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ABSTRACT

The incidence of severe maternal morbidity (SMM) in the U.S. has been rising among mothers over time, with especially pronounced increases 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 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. Decomposition methods show that the observed characteristics explain very little of the overall variation of SMM, but account for a substantial share of the Black-White SMM gap. Medical and pregnancy-related comorbid conditions are the largest drivers of the observed variations. The associational findings indicate that focusing on patients with comorbid conditions and delving more deeply into the features of hospital environments may help researchers identify policy-relevant drivers of SMM and SMM disparities.

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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; Moaddab et al., 2016). Severe maternal morbidity is the "unexpected outcomes of labor or delivery resulting in significant short- or long-term consequences to health" (CDC, 2024a). The SMM rate in the U.S. has more than doubled in recent years, increasing from 8.7 per 1,000 in-hospital deliveries in 1998 to 18.1 per 1,000 in-hospital deliveries in 2019 (authors' calculations, see Figure 1).[1] This striking trend in maternal morbidity is unique to the U.S. with current rates far higher than that of other high-income countries (Gunja et al., 2024).

Considerable variation also exists across racial/ethnic groups in maternal mortality and morbidity. Hispanics and non-Hispanic Blacks and Asian/Pacific Islanders all experience SMM at rates higher than non-Hispanic Whites. In 2021, the SMM rate for Blacks was 1.9 times higher than that of non-Hispanic Whites (Reid, 2024). These numbers also reflect the rapid rise in SMM among Blacks over time (see Figure 2).

Why have maternal mortality and morbidity rates been rising in the U.S., and why have some groups of mothers been disproportionately affected? Researchers hypothesize that increasing rates of SMM and mortality may be due to changes such as increased maternal age,

[1] These statistics are calculated from the 1998 to 2019 National Inpatient Sample (NIS) and include blood transfusions in the SMM rate. Non-transfusion SMM increased from 5.9 to 8 cases per 1000 deliveries. 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).

increased body weight, Cesarean delivery, cigarette and illegal drug use during pregnancy, preexisting chronic conditions, low socio-economic status (SES), and issues related to providers and medical care (Creanga et al., 2012; Callaghan et al., 2012; Creanga et al., 2014; Moaddab et al., 2016; Leonard et al. 2019; Admon et al. 2017; Robinson et al., 2024). Factors related to the health care system including low supplies of midwives and ob-gyns, or lack of mandated maternity leave policies are also thought to be contributors (Gunja et al., 2024). Systemic 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. (2025) 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 rural location 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-Hispanic Whites. Moreover, rates of uninsurance and Cesarean delivery have fallen over time, and adherence to treatments for chronic conditions such as diabetes and cardiovascular disease (CVD), which are risk factors for poor maternal outcomes, 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 one or a few specific contributors at a time. For example, Linsonkova et al. (2017) study the effect of older maternal age on SMM, Jarlenski et al. (2017)

and Hawkings et al. (2023) focus on state-level reproductive health policies, Fischer et al. (2024) look at obstetric unit closures, and Chatterji et al. (2023) examines Medicaid expansions.

Studies that focus on the relative contributions of larger sets of variables focus on small or specific populations including births in university-based hospitals (Grobman et al., 2014), patients in New York (Howland et al., 2019 and Guglielminotti et al. 2019) and in Texas (Milazzo 2024). There have been no systematic nationwide analyses of the determinants of SMM. This paper addresses this gap in the literature.

Papers that specifically examine the Black-White gap in SMM include Adams et al. (2023), Adams et al. (2025), and Milazzo (2024). The papers by Adams et al. analyze rates of SMM in Georgia, focusing on the contributions of 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. Milazzo's models, which use data from women in Texas, include patient age and payment source, location and distance to hospital, comorbid conditions, characteristics of the local community, and hospital fixed effects. Together these variables explain 78 percent of the gap with the comorbid conditions being the largest contributors.

In this paper, we use national hospital discharge data over a twenty-two year 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 factors contributing to the Black-White SMM gap. The methods we use highlight the main associative

determinants and produce results that 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 two different analyses to draw conclusions. We first use the Shapley-Owens-Shorrocks decomposition of the model R-squared to determine which variables contribute the most to explaining the overall variation in SMM. We do this for broad groups of years and then separately for years over time. We then use the Oaxaca-Blinder method to decompose the Black-White gap in SMM rates. Our results indicate that comorbid conditions appear to be the largest drivers of the overall variation in SMM across and within hospitals, although collectively the observed factors generally do not explain much of the total variation. By contrast, a large portion of the Black-White gap in SMM can be explained by the observed variables, with comorbid conditions and some hospital-specific factors being the largest contributors. 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. Data and Methods

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 non-Hispanic Black and White mothers. We focus on this specific 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. 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 comorbidities, 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. These data do not contain hospital identifiers that can be linked across time, but they do uniquely identify hospitals within each year. Given the changes in sampling and availability of identifiers, we run all analyses first

using all available years (1998-2019) and second on a limited set (1998-2011) that allows us to use the geographic information that is available in the earlier time period. We also run some models for each year from 2012 to 2019 separately, taking advantage of the presence of the within-year hospital identifiers.

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 comorbid and chronic conditions (which are used as covariates in the models), we used mapping provided by Leonard et al. (2022). Details are provided below and in Appendix A.

In each year of our sample, the NIS contains information on 6.8 to 8.0 million discharges from around 2500-2600 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 White mothers and 2,049,259 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 (2024b), with SAS coding provided by Rankin (2018).[2] Blood transfusion is 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 non-transfusion 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 maternal characteristics, hospital characteristics, and 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, delivery by Cesarian section, medical comorbidities, and pregnancy-related conditions. 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 used in 1998-2011 for the select states that report county identifiers.

