predominantly Black-serving hospital are all factors associated with SMM.

Tables 3 and 4 shows the MSE and adjusted-R^2 from the parsimonious to comprehensive models for SMM and SMM excluding blood transfusion. In each table, Panel A uses the full sample over time from 1998-2019, whereas panels B and C restrict the years to 1998-2011 but include hospital fixed effects (Panels B and C) and county characteristics (Panel C). For SMM, regardless of the years examined, the base model explains very little of the overall variation in SMM with an adjusted-R^2 of around 0.002. Adding variables generates large increases in the adjusted-R^2, with the largest increase coming from adding chronic conditions and delivery type. Hospital fixed effects also increase the measure some. Nevertheless, with all variables included and regardless of the ordering, the magnitude is still very small. The MSE indicates similar conclusions with the additional variables do not explain much additional variation in SMM. The results for SMM excluding blood transfusion are qualitatively similar but with smaller magnitudes. These results indicate that chronic conditions and c-sections may be the first places to look to explain the rising SMM rates over time. Measures of hospital quality and disparities do not appear to explain much of the variation.

The next question is whether the variables explain changes over time. The observed change in the probability of SMM from 1998 to 2019 is 0.0094 percentage points whereas the predicted change based on the LPM is 0.0141. Our model therefore over-predicts SMM. In Table 5 we break down, show the contribution to the total prediction accounted for by each set of variables. Chronic conditions and delivery type (C-section) are the largest contributors at 14 percent each, indicating that the changes in these variables over time may be a place to look for explaining the rise in SMM. For reference, Figures 3 and 4 show the year-by year changes in these variables, and as Figure 4 shows, many of the chronic conditions rise sharply over time.

To confirm these results, we conduct an Oaxaca-Blinder type of decomposition of SMM over time. We average the first three years of the sample and compare these to the last three years. This will give a sense as to whether the 0.0094 percentage point increase is being driven by the observable characteristics or different returns to the characteristics. In results not shown, we find that about 40 percent of the change over the full time period is explained by changes in the mean characteristics. These changes are again driven primarily by chronic conditions and C-section delivery, accounting for 76 percent of the explained variation.

Decomposition Analyses

Turning to the question of decomposing the racial gap, Table 6 shows results from the Oaxaca-Blinder decomposition of SMM and SMM excluding blood transfusion among Blacks and Whites. Analyses are shown for 1998-2019 and 1998-2011 using the same sets of variables with the addition of county-variables for the models ending in 2011. Across the models, the difference in the means in the sets of maternal and hospital characteristics explain 36%-44% of the gap. Differences in the betas explain the rest. Within the explained portion, payer type,

delivery type and chronic conditions explain non-trivial portions, however, the largest driver of the Black-White gap is the percent of a hospital's patients who are Black, accounting for 39 to 55 percent of the explained portion. Interestingly, the ratios of preventable conditions account for almost none of the gap, indicating that there is something specific about these Black-serving hospitals rather than the local health of the community served that contributes to the SMM racial gap. This implies that within hospital quality is a focus for further exploration.

Table 7 shows results from explaining the SMM gap using reweighting estimation, replacing the distributions of White mothers' characteristics with those of Black mothers. Based on the 1998-2019 analysis sample, the actual SMM gap (Black SMM rate − White SMM rate) is 0.11. The counterfactual White SMM rate is 0.016, and the explained gap (counterfactual White SMM rate − White SMM rate) is 0.004, constituting 39 percent of the total.[4] Using similar calculations, we find that the portion of the Black-White gap in outcomes that can be explained using observable characteristics ranges from 39-53 percent, depending on the sample and the outcome being considered. These results are similar to those found above using the Oaxaca-Blinder decomposition.

In Table 7, we also examine the contribution of individual factors. The reweighting matches distribution of a specified White mothers' factor with that of Black mothers and keeps the distributions of all other White mothers' characteristics as close to original as possible. Based on these preliminary findings, we make three observations. First, no single factor stands out as a

[4] Alternatively, if we replace Black mothers' characteristics to those of White mothers, we find that observed characteristics as a group explain about 69 percent of the Black-White SMM gap. This asymmetry may come from matching problems that vary by race. For example, assume very young maternal age is an important risk factor for SMM, and assume there are very few or no White mothers of very young age. When re-weighting the White mothers to give them the age distribution of Black mothers, the re-weighting does not work well since there are few or no very young White mothers, and one cannot explain much of the SMM gap. On the other hand, when re-weighting the Black mothers to replace their characteristics with those of White mothers, we would assign zero or very low weights to the youngest mothers, greatly reducing SMM and explaining much of the gap.

feature that explains a substantial portion of the Black-White gap in outcomes, highlighting the idea that health disparities are multifactorial (and probably driven by numerous unmeasured factors as well). Second, maternal age and maternal co-morbidities, which are measured extensively in the NIS and have been the focus of prior medical research, generally do not play the most important role in explaining the gap. Maternal age, in fact, is advantageous for Black mothers' outcomes vs. those of White mothers, which is why the explained portion of the gap can even be negative in sign. Finally, insurance status, median income in the zip code area where the mother lives, and some hospital characteristics are important explanatory variables. In future research, we will drill down into these variables further to better understand their role. It appears that giving birth in a Black-serving hospital is an important individual covariate in explaining the gap.

5. Conclusions

SMM rates have been rising for all mothers over time, and worse so among Black mothers. In this paper, we examine why this might be happening. Previous literature takes a limited-scope approach by focusing on a one or a few select variables as determinants of SMM. We do not focus on any particular hypothesis, rather we evaluate the contributions of a large set of variables over a long time span to let the data inform us a what factors may be most influential in determining SMM. Specifically, we use inpatient data from 1998-2019 to see how the broad sets of maternal, hospital, and county-level characteristics may be associated with both the rising trends and the racial disparity in SMM. We use three different analyses to draw conclusions. We first assess the model fit to see which variables may contribute the most to explaining the overall variation in SMM. Second, we calculate the contribution to the total prediction

accounted for by each set of variables over time. Third, we decompose the Black-White gap in SMM rates using mean and distributional techniques.

