Racial and Ethnic Infant Mortality Gaps and the Role of SES

Todd E. Elder
Michigan State University

John H. Goddeeris
Michigan State University

Steven J. Haider
Michigan State University

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Abstract

We assess the extent to which differences in socio-economic status are associated with racial and ethnic gaps in a fundamental measure of population health: the rate at which infants die. Using micro-level Vital Statistics data from 2000 to 2004 for whites, blacks, Mexicans, Puerto Ricans, Asians, and Native Americans, we first examine how infant mortality and its subcomponents are associated with background characteristics. Although the racial and ethnic groups differ along several observable dimensions, each of the between-group mortality gaps is strongly associated with three background characteristics: maternal marital status, education, and age. For example, if whites had the distribution of these three characteristics found among the high-IMR groups, we estimate that the white infant mortality rate would increase by about 1.9 deaths per 1000 live births, roughly one-third of the actual white infant mortality rate. Using data on new mothers from the Census, we further show that these three characteristics are each strongly associated with income and poverty. Overall, these results suggest that SES differences play a substantial role in the IMR gaps across these groups.

1. Introduction

The infant mortality rate (IMR), the number of deaths in the first year of life per 1000 live births, is a widely used indicator of population health and well-being. In 2006, the overall IMR for the United States was 6.68, but mortality rates differed dramatically across racial and ethnic groups (Matthews and MacDorman, 2010). Non-Hispanic blacks had the highest IMR at 13.35, compared to 5.58 among non-Hispanic whites. Among other race and ethnic groups, the IMRs among American Indians / Alaska Natives (8.28) and Puerto Ricans (8.01) were greater than that of non-Hispanic whites, while the IMRs for Mexicans (5.34), Central / South Americans (4.52), Cubans (5.08), and Asians / Pacific Islanders (4.55) were lower.[1]

Given the well-known disparities in socio-economic status (SES) between these groups and the accumulating evidence of the malleability of infant health (see Currie 2011 for a thorough review), it is natural to ask "to what extent are these IMR differences related to SES differences?" It is far from clear that the answer is "largely." For example, previous studies have found that only about one-third of the black-white gap can be accounted for by the background characteristics available on birth certificates. However, given that the set of SES characteristics available on birth certificates is limited, perhaps the inclusion of additional SES characteristics could account for more of the black-white gap. As another example, the relatively low IMR for Hispanics also fails to support an SES explanation because, compared to whites, Hispanics and blacks appear similarly disadvantaged on many dimensions of SES. However, the comparison of the Hispanic-white disparity to the black-white disparity is complicated because

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[1] The groups listed here are those that are identified in Vital Statistics data reported by all states between 2000 and 2004.

of the "Hispanic paradox", the finding that Hispanics tend to have better-than-expected health outcomes along many dimensions.

In this paper, we use U.S. micro-level Vital Statistics data from 2000 to 2004 to examine differences in infant mortality across a variety of racial and ethnic groups. We study several groups simultaneously for three reasons. First, previous research has largely focused on the large and persistent black-white IMR gap but has made relatively little progress understanding its sources; a systematic comparison to other racial and ethnic gaps could help shed light on this disparity. Second, these other racial and ethnic IMR gaps are interesting in their own right, in part because of shifting demographics in the U.S.[2] Third, we wish to examine whether the relationships between SES disparities and IMR gaps are similar across various between- group comparisons.

We adopt the approach to studying IMR gaps developed in Elder, Goddeeris and Haider (2011; hereafter EGH). This approach provides a common framework for examining how covariates predict between-group differences in IMR and other related outcomes. Specifically, overall IMR gaps are decomposed into three distinct and temporally-ordered components: fitness at birth, conditional (on fitness) mortality during the first month of life, and conditional mortality during the remaining first year. We then assess the predictability of IMR gaps and its components using reweighting methods.