The comorbid conditions we include are categorized into medical and pregnancy related. The full list and details on the construction of these variables are as described in Leonard (2022) and also in Appendix A. We use sixteen medical conditions including chronic diseases such as renal and cardiac disease, blood disorders, preexisting anemia, and substance

[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.

use disorder. Eight pregnancy related conditions are used and include variables such as previous C-section, gestational diabetes, and pre-eclampsia. We took care to make sure that no ICD code that is present in SMM is also present in the list of these comorbidities.

We generate two measures of potential 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. We compute the rate of privately insured admissions in the hospital in each year for preventable conditions for Blacks, Hispanics and Whites. The Black/White and Hispanic/White ratios are considered to be capturing 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 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. We refer to this set of variables as "preventable hospitalization ratios". Details on the construction of these measures are provided in Appendix B.

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:

(1) 1998-2019: $SMM_{iht} = \alpha_1 Maternal_{iht} + \alpha_2 Hospital_{ht} + \tau_t + \Gamma_d + \varepsilon_{it}$

(2) 1998-2011: $SMM_{iht} = \beta_1 Maternal_{iht} + \beta_2 Hospital_{ht} + \tau_t + \delta_h + \varepsilon_{it}$

(3) 1998-2011: $SMM_{ihct} = \gamma_1 Maternal_{ihct} + \gamma_2 Hospital_{hct} + \gamma_3 County_{ct} + \tau_t + \delta_h + \varepsilon_{it}$

(4) 2012; 2013…2019: $SMM_{ih} = \beta_1 Maternal_{ih} + \delta_h + \varepsilon_i$

In the equations above, the indicator for SMM or non-transfusion SMM (*SMM*) for individual (i) in hospital (h) and year (t) are a function of the vectors of covariates described in Table 1 for the individual maternal characteristics (M*aternal*), hospital-level characteristics (*Hospital*) and county-level characteristics when available (*County*). Equations 1, 2 and 3 also include dummy indicators for year (τ_t) to capture secular trends in the outcomes. In equation 1 we include a set of census division indicators (Γ_d) to reflect broad geographic characteristics since other geographic identifiers are not available after 2011. Hospital fixed effects (δ_h) are added to equations 2, 3, and 4.

Equation 4 describes models that are run separately by year when there are unique hospital identifiers within each year. Note that the hospital identifiers cannot be pooled over time, but since our outcomes are observed at the individual level, within a year we can include hospital fixed effects while excluding the observable hospital characteristics of bed size, ownership, teaching status, preventable hospitalization ratios, and percent of hospital patients who are Black. This exercise allows us to evaluate the contribution of measured and unmeasured hospital characteristics after the sampling change of 2012. It also allows us to see if the change of the

ICD codes in the 4th quarter of 2015 affects the estimates. For these models, year 2015 includes only the first three quarters when ICD-9-CM was in effect.

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 variables 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 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 the variation in SMM, we use the Shapley-Owens-Shorrocks (SOS) decomposition of the R-squared value. The method is described in detail by Audoly et al. (2025). Briefly, the SOS decomposition uses all possible combinations of a set of variables, calculates the change in R-squared for each variant, and weighs them by the probability of the variant occurring. This generates the proportion of the R-squared that can be attributed to each variable or groups of variables. The advantage to this method is that it is symmetric with respect to the order of the arguments, meaning the order each variable is removed from consideration does not matter.

The SOS decomposition is conducted first using the full sample from 1998-2019 and necessarily only includes maternal and hospital characteristics, year indicators, and census division indicators. We show the proportion of the total R-squared accounted for by the following groups of variables: Maternal characteristics (age, race, payer, zip code income); c-

section delivery; medical comorbidities; pregnancy-related conditions; hospital characteristics (including size, urban/rural/teaching, ownership, preventable hospitalization ratios), hospital percent Black, year indicators, and census division. We then limit the sample to 1998-2011 and compare models with and without hospital fixed effects, and with the county health care access and SES measures for the limited set of hospitals during this time period that report county identifiers. Lastly, we run the SOS decomposition for each year separately for 2012-2019 with hospital fixed effects included instead of the observed hospital characteristics listed above.

The second part of our analyses uses the Oaxaca-Blinder (O-B) decomposition to analyze the SMM gap between non-Hispanic Black mothers and non-Hispanic White mothers. We focus only on Blacks and Whites rather than Hispanics or other races as the gaps among the other groups are not large. The O-B 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 an "explained portion" which can be attributed to differences in the averages of the predictor variables across the groups; and 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 predicted racial difference in SMM would change if White mothers, who are treated as the base group, have same mean characteristics as Black mothers. We run the O-B decomposition for pooled years 1998-2019, 1998-2011 with and without hospital fixed effects, and separately by year for 2012-2019 with hospital fixed effects.[3]

[3] Hospital fixed effects are included with the following procedure. We first run a LPM model for Whites only using the "areg" command in stata with hospital identifiers as the absorbed variable. A value for the fixed effects is predicted as Y-XB within each hospital using the hospital average Y and X values. This predicted fixed effect is then merged into the full sample of Blacks and Whites based on the hospital identifier and is included as a right-

3. 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 shows trends in SMM and non-transfusion SMM 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 C displays Appendix Figures 1-8 showing standard linear probability models for SMM and non-transfusion SMM as the dependent variables. Results are shown for 1998-2019; 1998-2011 without hospital effects; 1998-2011 with hospital effects, and 1998-2011 with hospital fixed effect and county variables. Overall, the results are in line with what many others have found. Older and very young mothers, mothers with certain comorbid and chronic health conditions, and mothers having C-sections have elevated risk of adverse outcomes. Having public insurance, delivering in rural hospitals, and delivering in hospitals with larger percentages of Black patients are all factors associated with a higher probability of both SMM and non-transfusion SMM. The sample of years examined has little effects on the magnitudes of the coefficients, and many of the results hold even after hospital fixed effects are included. One

hand side variable in the standard "oaxaca" command. This procedure yields the same estimates as including a series of indicator variables for each hospital into the model. Given that we observe around 2500 hospitals each year, including the individual indicators is not feasible. This method allows us both to include the fixed effects and measure their contribution to the explained portion of the SMM gap.

exception is that the percent of hospital patients who are Black falls in magnitude and becomes statistically insignificant.