We draw the following conclusions from our analyses: 1) There is a lot of randomness to each incident of SMM. The observed characteristics explain very little of the overall variation of SMM. However, of what is explained, chronic conditions and C-sections appear to be the largest drivers. This is supported by increasing trends among new mothers in conditions such as respiratory disease, hypertension, substance abuse and obesity over time. 2) The Black-White gap in SMM is large and about half can be explained by differences in the observable characteristics we include. The largest driver of the gap by far the variable that measures the percent of a hospital's patients that are black. To some degree, this may reflect the unmeasured quality of hospitals. Previous literature has shown that hospitals serving high proportions of Black patients fare worse in terms of patient safety indicators. This measure may also pick up some community-based health metrics, however, given that the preventable hospitalization ratios contribute very little to the explained part of the gap, this explanation seems less likely.

This project is designed to give researchers some ideas of where to focus prevention efforts. We emphasize that our results are not causal and our methods are designed to highlight strong associations that would serve as a starting point for future causal analyses. The results indicate that focusing on patients with co-morbid chronic conditions, who deliver by C-sections, and who deliver in hospitals with large portions of Black patient would be promising places to start.

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Figure 1: SMM Rates Over Time

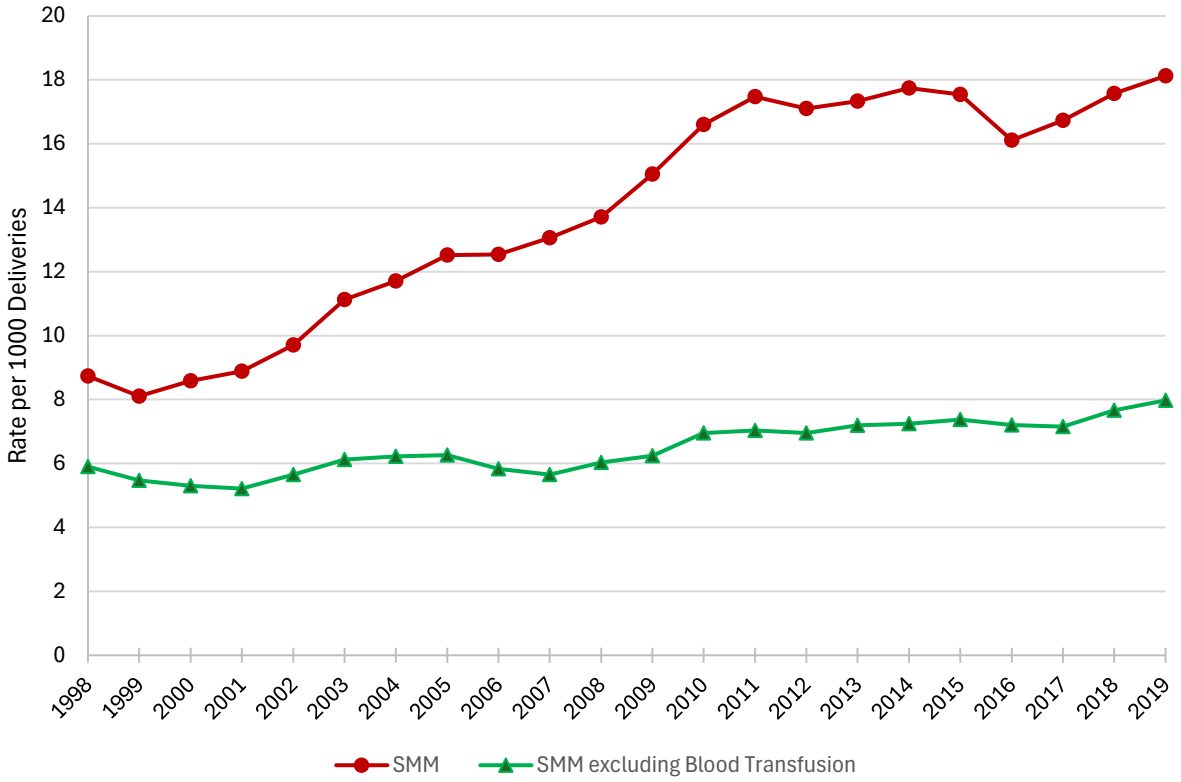
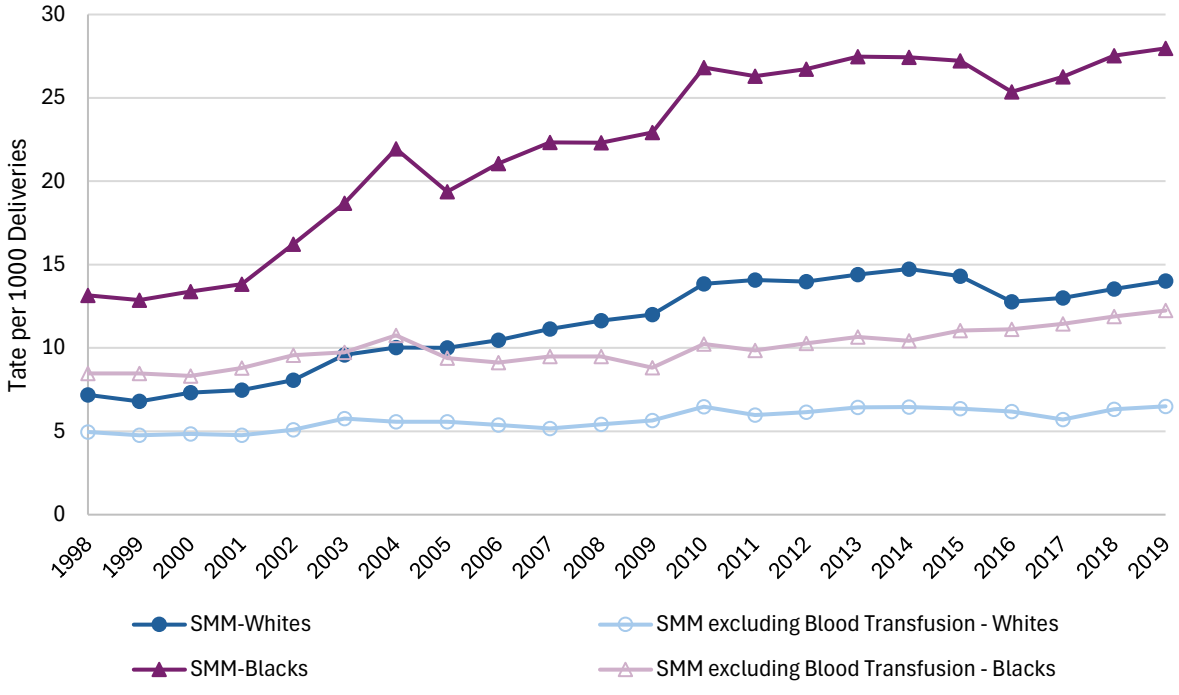
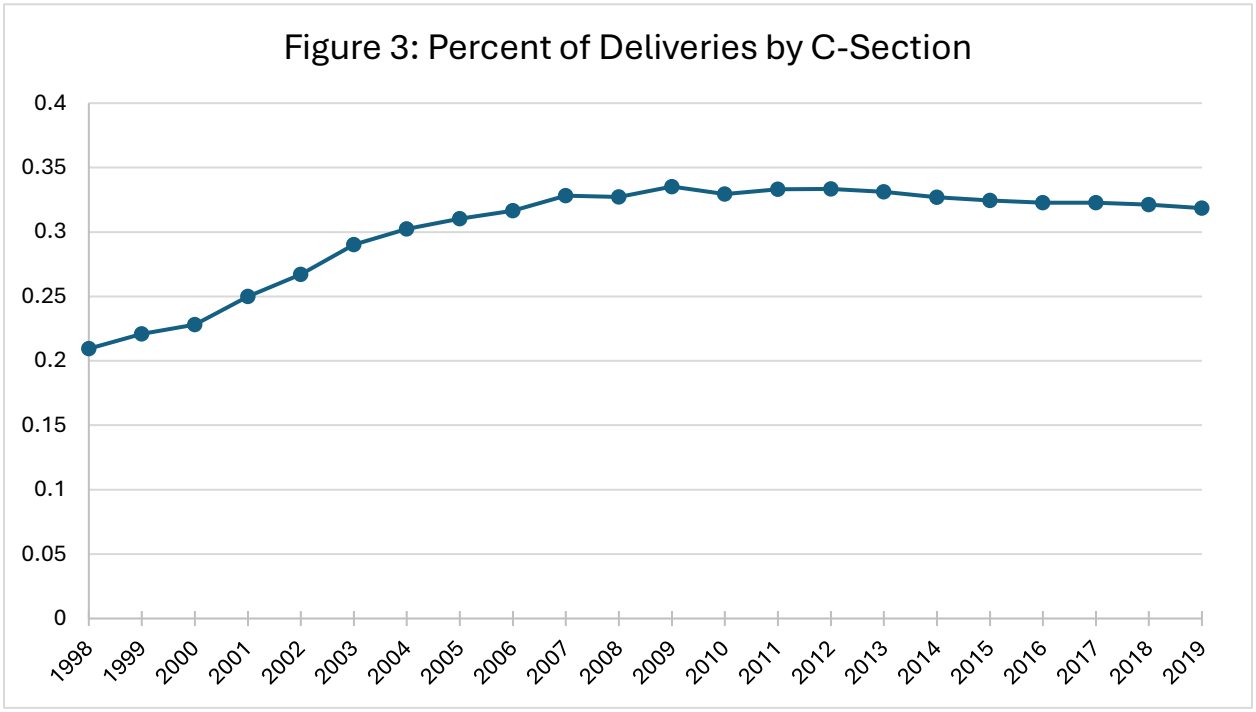