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[2] Between 1996 and 2006, the share of births to non-Hispanic whites and non-Hispanic blacks fell from 60.6 to 54.1 percent and from 14.9 to 14.5 percent, respectively. In contrast, the share of births to Hispanics grew from 18.0 to 24.4 percent, the share to American Indians / Alaska Natives grew from 1.0 to 1.1 percent, and the share to Asians grew from 4.3 to 5.7 percent (Martin, Hamilton et al. 2008).

This paper makes several substantive contributions to the literature. First, by studying the various racial and ethnic groups jointly, we are able to draw broader conclusions about IMR gaps and their predictability. For example, we find that the roles of the temporal components vary substantially across the three high-IMR groups: the Puerto Rican-white gap, like the well-studied black-white gap, is largely apparent at the time of birth, whereas the Native American-white gap primarily emerges during the post-neonatal period (days 29 to 365 following birth). We also show that the Native American gap is much more predictable than is the black or Puerto Rican gap. These sets of findings are related: we show that post-neonatal gaps are more predictable than gaps in fitness across all ethnicities.

Second, we assess which of the background characteristics matter. For example, we find that group differences in marital education, marital status and age drive most of the predictable gaps across all groups. In addition, we provide supplementary results from Census data that show that these three key predictors are all strongly related to income and poverty. Furthermore, using Census data, we show that substantial poverty gaps remain between the race and ethnic groups after controlling for the typical characteristics found on birth certificates, and these unpredicted poverty gaps appear to be correlated with the unpredicted IMR gaps. These findings suggest that the measured role of SES is substantial, and this measured role would be larger if better SES measures were available on birth certificates.

Third, given that the Hispanic IMR paradox stands in such contrast to an SES explanation for IMR gaps, we provide several additional analyses regarding how it operates. We show that the paradox exists for Mexicans, but not Puerto Ricans, and emerges primarily through lower conditional post-neonatal mortality. We also find that the paradox largely disappears once we account for whether the mother was foreign-born, a characteristic associated with an infant mortality advantage among all racial/ethnic groups. Thus, the Mexican mortality advantage is not as paradoxical as it initially appears.

2. Background and Literature Review

Our analysis is related to many large literatures, both within and beyond economics. Here, we focus on three of the strands that are most closely related to our research question.

The Malleability of Infant Health. In recent years, there has been a burgeoning of studies that have linked infant health and mortality to economic, policy, and ecological environments. See Currie (2011) for an elegant integrative review of these studies. For example, several studies have linked infant mortality to the business cycle (e.g., Ruhm 2000; Dehejia and Lleras-Muney 2004; Miller, Page, Stevens, and Filipski 2009). Interestingly, higher unemployment is linked to declines in infant mortality, with these effects partly driven by selection into who gives birth (Dehejia and Lleras-Muney 2004). In addition, infant mortality has been linked to a variety of social assistance policies, including Medicaid (Currie and Gruber 1996), cash transfer programs (Leonard and Mas 2008) and food assistance programs (Almond, Hoynes, and Schanzenbach 2011; Hoynes, Page, and Stevens 2011). Numerous studies have also linked infant mortality to pollution in the environment (Chay and Greenstone 2003; Chay and Greenstone 2005; Currie and Neidell 2005; Currie, Neidell, and Schmieder 2009; Currie and Schmieder 2009; Currie, Greenstone, and Morretti 2011; Currie and Walker 2011).

SES and Infant Health. Numerous studies have focused explicitly on the relationship between SES and infant health. For example, Case, Lubotsky, and Paxson (2002) show that higher SES is associated with better health for children throughout the age distribution, including those less than four years old. Finch (2003), analyzing a sample of nearly 13,000 births from

1988, finds that household income matters for infant mortality, especially at very low income levels and even when controlling for a rich set of covariates. Nepomnyaschy (2009), using a sample of 8,600 births in 2001, similarly finds an income gradient, especially for whites, in the probability of low birth weight (under 2500 grams).

An important recent contribution to this literature is Hoynes, Miller and Simon (2012), who exploit variation in income based on the expansion of the EITC to attempt to uncover the causal effect of income on birth weight. They find that an increase of $1000 in EITC income is associated with about a 10 percent reduction in the number of children who are low birth weight.