Shapley-Owens-Shorrocks Decomposition

Table 3 shows results from the SOS decomposition of the R-squared for SMM and non-transfusion SMM. We first note that the actual values of the R-squared are very low in all models. For SMM, the R-squared ranges 0.055 to 0.09, and for non-transfusion SMM, the range is smaller at 0.05 to 0.069. While small R-squared values are typical of individual-level pooled cross-sectional data, nevertheless, these values indicate that the variables we include do not explain much of the overall variation in the incidence of SMM. With that caveat in mind, for both measures of SMM, medical comorbidities are by far the largest contributors to the R-squared ranging from 43 to 76 percent for SMM and 57 percent to 83 percent for non-transfusion SMM. It appears that the switch to ICD-10-CM codes matters, with the contribution falling for both outcomes after 2015.

Pregnancy related conditions are also important with a contribution of 15 to 26 percent for SMM and 9.7 percent to 21 percent for non-transfusion SMM. The higher ends of the ranges occur after 2015, concurrent with the drop in the magnitude for the medical conditions after the code switch.

Regardless of the time period studied and regardless of the inclusion of other included variables such as hospital fixed effects and county-level variables, the medical and pregnancy variables constitute 68 percent to 94 percent of the measured variation in SMM and 78 percent to 96 percent of non-transfusion SMM. Clearly these sets of variables make up the bulk of the observed variation in the outcomes indicating that the pathway to improving SMM rates may lie

in the attention to these pre-existing conditions. This is a departure from previous literature that points to factors such as older maternal age (Linsonkova et al. 2017), C-sections (Robinson et al. 2024) and income (Kennedy-Moulton et al. 2025) as drivers of maternal morbidities, while confirming the focus on medical comorbidities as per Leonard et al. (2020) and Leonard et al. (2022).

The hospital fixed effects do not explain much of the variation in the R-squared in the early years of the panel, however, as time progresses, the hospital fixed effects become more important, replacing some of the effects of the medical and pregnancy related conditions. It is likely that the differing magnitudes are a result of the changing sampling framework after 2011 and the ICD-9 to ICD-10 coding switch making it difficult to compare results across these time periods. Clean comparisons can be made within 2016-2019 and here we see the hospital fixed effects accounting for around 20 percent of the R-squared for SMM and 11 percent to 18 percent for non-transfusion SMM. These results indicate that there may be something specific to certain hospitals that results in worse outcomes. In results not shown, we rerun the models in Tables 3 by year excluding the hospital fixed effect and including instead all observable hospital characteristics. The contribution of these variables remains very small. Bed size, urban/rural/teaching status, ownership, preventable hospitalization ratios, and percent of hospital patients Black constitute at most 2 percent of the R-squared for SMM and less than 1 percent for non-transfusion SMM. It therefore appears that there are other unobserved factors present in certain hospitals that are associated with increased SMM. Identifying these specific factors is a direction for future research.

Oaxaca-Blinder Decomposition

Turning to the question of decomposing the Black-White gap in SMM, Tables 4, 5, and 6 show results from the Oaxaca-Blinder decomposition of SMM and non-transfusion SMM among Blacks and Whites. Analyses are shown for 1998-2019 and 1998-2011 using comparable sets of variables are in Table 4. Analyses with hospital fixed effects for 1998-2011 are also in Table 4, and analyses with hospital fixed effects by year for 2012-2015 and 2016-2019 are in Tables 5 and 6, respectively.

The results in Table 4 show that across the models, the observed maternal and hospital characteristics along with year and census division indicators collectively explain large portions of the Black-White SMM gap. The explained proportion ranges from 73 percent to 86 percent for SMM and 66 percent to 67 percent for non-transfusion SMM. Including the hospital fixed effects raises the percent of the gap explained by the observed characteristics but by very little for non-transfusion SMM.

Within the explained portion, the medical comorbidities and pregnancy-related conditions are the largest contributors which is consistent with the results of the SOS decomposition of the R-squared. But contrary to the SOS decomposition results, here, the hospital fixed effects explain a fairly large share of the Black-White SMM gap. When these fixed effects are excluded, the percent of a hospital's patients who are Black account for around 15 percent of the explained portion. The other observed hospital characteristics contribute much smaller amounts to the explained portion, indicating that the size, type, and the preventable hospitalization ratios across hospitals are not informative of the SMM gap.

Table 5 contains results by year for 2012-2015 when ICD-9-CM codes are in effect. Models are shown first with the observed hospital characteristics including size, type, preventable hospitalization ratios, and percent of hospital patients who are Black. These

variables are then replaced with hospital fixed effects. Overall, the year-based models explain a fairly substantial portion of the SMM gap, with a range from 60 percent to 100 percent. The medical comorbidities are still the largest driver of the explained portion (54 percent to 78 percent). Pregnancy-related conditions are less important but still have a non-negligible contribution at a range of 10 percent to 20 percent. The contribution of the hospital fixed effects varies greatly by year making it difficult to draw conclusions here. A similar statement can be made for the percent of hospital patients who are Black.