Figure 2: SMM Rates Over Time, Blacks and Whites




Figure 3: Percent of Deliveries by C-Section
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

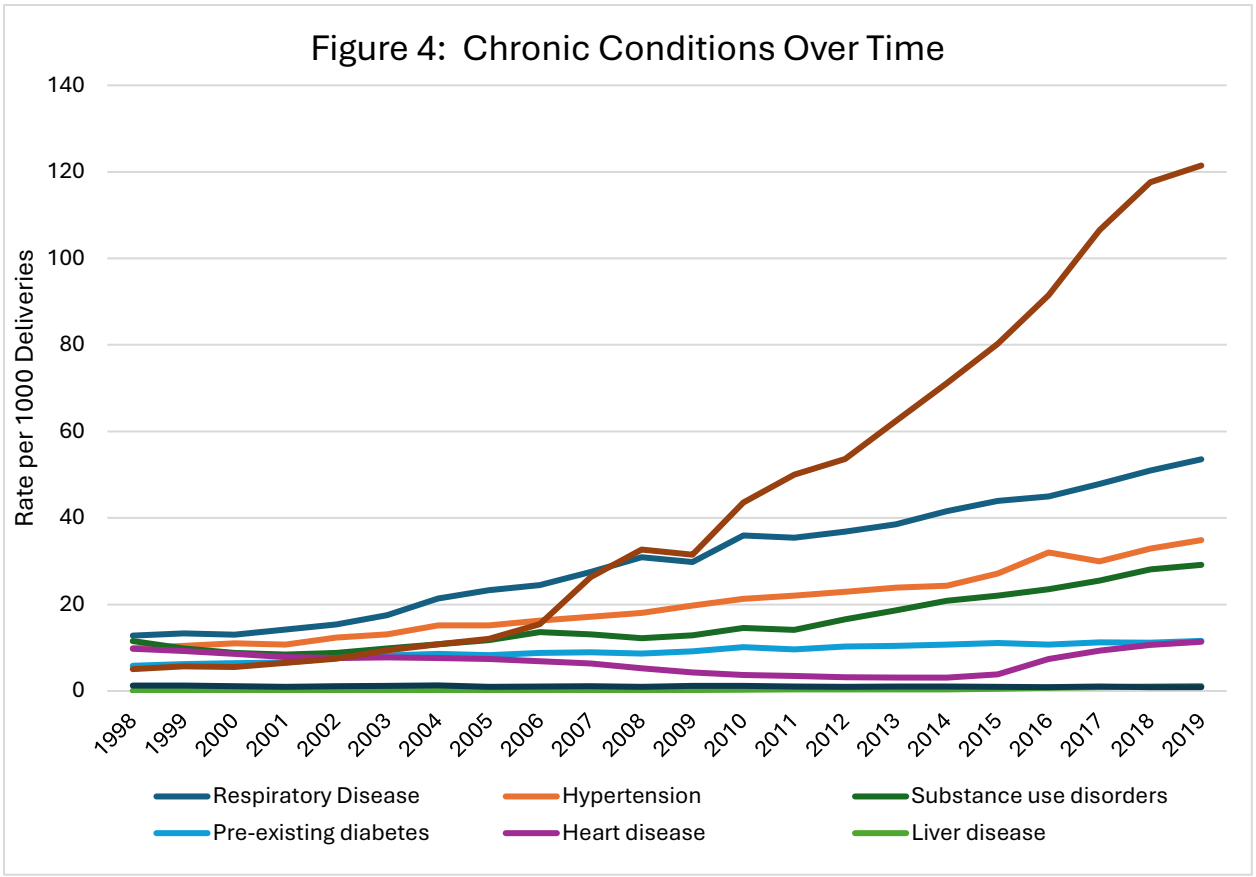

Figure 4: Chronic Conditions Over Time
Rate per 1000 Deliveries
140
120
100
80
60
40
20
0
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
Respiratory Disease
Hypertension
Substance use disorders
Pre-existing diabetes
Heart disease
Liver disease

Table 1: Dependent and Independent Variables

Variable:	Source:	Indicator(s):	Years available:
Dependent Variables:			
SMM	NIS	SMM during delivery hospitalization (see table notes for list)	1998-2019
SMM excluding blood transfusion	NIS	SMM during delivery hospitalization excluding SMM for blood transfusion only (see table notes for list)	
Independent Variables:			
Maternal Characteristics:			
Age	NIS	Age of mother (<20, 20-24, 25-29 30-34, 35-39, 40+)	1998-2019
Race	NIS	White, Black, Hispanic, Asian, Native American, other races, race missing	
Payer	NIS	Medicare, Medicaid, private, other payer, payer missing	
Zip code income> median	NIS	Income in patient's zip code > median national income, zip code income missing	
Chronic conditions	NIS	Respiratory disease, hypertension, substance use disorders, pre-existing diabetes, heart disease, renal disease, liver disease, HIV, obesity	
Type of delivery	NIS	C-section	
Hospital Characteristics:			
Size	NIS	Small, medium, large, (thresholds determined by rurality and teaching status of hospital, see table notes)	1998-2019
Urban, Rural, Teaching status	NIS	Rural, urban teaching, urban non-teaching, status missing	
Ownership status	NIS	Government (non-federal), private (not-for-profit or for-profit), ownership missing	
Percent Black	NIS	Percent of hospital's deliveries to Black mothers, percent race missing	
Health disparities among publicly-insured	NIS	Ratio of Black/White preventable hospitalizations among publicly insured adult males at hospital. Includes indicators for zero in numerator, zero in denominator, and ratio missing	
Health disparities among privately-insured	NIS	Ratio of Black/White preventable hospitalizations among privately insured adult males at hospital. Includes indicators for zero in numerator, zero in denominator, and ratio missing	
County Health Care Access:			

OB/GYN density	AHRF	Number of OB/GYNs per 1000 women age 15-44 in county of hospital. (Converted to above median, at or below median)	1998-2011
Primary care physician density	AHRF	Number of primary care physicians 1000 women age 15-44 in county of hospital. (Converted to above median, at or below median)	1998-2011
Medically underserved county	AHRF	Hospital county has a designation of medically underserved.	1998-2011
County SES:			
Poverty	AHRF	Percent of hospital county below federal poverty line. (Converted to above median, at or below median, or missing)	1998-2011
Unemployment	AHRF	Hospital county unemployment rate (Converted to above median, at or below median, or missing)	1998-2011
Population	AHRF	Population of county of hospital <100,000; greater than 100,000, population is missing	1998-2011
Per capita income	AHRF	Real per capital income in hospital county. (For reweighting analysis, converted to above median, at or below median, or missing)	1998-2011

Notes: NIS: National (Nationwide) Inpatient Sample; AHRF: Area Health Resource File. SMM includes the following diagnoses and procedures: Acute myocardial infarction, aneurysm, acute renal failure, acute respiratory distress syndrome, amniotic fluid embolism, cardiac arrest / ventricular fibrillation, conversion of cardiac rhythm, disseminated intravascular coagulation, blood transfusion, eclampsia, heart failure / arrest during surgery or procedure, puerperal cerebrovascular disorders, pulmonary edema / acute heart failure, severe anesthesia complications, sepsis, shock, sickle cell disease with crisis, air and thrombotic embolism, hysterectomy, temporary tracheostomy, and ventilation.