IMR Gaps. Large and varied literatures have investigated many aspects of IMR gaps, often concentrating on the black-white IMR gap. Numerous articles have examined whether IMR differences across groups can be predicted based on differences in the background characteristics of group members. Examples include Eberstein, Nam, and Hummer (1990), Hummer, Biegler et al. (1999), Miller (2003), Frisbie, Song et al. (2004), and EGH. These studies typically use logit models with micro data, with infant death as the outcome variable and controls for various background characteristics and for racial / ethnic group; EGH uses the reweighting methods we use here. Typically, the black-white IMR gap remains large and significant after background variables are included.[3] Chay and Greenstone (2000) and Almond, Chay and Greenstone (2006) show that the black-white gap declined precipitously following the 1964 Civil Rights Act, with the latter paper providing evidence that this decline was linked to the desegregation of hospitals.

[3] Sometimes researchers will control for birth weight or gestational age in models of infant mortality, in which case black-white gaps can be fully or almost-fully predicted. As discussed below, we instead treat these fitness measures as additional outcome variables.

To shed further light on IMR gaps, studies commonly distinguish between the part that is related to fitness at birth, as measured by birth weight and gestational age, and the part that is related to mortality rates conditional on fitness. This distinction is useful because, for example, the part of infant mortality related to fitness at birth is related to the health and behavior of the mother before the child is born, but not related to factors such as medical care after birth and the ensuing home environment. Numerous studies have found that most of the black-white IMR gap is due to differences in measures of fitness at birth, rather than due to differences in IMR conditional on fitness (e.g., Carmichael and Iyasu 1998; Schempf, Branum et al. 2007; and Alexander et al. 2008). Similarly, studies often distinguish between deaths in the neonatal period and the post-neonatal period. In examining black-white IMR gaps, both Carmichael and Iyasu (1998) and Schempf, Branum, et al. (2007) find that fitness differences can more than fully account for black-white gaps in neonatal mortality but not post-neonatal mortality. Wise (2003) provides a useful conceptual discussion relating fitness, neonatal mortality, post-neonatal mortality differences to the black-white IMR gap.

A growing literature has examined the IMR gap between whites and Hispanics, consistently finding that Hispanics have similar (or slightly lower) infant mortality rates compared to non-Hispanic whites. Frisbie and Song (2003) analyze mortality and indicators for short gestational age and low birth weight, differentiating Hispanics by country of origin and birthplace of the mother. They find that most Hispanic groups have lower IMRs than whites, with particularly large advantages for foreign-born Mexican mothers. Hummer, Powers, et al. (2007) find that the relative advantage of Hispanics cannot be explained by selective out-migration, as much of the advantage develops within one day of birth. Powers (2012) finds that the mortality advantage exists for younger Mexican-origin mothers, but not for older ones.

Relatively little work has analyzed the high infant mortality of Native Americans. Tomashek, Qin et al. (2006) compare infant mortality by birth weight between whites and Native Americans in 1989-91 and 1998-2000, finding that most of the excess Native American mortality can be traced to higher post-neonatal mortality conditional on birth weight. Watson (2006) finds that a series of sanitation interventions dramatically reduced the Native American-white IMR gap between 1960 and 1998.

3. Methods

The primary outcomes we study are the IMR gaps between race and ethnic groups. To provide further information about when these gaps emerge, we also study a three-way decomposition that the separates IMR gaps into three, temporally ordered outcomes. Specifically, we partition births into *K* mutually exclusive and exhaustive categories of birth weight and define three $K\times 1$ vectors: s_g to be the shares of births in the different birth weight categories, π_g^n to be the birth weight-specific neonatal mortality rates, and π_g^p to be the birth weight-specific post neonatal mortality rates conditional on surviving the neonatal period.[4] Then, the difference in the infant mortality rate between two groups, denoted *A* and *B*, may be written as

$$(1) \qquad IMR_B - IMR_A = \pi_B'(s_B - s_A) + (\pi_B^n - \pi_A^n)'[(1-\pi_B^p) \bullet s_A] + (\pi_B^p - \pi_A^p)'[(1-\pi_A^n) \bullet s_A] \; ,$$