Table 6 contains results by year for 2016-2019 when ICD-10-CM codes are in effect, with the model inclusion following the same pattern as in Table 5. Once again, the year-based models explain a fairly substantial portion of the SMM gap, with a range from 55 percent to 85 percent. The medical comorbidities remain largest driver of the explained portion although the magnitudes fall compared to the earlier years. Pregnancy related conditions grow in importance now contributing range of 14 percent to 23 percent to the explained portion of the SMM gap, and 22 percent to 40 percent of the non-transfusion SMM gap. As with the earlier years, the contribution of the hospital fixed effects and of percent of hospital patients who are Black varies by year and outcome under consideration but appear to grow in importance as time progressed.

Overall, these results suggest that the places to look for improvements in the Black-White SMM gap lie in the medical and pregnancy comorbidities of the patient, and within the unmeasured quality of hospitals, especially those who serve high proportions of Black patients. Other factors such as maternal age, c-section delivery, hospital size, type, preventable hospitalization ratios, county access and county SES are not the large drivers of the race-based gap.

4. 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 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 as to 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 Black-White disparity in SMM. We use two 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. Then we decompose the Black-White gap in SMM rates using differences in mean values.

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, medical comorbidities and pregnancy related conditions appear to be the largest drivers. This is supported by increasing trends among new mothers in preexisting conditions such as asthma, chronic hypertension, gastrointestinal diseases, chronic renal disease and obesity. 2) The Black-White gap in SMM is large and much of the gap can be explained by differences in the observable characteristics. The largest driver of the gap is again the medical and pregnancy related comorbidities, but the hospital fixed effects and the percent of a hospital's patients that are Black both have non-negligible contributions. These variables likely 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 (Ly et

al. 2010). These hospital-based measures 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 comorbid chronic medical and pregnancy-related conditions, 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