Table 2: Sample Means

	Full Sample 1998-2019	Sample with Hospital Identifiers 1998-2011	Sample with County Identifiers 1998-2011	Whites 1998-2019	Blacks 1998-2019
SMM	0.014	0.012	0.011	0.012	0.023
SMM excluding blood transfusion	0.006	0.006	0.006	0.006	0.010
Age <20	0.090	0.106	0.097	0.066	0.139
Age 20-24	0.233	0.244	0.230	0.206	0.305
Age 25-29	0.278	0.273	0.272	0.284	0.258
Age 30-34	0.249	0.235	0.247	0.278	0.181
Age 35-39	0.123	0.116	0.126	0.136	0.093
Age 40 and up	0.028	0.026	0.029	0.030	0.024
White	0.440	0.409	0.427		
Black	0.116	0.104	0.100		
Hispanic	0.184	0.178	0.180		
Asian	0.043	0.036	0.041		
Native American	0.006	0.005	0.005		
Other race	0.039	0.036	0.034		
Race missing	0.172	0.232	0.213		
C-section	0.302	0.290	0.285	0.305	0.332
Chronic respiratory disease	0.030	0.023	0.024	0.033	0.051
Chronic hypertension	0.020	0.015	0.014	0.018	0.044
Substance use disorders	0.015	0.011	0.012	0.018	0.028
Pre-existing diabetes	0.009	0.008	0.008	0.008	0.013
Chronic heart disease	0.007	0.007	0.007	0.009	0.006
Chronic renal disease	0.004	0.002	0.002	0.004	0.005
Chronic liver disease	0.0003	0.0002	0.0002	0.0003	0.0003
HIV	0.001	0.001	0.001	0.000	0.005
Obesity	0.042	0.019	0.019	0.042	0.075
Private pay	0.526	0.536	0.564	0.654	0.331
Medicare	0.006	0.005	0.004	0.006	0.011
Medicaid	0.407	0.396	0.373	0.290	0.607

Other payer	0.059	0.061	0.057	0.049	0.050
Payer missing	0.002	0.002	0.002	0.002	0.002
Large hospital	0.584	0.612	0.619	0.568	0.586
Small hospital	0.133	0.116	0.123	0.153	0.116
Medium hospital	0.280	0.268	0.257	0.276	0.294
Hospital size missing	0.003	0.004	0.000	0.003	0.004
Teaching hospital	0.511	0.447	0.455	0.471	0.651
Rural hospital	0.112	0.119	0.102	0.137	0.066
Urban nonteaching hospital	0.374	0.429	0.442	0.388	0.279
Location/teaching missing	0.003	0.004	0.000	0.003	0.004
Private hospital	0.623	0.491	0.482	0.663	0.616
Government hospital	0.100	0.091	0.082	0.090	0.115
Hospital ownership missing	0.277	0.418	0.436	0.247	0.269
High zip code income	0.546	0.589	0.628	0.601	0.358
Zip code income missing	0.016	0.018	0.019	0.012	0.018
Percent black	0.119	0.107	0.104	0.113	0.320
Percent black missing	0.146	0.204	0.179	0.000	0.000
Ob/Gyns per capita	0.682	0.682	0.682	0.679	0.752
Primary care MDs per capita	1.425	1.425	1.425	1.413	1.211
Medically underserved area	0.007	0.007	0.007	0.009	0.011
Percent pop in poverty	12.495	12.495	12.495	11.663	13.671
Unemployment	5.915	5.915	5.915	5.634	6.107
County pop < 100,000	0.123	0.123	0.123	0.150	0.069
Real income per capita	19.299	19.299	19.299	19.216	19.306
Black-White PQI private pay ratio	1.844	1.715	1.757	2.075	2.527
Black-White PQI private ratio numerator zero	0.104	0.068	0.068	0.142	0.038
Black-White PQI private ratio denominator zero	0.020	0.008	0.006	0.013	0.031
Black-White PQI private ratio missing	0.216	0.253	0.222	0.090	0.028
Black-White PQI public pay ratio	1.190	1.057	1.082	1.330	1.592
Black-White PQI public ratio	0.070	0.053	0.053	0.104	0.018

numerator zero					
Black-White PQI public ratio denominator zero	0.010	0.005	0.004	0.008	0.009
Black-White PQI public ratio missing	0.207	0.252	0.224	0.077	0.024
Hisp-White PQI private pay ratio	0.931	0.857	0.915	1.016	1.109
Hisp-White PQI private ratio numerator zero	0.186	0.131	0.130	0.270	0.259
Hisp-White PQI private ratio denominator zero	0.019	0.007	0.008	0.013	0.024
Hisp-White PQI private ratio missing	0.294	0.327	0.284	0.217	0.184
Hisp-White PQI public pay ratio	0.782	0.727	0.779	0.829	0.932
Hisp-White PQI public ratio numerator zero	0.147	0.113	0.113	0.219	0.209
Hisp-White PQI public ratio denominator zero	0.012	0.007	0.005	0.010	0.010
Hisp-White PQI public ratio missing	0.303	0.342	0.295	0.232	0.194
New England	0.042	0.043	0.060	0.063	0.030
Middle Atlantic	0.118	0.117	0.163	0.144	0.145
East North Central	0.140	0.138	0.107	0.135	0.106
West North Central	0.071	0.071	0.073	0.082	0.047
South Atlantic	0.214	0.227	0.228	0.201	0.379
East South Central	0.048	0.041	0.020	0.066	0.074
West South Central	0.120	0.111	0.009	0.110	0.132
Mountain	0.070	0.067	0.091	0.076	0.022
Pacific	0.177	0.184	0.250	0.124	0.066
Observations	17,648,783	11,683,664	8,393,985	7,767,180	2,049,259

Table 3: Metrics of Model Fit, Dependent variable = SMM

		Maternal characteristics, census division and year indicators	+ Chronic conditions and delivery type	+ Hospital characteristics	+ Hospital Percent Black + Hospital disparities	+ County characteristics	+ Hospital fixed effects
Panel A: 1998-2019	MSE	0.34123	0.34039	0.34037	0.34036		
	Adjusted-R^2	0.00254	0.01232	0.01254	0.01268		
Panel B: 1998-2011	MSE	0.32978	0.32919	0.32917	0.32916		0.32892
	Adjusted-R^2	0.002	0.00914	0.00938	0.00948		0.01248
Panel C: 1998-2011	MSE	0.32593	0.32536	0.32534	0.32533	0.32532	0.3251
	Adjusted-R^2	0.00202	0.00908	0.00933	0.00945	0.00947	0.01216