[4] We report infant mortality rates in terms of 1000 live births in our empirical results, as in previous studies, but we treat π's as probabilities of death in mathematical expressions. The formulas are identical if we instead classify births by gestational age, another common measure of an infant's fitness at birth.

where the dot operator "•" denotes element-by-element vector multiplication. The first component on the right-hand side of (1) isolates the role of differences in the birth weight distributions $(s_B - s_A)$. The second component isolates the role of differences in conditional neonatal mortality rates ($\pi_B^n - \pi_A^n$). The third component isolates the role of differences in conditional post-neonatal mortality rates among those infants who survive the neonatal period $(\pi_B^p - \pi_A^p)$. However, we stress that this decomposition reflects when evidence of fitness / mortality differences is observed, not when the underlying causes arise. In other words, neonatal mortality conditional on birth weight may reflect processes that began *in utero*, and post-neonatal mortality may reflect processes that began *in utero* and during the first 28 days of life.

3.1. Assessing the Combined Effect of All Background Characteristics

To examine how background characteristics affect IMR gaps and their temporal components, we use inverse probability weighting methods to create counterfactual objects.[5] These methods allow us to examine in a common framework both simple objects like IMR gaps and more complex objects like the decomposition given above in (1). The intuition for the method is straightforward: to measure the influence of differences across groups in the distributions of characteristics, we reweight the infants in group *A* (the reference group) so that their distribution of characteristics closely matches that of one of the other groups.

[5] Our development is similar to DiNardo, Fortin, and Lemieux (1996). Several studies have assessed the statistical properties of reweighting methods, including Hirano, Imbens, and Ridder (2003), Imbens (2004), Wooldridge (2007), and Busso, DiNardo, and McCrary (2009).

Formally, let $f(y \mid g)$ be the probability density of an outcome *y* for group *g* and let $F(x \mid g)$ be the cumulative distribution of background characteristics *x* for group *g*. We may write

$$(2) \qquad f(y \mid g) = \int_x f(y \mid g, x) dF(x \mid g) \equiv f(y; g_{y|x}, g_x),$$

expressing $f(y \mid g)$ as a density conditional on *x* integrated over the distribution of *x* of individuals who are in group *g*. This formulation highlights the potential for creating counterfactual densities by using the distribution of characteristics associated with different groups. To see this, define

$$(3) \qquad f(y; g_{y|x} = A, g_x = B) \equiv \int_x f(y \mid g = A, x) dF(x \mid g = B)$$

as the distribution of outcomes that would result if group *A* retained its own mapping from characteristics to outcomes, but had the group *B* distribution of characteristics.

The counterfactual density in (3) can be estimated as a weighted function of the actual group *A* data, with weights that are simple to construct. Specifically,

$$(4) \qquad f(y; g_{y|x} = A, g_x = B) \equiv \int_x f(y \mid g = A, x) \psi_{A \to B}(x) dF(x \mid g = A),$$

where the weights $\psi_{A \to B}(x)$ are defined as

$$(5) \qquad \psi_{A \to B}(x) \equiv \frac{dF(x \mid g = B)}{dF(x \mid g = A)} = \frac{\Pr(g = B \mid x)}{\Pr(g = A \mid x)} \times \frac{\Pr(g = A)}{\Pr(g = B)}.$$

The last equality in (5) follows from Bayes' Rule. The first fraction to the right of the equality can be estimated using a binary model (such as a logit or probit) of group membership as a function of covariates *x*, and the second fraction involves only the sample proportions of individuals in each group.