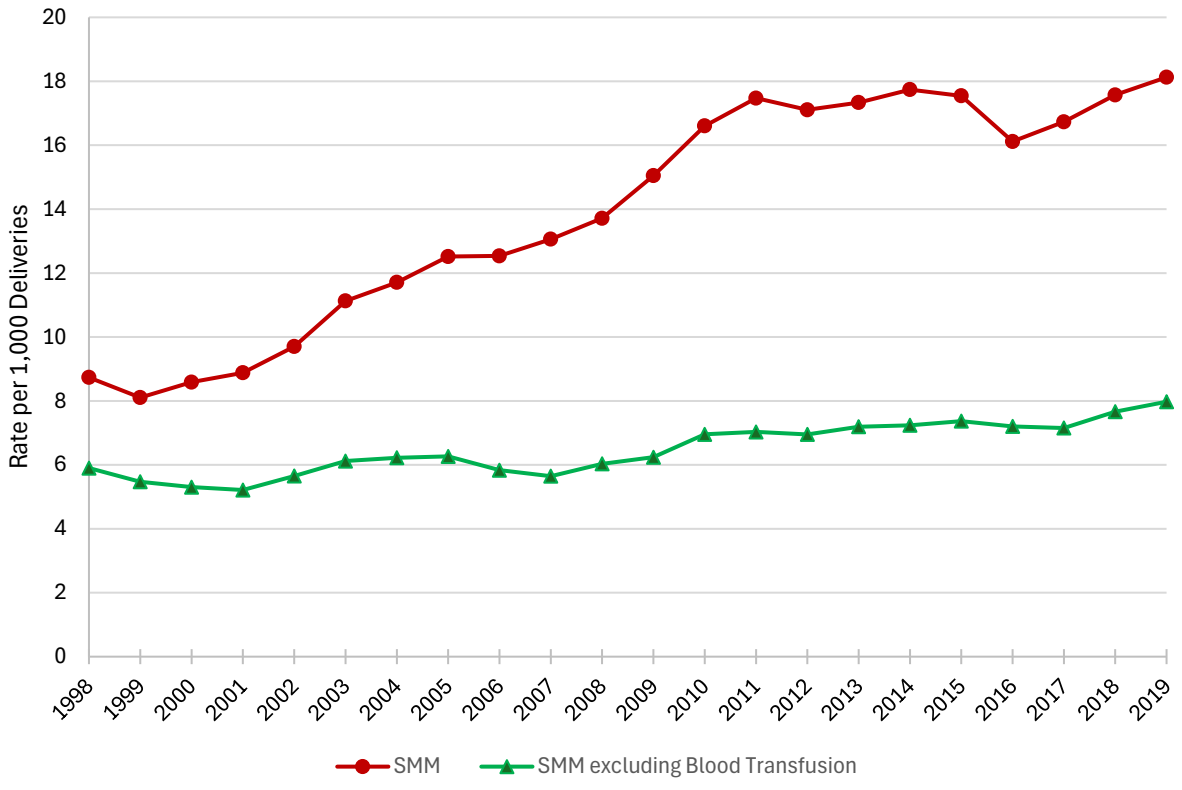

Figure 2: SMM Rates Over Time, Blacks and Whites

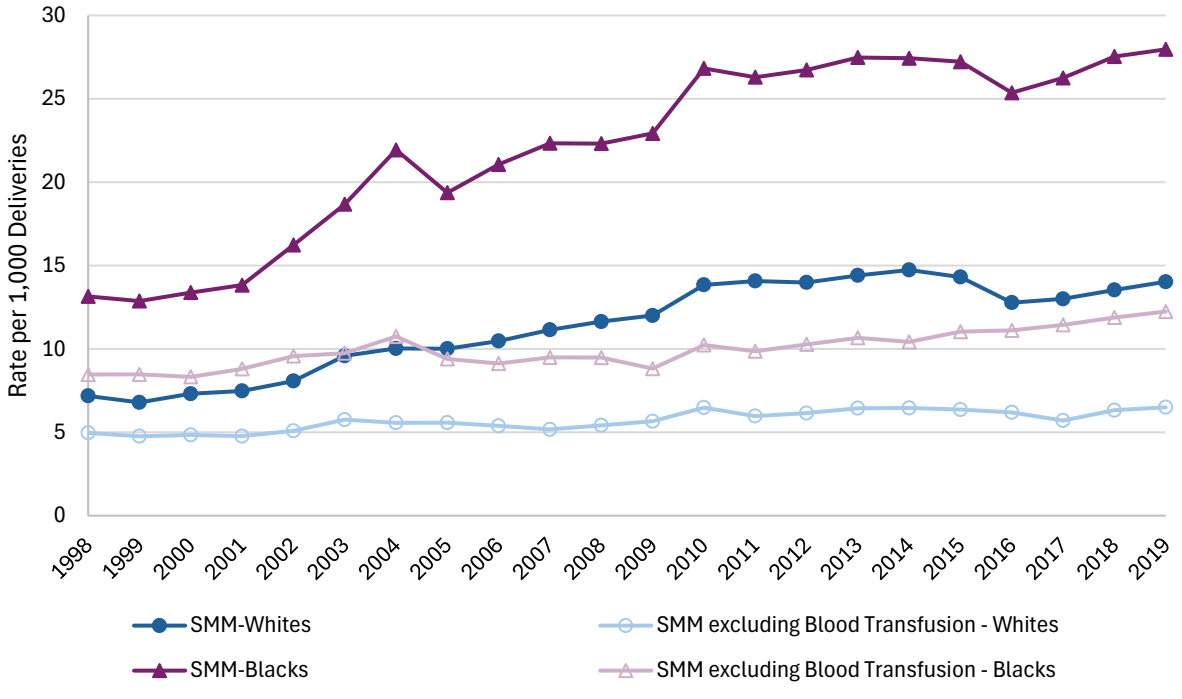

Table 1: Dependent and Independent Variables

Variable:	Source:	Indicator(s):	Years available:
Dependent Variables:			
SMM	NIS	SMM during delivery hospitalization (see table notes for list)	1998-2019
Non-transfusion SMM	NIS	SMM during delivery hospitalization excluding blood transfusion	
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; indicator for zip code income missing	
Type of delivery	NIS	C-section	
Medical comorbidities	NIS; Leonard (2022)	Anemia, asthma, bleeding disorder, cardiac disease, chronic hypertension, chronic renal disease, connective tissue or autoimmune disease, gastrointestinal disease, HIV/AIDS, neuromuscular disease, obesity, preexisting diabetes millitus, pulmonary hypertension, substance use disorder, thyrotoxicosis, uterine fibroids	
Pregnancy-related conditions	NIS; Leonard (2022)	Gestational diabetes mellitus, placental abruption, placenta previa, complete or partial, preeclampsia with severe features, preeclampsia without severe features or gestational hypertension, preterm birth (less than 37 weeks), previous cesarean birth, twin or multiple pregnancy	
Hospital Characteristics			
Size	NIS	Small, medium, large, size missing (thresholds determined by rurality and teaching status of hospital)	1998-2019

Urban, rural, teaching status	NIS	Rural, urban teaching, urban non-teaching, missing	
Ownership status	NIS	Government (non-federal), private (not-for-profit or for-profit), ownership missing	
Pct hospital patients Black	NIS	Percent of hospital's deliveries to Black mothers, indicator for percent race missing	
Preventable hospitalizations among publicly-insured	NIS	Ratios of Black/White and Hispanic/White preventable hospitalizations among publicly insured adult males at hospital. Includes indicators for zero in numerator, zero in denominator, and ratio missing	
Preventable hospitalizations among privately-insured	NIS	Ratios of Black/White and Hispanic/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 and SES			
OB/GYN density	AHRF	Number of OB/GYNs per 1000 women age 15-44 in county of hospital	1998-2011
Primary care physician density	AHRF	Number of primary care physicians 1000 women age 15-44 in county of hospital	
Medically underserved county	AHRF	Hospital county designated as medically underserved.	
Poverty	AHRF	Percent of hospital county below federal poverty line.	
Unemployment	AHRF	Hospital county unemployment rate	
Population	AHRF	Population of county of hospital <100,000	
Per capita income	AHRF	Real per capital income in hospital county	

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. Non-transfusion SMM excludes blood transfusion from the list of procedures.

Table 2: Sample Means

	Full Sample 1998-2019	Sample with Hospital Identifiers 1998-2011	Sample with County Identifiers 1998-2011	Non-Hispanic White 1998-2019	Non-Hispanic Black 1998-2019
Dependent Variables					
SMM	0.014	0.012	0.011	0.012	0.023
Non-transfusion SMM	0.006	0.006	0.006	0.006	0.010
Maternal Characteristics-Demographics/SES					
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	1.000	0.000
Black	0.116	0.104	0.100	0.000	1.000
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		
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
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
Maternal Characteristics-Type of delivery					
C-section	0.302	0.290	0.285	0.305	0.332