Num obs for Panel A =17,648,783
Num obs for Panel B =11,683,664
Num obs for Panel C =8,393,985

Table 4: Metrics of Model Fit, Dependent variable = SMM Excluding Blood Transfusion

		Maternal characteristics, census division and year indicators	+ Chronic conditions and delivery type	+ Hospital characteristics	+ Hospital Percent Black + Hospital disparities	+ County characteristics	+ Hospital fixed effects
Panel A: 1998-2019	MSE	0.28279	0.28219	0.28218	0.28217		
	Adjusted-R^2	0.00098	0.00937	0.00957	0.00960		
Panel B: 1998-2011	MSE	0.27767	0.27732	0.27731	0.2773		0.27718
	Adjusted-R^2	0.00076	0.00585	0.00605	0.00608		0.00783
Panel C: 1998-2011	MSE	0.2761	0.27574	0.27573	0.27572	0.27572	0.27562
	Adjusted-R^2	0.0008	0.00596	0.00614	0.00617	0.00619	0.00771

Num obs for Panel A =17,648,783
Num obs for Panel B =11,683,664
Num obs for Panel C =8,393,985

Table 5: Changes from 1998 – 2019

Observed change in SMM	0.0094	
Total predicted change in SMM	0.0141	
	Amount of predicted	% of predicted
Age	-0.0002	-0.0124
Race	0.0001	0.0042
Payer	0.0002	0.0138
Zip code income	0.0002	0.0125
Chronic conditions	0.0020	0.1447
Delivery type	0.0020	0.1454
Hospital characteristics	0.0007	0.0473
Percent black	0.0002	0.0118
PQI ratios	0.0001	0.0064
Census divisions	0.0002	0.0163
Year indicators and constant	0.0085	0.6039

Predicted amounts calculated by $[\overline{X}_{2019} — \overline{X}_{1998}]\beta$

Table 6: Oaxaca-Blinder Decomposition of SMM Among Blacks and Whites

	SMM	SMM	SMM Excluding Blood Transfusion	SMM Excluding Blood Transfusion
	1998-2019	1998-2011	1998-2019	1998-2011
Black SMM	0.023	0.019	0.010	0.010
White SMM	0.012	0.010	0.006	0.005
Difference	0.011 (0.0001)	0.010 (0.0002)	0.004 (0.0001)	0.004 (0.0001)
Explained	0.004 [36%] (0.0001)	0.004 [42%] (0.0001)	0.002 [42%] (0.0001)	0.002 [44%] (0.0001)
Unexplained	0.007 [64%] (0.0001)	0.006 [58%] (0.0002)	0.003 [58%] (0.0001)	0.002 [56%] (0.0002)
Components of explained portion				
Age	3.93%	1.24%	-5.94%	-5.54%
Payer	16.12%	13.27%	13.14%	11.93%
Income	6.66%	3.86%	7.21%	4.05%
Chronic conditions	13.54%	10.45%	21.85%	15.19%
Delivery type	10.11%	7.05%	11.60%	9.09%
Hospital characteristics	7.12%	10.84%	18.62%	21.41%
Hospital percent Black	41.41%	55.49%	38.72%	54.78%
Hospital PQI ratios	0.21%	-2.80%	1.10%	-2.61%
County Characteristics		0.90%		-5.35%
Census divisions	-0.94%	-2.23%	-5.40%	-3.23%
Years	1.84%	1.93%	-0.90%	0.28%

Notes: The decompositions include the full set of explanatory variables detailed in the data section. Rows 1 and 2 present the probability of SMM and the difference is shown in row 3. Rows 4 and 5 present the contribution of the explained and unexplained components with the percent of the difference in brackets. Heteroskedastic robust standard errors in parentheses.

Table 7: Aggregate Decomposition: Giving White mothers the distributions of characteristics of Black mothers

	SMM	SMM Excluding Blood Transfusion
	1998-2019 sample	1998-2019 sample
Actual Black	0.023	0.010
Actual White	0.012	0.006
Counterfactual White	0.016	0.008
Actual gap	0.011	0.004
Explained gap	0.0043 [38.55%]	0.0020 [46.10%]
Select components of explained portion		
Age	0.30%	-0.50%
Payer types	6.90%	6.10%
Median HH income in zip code	3.60%	2.70%
Black-serving hospital	3.80%	3.60%
Substance use disorder	0.80%	1.00%
Obesity	0.60%	1.00%
Hypertension	1.70%	3.20%
Diabetes	0.30%	0.60%
C-section	3.60%	4.70%
Black-White gap in ACS, public ins.	0.10%	0.50%
Black-White gap in ACS, private ins.	0.50%	1.20%

Notes: "Actual" are unweighted rates based on live in-hospital deliveries in the NIS sample. "Counterfactual" are rates if White mothers were given the distributions of all of the characteristics of the Black mothers using reweighting methods developed by Elder et al. (2011, 2015, 2016).

Appendix to Exploring Trends in Severe Maternal Morbidity in the U.S.

1. Reweighting Decomposition

In our context, by Elder et al. (2015) we should estimate the following sample weights for the White mothers:

$$\psi^{z}_{W\to B}(z,x_1)=\frac{dF(z|t=B)-dF(z|t=W)+dF(z|x_1,t=W)}{dF(z|x_1,t=W)},$$

where $F(z|\cdot)$ denote the conditional cumulative distribution function of z. Note that $dF(z|\cdot)$ becomes $P(z|\cdot)$ when the support of z is discrete.