In our empirical analyses, whites serve the role of group *A*, and the other racial and ethnic groups serve as group *B*. For each of the other groups, we pool its data with the data for whites and estimate a logit function to predict group membership as a function of x. We use the results to construct weights as in (5) for each observation in the white population. With the reweighted data (e.g., "white infants reweighted to have the distribution of background characteristics found among blacks"), we can compute counterfactual quantities to assess predictability. For example, the gap between the counterfactual IMR and the white IMR is an estimate of how much of the black-white IMR gap is predictable based on differences in characteristics between these groups. We consider the effect of using other reference groups as an additional analysis below.

Unless otherwise specified, we compute standard errors for estimated quantities with a bootstrap procedure. Specifically, we construct 100 replicate samples based on random sampling with replacement, and then compute all estimates reported in the paper for each of the replicate samples. The standard errors are then computed from the empirical distribution of the estimates across the 100 replicate samples.

3.2. Assessing the Roles of Individual Background Characteristics

In addition to predicting differences across groups based on differences in the entire distribution of background characteristics, we also study the role of particular characteristics, such as mother's education, using the reweighting methods developed in Elder, Goddeeris and Haider (2012). Analogous to interpreting the role of an individual covariate in a multiple regression, the method answers questions like "What would be the white birth weight distribution if white mothers had the black distribution of education while retaining their own joint distribution of all other background characteristics?"

To apply the method, we partition the set of background characteristics x into two parts, z and x_{-z}. The variable being switched from the group A distribution to the group B distribution is denoted as z (e.g., z could be a vector of dichotomous variables denoting various levels of education), with all other background characteristics denoted as x_{-z}. We construct weights so that the reweighted (counterfactual) population has group B's marginal distribution of z and group A's marginal distribution of x_{-z}. We then assess the role of the variable z for the IMR gap, for example, by comparing the black population with this newly reweighted population.

We use weights of the following form:

$$(6) \qquad \psi^{z}_{A\to B}(z, x_{-z}) = \frac{dF(z \mid j=B) - dF(z \mid j=A) + dF(z \mid x_{-z}, j=A)}{dF(z \mid x_{-z}, j=A)}.$$

We calculate the weights using sample analogs of the objects on the right-hand-side of (6). For further details see Elder, Goddeeris and Haider (2012). As a robustness check, we also assess the effects of differences in individual characteristics on IMR gaps using Oaxaca-Blinder decompositions.[6]

4. Data

Vital Statistics data. Our primary data are the linked birth / infant death cohort data compiled by the National Center for Health Statistics (NCHS) from 2000 through 2004. These

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[6] These estimates are calculated as $\beta'_A(\bar{z}_B - \bar{z}_A)$, where $\bar{z}_g$ is a vector of sample means for a subset of variables and β_A is the corresponding vector of coefficients from a regression of y on x in group A.

data include information from the birth certificates of all live births occurring in the U.S. in the relevant calendar year, linked to death certificates for all infants who die within their first year of life. We limit our analysis to births that occur in the fifty U.S. states or the District of Columbia to mothers who are U.S. residents. NCHS is unable to match a small fraction of death certificates to birth certificates (about 1 percent); we ignore the unmatched deaths in our analysis.

We classify births based on the race and ethnicity of the mother. From 2000 to 2004 all states classified births into at least four racial categories: White, Black, Native American, and Asian.[7] The data also distinguish between those who report Hispanic ethnicity and those who do not, defining five Hispanic groups by place of origin: Mexico, Puerto Rico, Cuba, Central or South America, and other or unknown origin. Among Hispanics, we include mothers who report their place of origin as Mexico or Puerto Rico.[8] Based on this information, we analyze six mutually exclusive categories of births: non-Hispanic White, non-Hispanic Black, Hispanic of Mexican origin, Hispanic of Puerto Rican origin, Asian, and Native Americans / Alaska Natives. For simplicity, we refer to these groups as whites, blacks, Mexicans, Puerto Ricans (abbreviated "PR"), Asians, and Native Americans (abbreviated "NA"), respectively.

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[7] Most states distinguish among at least several subcategories of Asian or Pacific Islander (NCHS, 2005) and infant mortality differs somewhat across subgroups. Because not all states report in the same way, we consider aggregated categories.