Maternal Characteristics-Medical Comorbidities					
Anemia	0.103	0.088	0.085	0.084	0.181
Asthma	0.030	0.022	0.024	0.033	0.050
Bleeding disorder	0.011	0.007	0.007	0.013	0.013
Cardiac disease	0.010	0.010	0.010	0.012	0.011
Chronic hypertension	0.020	0.015	0.014	0.018	0.044
Chronic renal disease	0.002	0.002	0.002	0.002	0.003
Connective tissue/autoimmune	0.002	0.002	0.002	0.002	0.002
Gastrointestinal	0.009	0.007	0.007	0.010	0.007
HIV/AIDS	0.001	0.001	0.001	0.000	0.005
Neuromuscular	0.003	0.002	0.002	0.003	0.004
Obesity	0.042	0.019	0.019	0.042	0.075
Preexisting diabetes millitus	0.010	0.008	0.008	0.008	0.014
Pulmonary hypertension	0.0002	0.0001	0.0001	0.0001	0.0004
Substance use disorder	0.026	0.028	0.027	0.031	0.034
Thyrotoxicosis	0.002	0.002	0.002	0.002	0.003
Uterine fibroids	0.011	0.010	0.010	0.008	0.027
Maternal Characteristics-Pregnancy-related conditions					
Placental abruption	0.011	0.011	0.011	0.010	0.015
Gestational diabetes	0.056	0.048	0.049	0.051	0.047
Previous c-section	0.154	0.143	0.140	0.151	0.170
Preterm birth	0.076	0.073	0.072	0.070	0.110
Mild preecampsia	0.058	0.052	0.049	0.064	0.071
Severe preecampsia	0.020	0.015	0.014	0.017	0.037
Placenta previa	0.005	0.005	0.005	0.005	0.005
Twins/Multiple pregnancy	0.018	0.017	0.018	0.020	0.020
Hospital Characteristics					
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
Pct hospital patients Black	0.119	0.107	0.104	0.113	0.320
Pct hospital patients Black missing	0.146	0.204	0.179	0.000	0.000
Black-White preventable hospitalization ratios					
Private pay ratio	1.844	1.715	1.757	2.075	2.527
Private pay numerator zero	0.104	0.068	0.068	0.142	0.038
Private pay denominator zero	0.020	0.008	0.006	0.013	0.031
Private pay ratio missing	0.216	0.253	0.222	0.090	0.028
Public pay ratio	1.190	1.057	1.082	1.330	1.592
Public pay numerator zero	0.070	0.053	0.053	0.104	0.018
Public pay denominator zero	0.010	0.005	0.004	0.008	0.009
Public pay ratio missing	0.207	0.252	0.224	0.077	0.024
Hispanic-White preventable hospitalization ratios					
Private pay ratio	0.931	0.857	0.915	1.016	1.109
Private pay numerator zero	0.186	0.131	0.130	0.270	0.259
Private pay denominator zero	0.019	0.007	0.008	0.013	0.024
Private pay ratio missing	0.294	0.327	0.284	0.217	0.184
Public pay ratio	0.782	0.727	0.779	0.829	0.932
Public pay numerator zero	0.147	0.113	0.113	0.219	0.209
Public pay denominator zero	0.012	0.007	0.005	0.010	0.010
Public pay ratio missing	0.303	0.342	0.295	0.232	0.194
County Characteristics					
Ob/Gyn density	0.682	0.682	0.682	0.679	0.752
Primary care physician density	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	19.299	19.299	19.299	19.216	19.306
Census Division					
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: Shapley-Owens-Shorrocks Decomposition of SMM and Non-Transfusion SMM

Years	1998-2019	1998-2011	1998-2011	1998-2011	2012	2013	2014	2015	2016	2017	2018	2019
SMM												
R-squared	0.065	0.075	0.078	0.076	0.090	0.088	0.085	0.082	0.055	0.058	0.059	0.061
Group relative contribution												
Maternal characteristics	1.3%	0.9%	0.8%	0.8%	1.1%	0.9%	1.0%	1.2%	1.9%	1.9%	1.8%	1.6%
C-section delivery	5.5%	4.3%	4.1%	4.1%	4.1%	4.3%	4.5%	4.8%	6.9%	6.9%	7.6%	7.5%
Medical comorbidities	70.2%	75.5%	72.4%	71.8%	68.9%	67.4%	63.8%	64.0%	43.1%	45.1%	45.9%	44.8%
Pregnancy-related conditions	21.4%	18.1%	17.1%	17.8%	15.3%	15.9%	17.4%	16.5%	25.1%	23.7%	23.5%	26.1%
Hospital characteristics	0.5%	0.4%	0.3%	0.3%								
Pct hospital patients Black	0.4%	0.2%	0.2%	0.2%								
Year	0.5%	0.3%	0.3%	0.3%								
Census division	0.2%	0.2%										
Hospital Fixed Effects			4.9%	4.6%	10.6%	11.4%	13.4%	13.5%	23.1%	22.3%	21.2%	20.0%
County Vars				0.2%								
Non-Transfusion SMM												
R-squared	0.051	0.059	0.060	0.058	0.068	0.069	0.064	0.063	0.050	0.058	0.060	0.062
Group relative contribution												
Maternal characteristics	0.8%	0.6%	0.6%	0.6%	0.8%	0.6%	0.8%	0.9%	1.2%	1.2%	1.1%	1.0%
C-section delivery	3.9%	3.3%	3.2%	3.4%	2.7%	2.6%	2.7%	2.9%	3.4%	3.6%	3.8%	3.7%
Medical comorbidities	78.0%	82.7%	80.3%	79.1%	77.3%	73.5%	71.9%	70.4%	56.8%	61.5%	63.3%	63.7%
Pregnancy-related conditions	16.6%	12.8%	12.3%	13.4%	9.7%	11.4%	13.9%	12.9%	20.8%	19.7%	19.1%	20.7%
Hospital characteristics	0.4%	0.3%	0.2%	0.2%								
Pct hospital patients Black	0.1%	0.1%	0.1%	0.1%								
Year	0.1%	0.1%	0.1%	0.1%								
Census division	0.1%	0.1%										
Hospital Fixed Effects			3.3%	3.0%	9.6%	11.8%	10.8%	13.0%	17.8%	14.1%	12.8%	10.9%
County Vars				0.1%								
N	17,648,783	11,683,664	11,683,664	8,393,985	753,128	748,224	760,247	571,936	756,770	740,828	726,916	716,645

Notes: Maternal characteristics include age, race, payer, income. Hospital characteristics include bed size, urban/rural, ownership, and preventable hospitalization ratios. In 1998-2019, the group with year indicators includes an indicator variable for observations in the 4th quarter of 2015 and later, representing the use of ICD-10-CM codes. The model in column eight for 2015 includes only the first three quarters of the year when ICD-9-CM codes were in use.