Elder et al. (2015) suggests that the reweighting $\psi^{z}_{W\to B}(z,x_1)$ has nice theoretical properties. But for the reweighting method to work, it requires the following support condition to be satisfied: $dF(z,x_1|t=W)>0,\forall z,x_1$ for which $dF(z)>0$ and $dF(x_1|t=W)>0$. Elder et al. (2015) use sample analogue to estimate the conditional probabilities in $\psi^{z}_{W\to B}(z,x_1)$. However, such estimation could violate the support condition in common situations. Suppose that the supports of x_1 and z are discrete, and x_1 can take many different values when $t=W$. Then some combinations of values of x_1 and z may be not observable conditional on $t=W$ in finite sample, then it results in the estimated $P(z,x_1|t=W)$ equaling zero if using the sample analogue estimation, which violates the support condition.

Elder et al. (2015) recognizes this issue and proposes two ways to deal with it. One way is to reduce the number of possible values that x_1 can take, while another way is to adjust the original sample analogue estimates as described in Elder et al. (2015) . In this paper, we propose a third simple way to deal with this issue. Note that by the Bayes' rule, we have:

$$dF(z, x_1|t = W) = \frac{P(t = W|z, x_1) \times dF(z|x_1) \times dF(x_1)}{P(t = W)}.$$

Therefore, for the support condition to hold, the estimated value for the numerator of the above equation should be positive for all possible z and x_1. For simplicity let the support of z be finite and discrete so that $dF(z|x_1)$ can be replaced with $P(z|x_1)$. If we estimate $P(t = W|z, x_1)$ and $P(z|x_1)$ using the logistic transformation, then the estimates must be positive if the logits are bounded, which is guaranteed to be the case if we use boosted trees or penalized logistic regression to estimate the logits, and thus the support condition must hold. Given such idea, we can rewrite $\psi^z_{W\to B}(z, x_1)$ further. Note that by the Bayes' rule we have:

$$dF(z|t = W) = \frac{P(t = W|z) \times dF(z)}{P(t = W)},$$

$$dF(z|x_1, t = W) = \frac{P(t = W|z, x_1)}{P(t = W|x_1)} \times dF(z|x_1),$$

then we can rewrite $\psi^z_{W\to B}(z, x_1)$ as:

$$\psi^z_{W\to B}(z, x_1) = \frac{\frac{1 - P(t = W|z)}{1 - P(t = W)} - \frac{P(t = W|z)}{P(t = W)} + \frac{P(t = W|z, x_1)}{P(t = W|x_1)} \times \frac{dF(z|x_1)}{dF(z)}}{\frac{P(t = W|z, x_1)}{P(t = W|x_1)} \times \frac{dF(z|x_1)}{dF(z)}}.$$

Suppose that the support of z is finite and discrete so that $dF(z|x_1)$ can be replaced with $P(z|x_1)$. We can see that if we estimate all the conditional probabilities in the equation above simple probit models, then the estimated conditional probabilities must be positive and thus the support condition must hold.

2. Linear Probability Models—Full Results

	(1) SMM	(2) SMM	(3) SMM	(4) SMM excluding blood transfusion	(5) SMM excluding blood transfusion	(6) SMM excluding blood transfusion
Age 20-24	-0.0031***	-0.0023***	-0.0020***	-0.0013***	-0.0010***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age 25-29	-0.0042***	-0.0030***	-0.0026***	-0.0012***	-0.0009***	-0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age 30-34	-0.0037***	-0.0022***	-0.0019***	-0.0006***	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age 35-39	-0.0018***	-0.0005***	-0.0002	0.0008***	0.0011***	0.0010***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Age 40 and up	0.0031***	0.0040***	0.0041***	0.0040***	0.0040***	0.0039***
	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Black	0.0059***	0.0055***	0.0054***	0.0024***	0.0025***	0.0027***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Hispanic	0.0026***	0.0018***	0.0016***	0.0003***	0.0002**	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Asian	0.0026***	0.0020***	0.0020***	0.0007***	0.0003*	0.0005***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Native American	0.0063***	0.0040***	0.0037***	0.0016***	0.0010**	0.0009*
	(0.0004)	(0.0005)	(0.0006)	(0.0003)	(0.0003)	(0.0004)
Other race	0.0027***	0.0014***	0.0011***	0.0007***	0.0002	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Race missing	0.0021***	0.0010***	0.0009***	0.0005***	0.0004*	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Medicare	0.0127***	0.0117***	0.0116***	0.0083***	0.0072***	0.0077***
	(0.0004)	(0.0005)	(0.0006)	(0.0003)	(0.0003)	(0.0004)
Medicaid	0.0025***	0.0016***	0.0016***	0.0008***	0.0005***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)

Other payer	0.0023***	0.0018***	0.0019***	0.0007***	0.0005***	0.0007***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Payer missing	0.0015*	0.0017*	0.0030**	0.0007	0.0004	0.0020**
	(0.0006)	(0.0007)	(0.0009)	(0.0004)	(0.0005)	(0.0007)
High zip code income	-0.0013***	-0.0010***	-0.0009***	-0.0005***	-0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Zip code income missing	0.0011***	0.0004	0.0010***	0.0001	0.0000	0.0002
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Chronic respiratory disease	0.0044***	0.0030***	0.0029***	0.0029***	0.0022***	0.0019***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Chronic hypertension	0.0163***	0.0160***	0.0163***	0.0125***	0.0124***	0.0124***
	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Substance use disorders	0.0112***	0.0093***	0.0089***	0.0060***	0.0044***	0.0042***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Pre-existing diabetes	0.0080***	0.0061***	0.0063***	0.0067***	0.0050***	0.0050***
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0003)
Chronic heart disease	0.0451***	0.0199***	0.0193***	0.0388***	0.0176***	0.0170***
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0003)
Chronic renal disease	0.0823***	0.0566***	0.0552***	0.0636***	0.0446***	0.0439***
	(0.0004)	(0.0007)	(0.0008)	(0.0003)	(0.0005)	(0.0006)
Chronic liver disease	0.0945***	0.1344***	0.1344***	0.0765***	0.1018***	0.1022***
	(0.0015)	(0.0024)	(0.0027)	(0.0010)	(0.0017)	(0.0019)
HIV	0.0137***	0.0095***	0.0094***	0.0030***	0.0015*	0.0012
	(0.0008)	(0.0010)	(0.0011)	(0.0006)	(0.0007)	(0.0008)
Obesity	0.0009***	0.0002	0.0006*	0.0015***	0.0009***	0.0010***
	(0.0001)	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
C-section	0.0188***	0.0175***	0.0169***	0.0091***	0.0092***	0.0092***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Small hospital	-0.0011***	0.0001	-0.0000	-0.0016***	-0.0005**	-0.0008***
	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)