[8] In an unpublished appendix, we present some results for Cubans and Central / South Americans. We do not include these groups throughout the analysis because the Cuban sample is small and the Central / South American group is likely to be very heterogeneous.

For sufficient statistical power for the smaller racial / ethnic groups, we pool births from 2000 to 2004. The smallest group, Native Americans, includes about 184,000 observations. For computational reasons, we use random samples for the largest racial / ethnic groups: 20 percent for whites, blacks and Mexicans, and 70 percent for Asians. This sampling scheme gives us the largest sample for whites (over 2.25 million), the group that we repeatedly reweight, and roughly 600,000 observations each for blacks, Mexicans and Asians. We exclude observations with missing information on race or ethnicity, maternal education, prenatal care, birth order, and previous pregnancy loss.

We use birth weight as our measure of infant fitness. We divide births into cells by, leading to 173 cells (9 ounces and less, 10 ounces, 11 ounces, …, 179 ounces, 180 ounces and more, and missing). For comparability with other research, we express birth weight in grams when displaying or discussing our results. In an unpublished appendix, we show that our main results are very similar if instead we measure fitness by gestational age, using the NCHS-edited gestational age variable provided in the public data files and disaggregating gestational age by integer values of completed weeks.

Background characteristics. Conceptually, we consider as background characteristics those observable attributes that are determined prior to information the mother might have received about the fitness of the fetus. Such predetermined characteristics can provide important insight into the factors that cause IMR disparities. In contrast, characteristics that are not predetermined may be endogenous in the sense that they are influenced by behavioral responses to information about fetal health. For example, information that a pregnancy is at high risk may lead to a greater number of prenatal visits, inducing a positive association between prenatal care and mortality and obscuring any causal positive effect of prenatal care. We do not treat birth weight and gestational age as background characteristics, but instead view them as other outcomes of interest.

It is important to recognize that associations between background characteristics and outcomes are only a starting point for understanding the causal mechanisms at work. For example, educational attainment may be associated with lower infant mortality because education imparts knowledge and income that aid in the production of a healthy infant, but the association might also reflect the influence of omitted maternal characteristics that lead to both more schooling and healthier infants. Regardless of the precise causal mechanism, characteristics that are predetermined shed light on what factors lead to different later health outcomes, without reflecting parental responses to information about the health of the fetus.

Implementing our conceptual definition of predetermined is not always straightforward due to data limitations and our desire to connect to the previous literature. We include variables that are commonly used in previous studies and clearly predetermined to information on infant fitness: maternal education, maternal age, previous pregnancy loss (either elective or spontaneous), infant sex, live birth order, and plurality.[9] Two others that we examine, prenatal care and marital status, are less clearly predetermined but are often included in previous studies. In light of our concerns about prenatal care, we use only an indicator variable for whether it is

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[9] We specify indicator variables for four education groups (<12 years, 12 years, 13-15 years, and >15 years), five maternal age groups (<20, 20-24, 25-29, 30-34, and >34), and three live birth order groups (1^{st}, $2^{nd}/3^{rd}$, $>3^{rd}$). We use single indicators for whether the infant is male, whether the birth was plural, and whether the mother experienced a previous pregnancy loss.

begun in the first trimester. Marital status is measured at the time of birth, so it could potentially be affected by information on health of the fetus.[10]

Unlike most previous studies of IMR disparities, we also include indicator variables that identify the mother's state of residence (including the District of Columbia). Racial and ethnic groups are distributed very differently across states, and many important inputs for the production of healthy infants vary by geography, such as employment opportunities, social services, pollution, and health care access and quality. Rather than try to quantify each of the possible avenues through which states differ from each other, we took the simpler approach of including state indicators, so that unpredicted differences across groups are due to within-state mortality differences.