Table 4: Oaxaca-Blinder Decomposition of SMM Among Blacks and Whites, Pooled Years

SMM	**1998-2019**	**1998-2011**	**1998-2011**	**1998-2011**
Black SMM	0.023	0.020	0.020	0.019
White SMM	0.012	0.010	0.010	0.010
Difference	0.011	0.010	0.010	0.010
Explained	0.008 [73.4%]	0.007 [75.1%]	0.008 [83.4%]	0.008 [85.7%]
Unexplained	0.003 [26.6%]	0.002 [24.9%]	0.002 [16.6%]	0.001 [14.3%]
Percent of explained portion				
Maternal characteristics	6.9%	5.3%	3.0%	2.3%
C-section delivery	3.2%	2.0%	1.8%	1.9%
Medical comorbidities	62.0%	62.1%	58.2%	57.8%
Pregnancy-related conditions	16.1%	15.5%	13.7%	13.9%
Hospital characteristics	-1.3%	*-0.2%*		
Pct hospital patients Black	13.6%	15.7%		
Year	*0.02%*	0.18%		
Census division	-0.5%	*-0.6%*		
Hospital fixed effects			23.3%	23.1%
County Characteristics				1.0%
Non-Transfusion SMM				
Black SMM	0.010	0.009	0.009	0.010
White SMM	0.006	0.005	0.005	0.005
Difference	0.004	0.004	0.004	0.004
Explained	0.003 [67.1%]	0.003 [65.7%]	0.003 [67.5%]	0.003 [66.4%]
Unexplained	0.001 [32.9%]	0.001 [34.3%]	0.001 [32.5%]	0.001 [33.6%]
Percent of explained portion				
Maternal characteristics	6.2%	5.0%	-2.0%	*0.3%*
C-section delivery	5.1%	3.8%	3.6%	4.0%
Medical comorbidities	48.8%	47.5%	46.6%	48.5%
Pregnancy-related conditions	27.0%	25.2%	24.1%	24.6%
Hospital characteristics	3.9%	4.9%		
Pct hospital patients Black	13.9%	14.9%		
Year	-1.85%	-1.01%		
Census division	-3.0%	*-0.3%*		
Hospital fixed effects			27.7%	35.5%
County Characteristics				-12.8%
N	9,816,439	5,989,343	5,989,343	4,426,813

Notes: The decompositions include the full set of explanatory variables detailed in the data section. Rows labeled Black SMM and White SMM present the unadjusted probabilities. The difference in the probabilities is shown, as is the contribution of the explained and unexplained components with the percent in brackets. Models that span 1998-2019 include an indicator variable for observations in the 4th quarter of 2015 and later, representing the use of ICD-10-CM codes in the year grouping. Numbers in italics indicate estimates that are statistically insignificant (different from zero only at levels higher than the 10 percent level). Standard errors are heteroskedasticity robust.

Table 5: Oaxaca-Blinder Decomposition of SMM Among Blacks and Whites, by Year 2012-2015

SMM	**2012**	**2012**	**2013**	**2013**	**2014**	**2014**	**2015**	**2015**
Black SMM	0.027	0.027	0.027	0.027	0.027	0.027	0.027	0.027
White SMM	0.014	0.014	0.014	0.014	0.015	0.015	0.014	0.014
Difference	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013
Explained	0.009 [71.4%]	0.009 [69.6%]	0.009 [71.0%]	0.010 [74.8%]	0.011 [83.6%]	0.013 [100.9%]	0.010 [80.9%]	0.012 [93.7%]
Unexplained	0.004 [28.6%]	0.004 [30.4%]	0.004 [29.0%]	0.003 [25.2%]	0.002 [16.4%]	-0.0001 [-0.9%]	0.002 [19.1%]	0.001 [6.3%]
Percent of explained portion								
Maternal characteristics	6.7%	3.7%	*0.6%*	*-2.5%*	7.2%	3.3%	9.6%	5.1%
C-section delivery	3.3%	3.2%	3.4%	3.0%	3.7%	3.0%	4.2%	3.4%
Medical comorbidities	70.3%	77.6%	73.0%	73.5%	68.4%	59.8%	65.3%	60.0%
Pregnancy-related conditions	12.8%	13.2%	13.3%	12.6%	12.3%	10.1%	11.8%	10.2%
Hospital characteristics	-0.3%		-3.1%		*0.6%*		*-0.1%*	
Pct hospital patients Black	9.5%		10.8%		8.6%		9.4%	
Census division	-2.2%		*2.1%*		*-0.8%*		*-0.2%*	
Hospital fixed effects		2.3%		13.4%		23.8%		21.3%
Non-Transfusion SMM								
Black SMM	0.010	0.010	0.011	0.011	0.010	0.010	0.011	0.011
White SMM	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
Difference	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
Explained	0.003 [69.3%]	0.002 [59.2%]	0.003 [71.5%]	0.003 [77.9%]	0.003 [85.6%]	0.003 [83.5%]	0.003 [74.1%]	0.004 [85.2%]
Unexplained	0.001 [30.7%]	0.002 [40.8%]	0.001 [28.5%]	0.001 [22.1%]	0.001 [14.4%]	0.001 [16.5%]	0.001 [25.9%]	0.001 [14.8%]
Percent of explained portion								
Maternal characteristics	*0.6%*	*-3.0%*	-8.1%	-11.0%	8.4%	6.8%	8.7%	*4.9%*
C-section delivery	5.3%	6.0%	4.8%	4.2%	5.4%	5.4%	5.9%	4.8%
Medical comorbidities	56.3%	69.9%	61.1%	57.5%	60.6%	63.3%	59.1%	53.8%
Pregnancy-related conditions	17.4%	20.4%	19.6%	17.9%	18.4%	18.8%	19.3%	16.6%
Hospital characteristics	5.5%		5.0%		*3.8%*		8.5%	
Pct hospital patients Black	26.9%		23.6%		*8.1%*		*7.0%*	
Census division	-11.9%		-6.0%		-4.7%		-8.5%	
Hospital fixed effects included		6.7%		31.3%		5.7%		19.9%
N	481,221	481,221	475,688	475,688	483,233	483,233	362,752	362,752