Medium hospital	-0.0005***	0.0001	-0.0001	-0.0007***	-0.0002	-0.0004**
	(0.0001)	(0.0002)	(0.0002)	(0.0000)	(0.0001)	(0.0002)
Hospital size missing	-0.0020***	-0.0017*	-0.0004	-0.0012***	-0.0008	0.0012
	(0.0005)	(0.0007)	(0.0033)	(0.0004)	(0.0005)	(0.0024)
Rural hospital	-0.0012***	0.0001	-0.0003	-0.0024***	-0.0004	-0.0009*
	(0.0001)	(0.0005)	(0.0006)	(0.0001)	(0.0004)	(0.0004)
Urban nonteaching hospital	-0.0027***	-0.0005	-0.0004	-0.0018***	-0.0002	-0.0002
	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Government hospital	0.0030***	0.0024***	0.0026***	0.0010***	0.0004*	0.0001
	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Hospital ownership missing	0.0001	-0.0004*	-0.0008***	-0.0001	0.0000	-0.0001
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Percent Black	0.0105***	0.0005	0.0051***	0.0024***	-0.0034***	-0.0023*
	(0.0002)	(0.0008)	(0.0013)	(0.0002)	(0.0006)	(0.0009)
Percent Black missing	0.0010***	0.0000	-0.0003	0.0007***	-0.0004	-0.0000
	(0.0002)	(0.0005)	(0.0005)	(0.0002)	(0.0003)	(0.0004)
Black-White PQI private pay ratio	0.0001***	0.0001	0.0001	0.0001***	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Black-White PQI private ratio numerator zero	0.0001	-0.0001	-0.0001	0.0002**	-0.0001	-0.0002
	(0.0001)	(0.0002)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Black-White PQI private ratio denominator zero	0.0029***	0.0002	-0.0015	0.0007***	0.0007	-0.0001
	(0.0003)	(0.0009)	(0.0011)	(0.0002)	(0.0006)	(0.0008)
Black-White PQI private ratio missing	-0.0003*	-0.0003	-0.0002	0.0001	-0.0003	-0.0005
	(0.0002)	(0.0004)	(0.0004)	(0.0001)	(0.0003)	(0.0003)
Black-White PQI public pay ratio	0.0003***	-0.0001	-0.0000	0.0001***	-0.0001	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)

Black-White PQI public ratio numerator zero	0.0010***	0.0002	0.0006*	0.0003**	-0.0000	-0.0000
	(0.0001)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Black-White PQI public ratio denominator zero	0.0002	-0.0018	-0.0018	-0.0001	-0.0006	-0.0010
	(0.0005)	(0.0009)	(0.0012)	(0.0003)	(0.0007)	(0.0009)
Black-White PQI public ratio missing	0.0013***	0.0001	0.0002	0.0004**	-0.0004	-0.0006*
	(0.0002)	(0.0004)	(0.0004)	(0.0001)	(0.0003)	(0.0003)
Hisp-White PQI private pay ratio	0.0001**	0.0000	0.0001**	0.0000*	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hisp-White PQI private ratio numerator zero	0.0003**	-0.0001	0.0005*	0.0002***	-0.0002	-0.0000
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Hisp-White PQI private ratio denominator zero	-0.0010***	-0.0010	0.0011	-0.0005*	-0.0006	0.0004
	(0.0003)	(0.0008)	(0.0010)	(0.0002)	(0.0006)	(0.0007)
Hisp-White PQI private ratio missing	0.0004*	-0.0000	0.0007*	0.0001	0.0003	0.0005*
	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Hisp-White PQI public pay ratio	-0.0001***	0.0000	0.0000	-0.0001***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Hisp-White PQI public ratio numerator zero	-0.0009***	-0.0002	-0.0002	-0.0003***	0.0002	0.0002
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Hisp-White PQI public ratio denominator zero	0.0010*	0.0015	0.0008	0.0004	0.0002	0.0005
	(0.0004)	(0.0009)	(0.0012)	(0.0003)	(0.0006)	(0.0009)
Hisp-White PQI public ratio missing	-0.0004**	-0.0001	-0.0001	-0.0002*	0.0002	0.0000
	(0.0002)	(0.0003)	(0.0003)	(0.0001)	(0.0002)	(0.0002)
Ob/Gyns per capita			0.0007			0.0016***

			(0.0005)			(0.0003)
Primary care MDs per capita			-0.0008**			-0.0004*
			(0.0003)			(0.0002)
Medically Underserved area			0.0003			0.0003
			(0.0008)			(0.0006)
Percent pop in poverty			0.0001			-0.0000
			(0.0000)			(0.0000)
Unemployment			0.0000			-0.0000
			(0.0000)			(0.0000)
County pop < 100,000			0.0018*			-0.0004
			(0.0007)			(0.0005)
Real income per capita			-0.0001***			-0.0000
			(0.0000)			(0.0000)
Observations	17648783	11683664	8393985	17648783	11683664	8393985
MSE	0.3404	0.3289	0.3251	0.2822	0.2772	0.2756
Adjusted R^2	0.0127	0.0125	0.0122	0.0096	0.0078	0.0077