Census data. Despite the detailed information in VS data about the demographic and health characteristics of the mother and infant, the data contain fairly limited information related to the socio-economic status of the families. To supplement our analysis, we also use an extract from the 2000 Census that is intended to match our VS data as closely as possible. Specifically, using the 5% IPUMS version of the 2000 Census, we construct a data set of mothers of children less

[10] Bachu (1999) reports that among first-time mothers unmarried at conception, 30.5 percent of non-Hispanic whites and 10.2 percent of non-Hispanic blacks were married at the time of birth in the 1990-94 period. It is unknown whether information on the health of the fetus influences the probability that an unmarried woman marries during pregnancy. See Cooksey (1990) and Akerlof, Yellen, and Katz (1996) for analyses of the decision of pregnant women to marry.

than two years old and code the available background characteristics to match our VS sample as closely as possible.[11]

5. Descriptive Results

Table 1 presents descriptive statistics on measures of infant mortality and background characteristics in our VS data. The IMR varies widely across the groups. The overall IMR of whites in our sample was 5.35 per 1000 live births. Three groups had an IMR substantially higher: blacks at 12.35, Native Americans at 8.31, and Puerto Ricans at 7.61. In contrast, two groups had a lower IMR: Mexicans (at 5.04) and Asians (at 4.34). Most groups had about two-thirds of these infant deaths taking place during the neonatal period, although Native Americans had just under one-half during the neonatal period.

The IMR gaps and their temporal decomposition are shown in Table 2 and graphed in Figure 1. The overall black-white IMR gap of 7.00 (standard error of 0.17) is overwhelmingly accounted for by differences between blacks and whites in fitness at birth: about 88 percent (6.15 / 7.00) of the black-white gap is due to differences in birth weight. Differences in conditional post-neonatal death rates account for about 16 percent (1.13 / 7.00) of the gap, while the conditional neonatal component accounts for 4 percent (0.27 / 7.00) *fewer* black deaths. Puerto Ricans, also a high-IMR group, are similar to blacks in that much of the Puerto Rican-white IMR gap is accounted for by differences in birth weight. In contrast, almost the entire Native American-white IMR gap is due to differences in post-neonatal death rates. Only about 9

[11] We include the gender of the infant, 5 maternal age categories, 4 maternal education categories, an indicator for whether the mother is married, 3 indicators for the number of siblings, and 51 geography indicators.

percent (0.26 / 2.96) is accounted for by birth weight differences, while about 83 percent (2.46 / 2.96) is accounted for by the post-neonatal component. The IMR gaps for the remaining two groups, Mexicans and Asians, are small, so statements about the relative sizes of the components should be made cautiously. With that said, the Mexican advantage is concentrated in the birth weight component, whereas the Asian advantage is mainly concentrated in the neonatal and post-neonatal components. Thus, across all of the groups, there is much variation in the IMR gaps and in when these gaps emerge.

In the lower panel of Table 1, we show tabulations from the Census data on various measures of household income and poverty. Starting with mean household income, we find some suggestive evidence that income might matter: the three high IMR groups (blacks, Puerto Ricans, and Native Americans) are among the lowest income groups ($36,402, $41,951, and $37,649, respectively). As expected, however, Mexicans are an important anomaly: they have mean household income that is similar to these high-IMR groups ($40,919), but an IMR that is much lower. Examining median household income does little to change this basic conclusion. If we instead examine the poverty measures, the puzzle diminishes somewhat. Consider the deep poverty measure, defined as family income being less than one-half of the official poverty line. By this measure, the three high-IMR groups have the highest deep poverty rate (blacks at 0.23, Puerto Ricans at 0.20, and Native Americans at 0.18), while Mexicans have a deep poverty rate that is lower (0.13) but still substantially higher than the two other low-IMR groups (whites and Asians at 0.05).

6. Are Group Differences Predictable by Background Characteristics?

To illustrate the potential role of background characteristics in predicting group differences in IMR, we show how the characteristics vary by group in Table 1. For example, Asian mothers are more likely than whites to have at least 16 years of education, they are less likely to be teenagers, and they are more likely to be married. In contrast, black mothers are twice as likely as white mothers to have not completed high school (24 percent versus 12 percent) and more than twice as likely to be less than 20 years of age at the time of the birth (18 percent versus 8 percent). There are also substantial differences by geography: about half of Mexican, Asian, and Native American births take place in the West region, 57 percent of black births are in the South region, and 59 percent of Puerto Rican births are in the Northeast region.