Notes: The decompositions include the full set of explanatory variables detailed in the data section. Rows labeled Black SMM and White SMM present the unadjusted probabilities. The difference in the probabilities is shown, as is the contribution of the explained and unexplained components with the percent in brackets. Numbers in italics indicate estimates that are statistically insignificant (different from zero only at levels higher than the 10 percent level). Standard errors are heteroskedasticity robust. The models for 2015 include only the first three quarters of the year when ICD-9-CM codes were in use.

Table 6: Oaxaca-Blinder Decomposition of SMM Among Blacks and Whites, by Year 2016-2019

SMM	**2016**	**2016**	**2017**	**2017**	**2018**	**2018**	**2019**	**2019**
Black SMM	0.025	0.025	0.026	0.026	0.028	0.028	0.028	0.028
White SMM	0.013	0.013	0.013	0.013	0.014	0.014	0.014	0.014
Difference	0.013	0.013	0.013	0.013	0.014	0.014	0.014	0.014
Explained	0.007 [58.4%]	0.009 [69.2%]	0.008 [64.0%]	0.011 [85.0%]	0.008 [60.6%]	0.010 [71.2%]	0.009 [64.5%]	0.011 [75.5%]
Unexplained	0.005 [41.6%]	0.004 [30.8%]	0.005 [36.0%]	0.002 [15.0%]	0.006 [39.4%]	0.004 [28.8%]	0.005 [35.5%]	0.003 [24.5%]
Percent of explained portion								
Maternal characteristics	16.1%	8.0%	14.3%	6.6%	11.9%	4.9%	10.7%	3.5%
C-section delivery	6.6%	5.5%	5.9%	4.4%	7.2%	6.0%	6.4%	5.5%
Medical comorbidities	48.6%	42.2%	52.1%	40.2%	46.8%	41.6%	50.9%	44.3%
Pregnancy-related conditions	22.4%	18.8%	18.6%	14.0%	22.7%	19.2%	20.5%	17.4%
Hospital characteristics	*-1.9%*		4.1%		-3.3%		*-2.1%*	
Pct hospital patients Black	9.0%		*5.6%*		14.5%		14.1%	
Census division	*-0.8%*		*-0.5%*		*0.4%*		*-0.6%*	
Hospital fixed effects		25.5%		34.8%		28.2%		29.3%
Non-Transfusion SMM								
Black SMM	0.011	0.011	0.011	0.011	0.012	0.012	0.012	0.012
White SMM	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
Difference	0.005	0.005	0.006	0.006	0.006	0.006	0.006	0.006
Explained	0.003 [57.7%]	0.003 [57.8%]	0.003 [55.3%]	0.005 [81.7%]	0.004 [63.3%]	0.003 [61.7%]	0.004 [63.6%]	0.004 [71.8%]
Unexplained	0.002 [42.3%]	0.002 [42.2%]	0.003 [44.7%]	0.001 [18.3%]	0.002 [36.7%]	0.002 [38.3%]	0.002 [36.4%]	0.002 [28.2%]
Percent of explained portion								
Maternal characteristics	10.7%	*5.3%*	12.6%	6.7%	10.6%	9.1%	6.2%	*2.0%*
C-section delivery	7.9%	7.9%	7.4%	5.0%	7.8%	8.1%	7.5%	6.7%
Medical comorbidities	43.0%	43.0%	43.3%	29.8%	31.4%	32.5%	40.3%	35.6%
Pregnancy-related conditions	40.2%	39.5%	33.1%	22.1%	37.6%	38.1%	32.9%	28.6%
Hospital characteristics	*3.2%*		8.3%		*-0.7%*		*-1.3%*	
Pct hospital patients Black	*-0.5%*		*3.6%*		21.6%		21.0%	
Census division	-4.6%		-8.4%		-8.3%		-6.6%	
Hospital fixed effects included		4.3%		36.4%		12.2%		27.1%
N	483,266	483,266	475,373	475,373	474,341	474,341	470,972	470,972

Notes: The decompositions include the full set of explanatory variables detailed in the data section. Rows labeled Black SMM and White SMM present the unadjusted probabilities. The difference in the probabilities is shown, as is the contribution of the explained and unexplained components with the percent of the difference in brackets. Numbers in italics indicate estimates that are statistically insignificant (different from zero only at levels higher than the 10 percent level). Standard errors are heteroskedasticity robust.