In order for the group differences in background characteristics to contribute to IMR differences, the background characteristics must also be predictive of our fitness and mortality outcomes of interest. Table 3 shows regressions to demonstrate the predictive power of these characteristics within the white population for three outcomes: infant death, birth weight, and whether a birth is less than 1500g. All background characteristics are indicator variables, so each coefficient can be interpreted as a marginal effect relative to being in the omitted category. By far, the plural birth indicator has the largest marginal effect, but because plural births are relatively rare in all groups, differences in their prevalence across groups are small. Education has large effects on the outcomes as well. Combining these large effects with the large group differences implies that education is likely to be an important predictor of IMR gaps. Age and marital status also appear to be potentially important background characteristics.

6.1. The Combined Role of All Background Characteristics

We use the reweighting methods described in Section 3.1 to assess how much of the gaps and components of gaps are predictable by differences in background characteristics. Reweighting the population of white infants creates counterfactual populations that have the same distributions of characteristics as the other groups, while retaining the white mapping from characteristics to outcomes.[12] We refer to the IMR gaps between whites and these counterfactual populations as "predicted gaps". We show the point estimates and standard errors in Table 2 and graph the point estimates in Figure 1.

Turning to the results, the overall predicted gap for blacks is 2.54, which indicates that, of the 7.00 excess black infant deaths per 1000 live births, 2.54 are predictable from differences in the distribution of background characteristics between blacks and whites. The remaining 4.46 (7.00 – 2.54) of the black-white IMR gap is not predicted by the differences in background characteristics. Of the predicted gap, 1.13 is due to differences in fitness as measured by birth weight, 0.26 is due to differences in neonatal mortality, and 1.15 is due to differences in post-neonatal mortality.[13]

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[12] Appendix Table A1 shows summary statistics for whites and these counterfactual populations. As a comparison of this table to Table 1 shows, the reweighting procedure works well in terms of producing close matches in the distribution of characteristics.

[13] In EGH, we explored the robustness of our findings for the black-white IMR gap to several other factors, including different methods for handling missing data, different specifications for background characteristics, different methods of assessing predictability, and the inclusion of births beyond the first birth. Our results remained qualitatively similar in every case.

Looking across groups uncovers several interesting findings. First, smaller shares of the overall black and Puerto Rican gaps are predicted as compared to the overall Native American and Asian gaps. For example, about 36 percent (2.54 / 7.00) of the black gap and 44 percent (1.01 / 2.27) of the Puerto Rican gap is predicted. In contrast, over two-thirds of the Native American IMR gap is predicted (2.06 / 2.96), and the Asian IMR advantage over whites is more than completely predicted (-1.16 / -1.01). This difference is related to the differences in predictability of the fitness component versus the post-neonatal component: Background characteristics are predictive of post-neonatal mortality within the white population, and the post-neonatal component is a larger share of the total gap for Asians and Native Americans than for blacks and Puerto Ricans.

Second, the Hispanic paradox is strikingly clear for Mexicans, though not for Puerto Ricans. The predicted gap for Mexicans falls between those of Native Americans and Puerto Ricans, in spite of the fact that Mexicans have much lower actual IMRs than these groups. Put another way, Mexicans, Native Americans, and Puerto Ricans have background characteristics that are associated with high IMR among whites, but only Native Americans and Puerto Ricans actually have high IMRs. This prediction of a substantial positive gap when none exists represents the crux of the paradox. Our results, however, go a step further in shedding light on when the paradox emerges. The actual and predicted fitness and conditional neonatal components of the Mexican gap are all relatively small. In contrast, the actual post-neonatal component is essentially zero, but the predicted post-neonatal component for Mexicans is the largest of any group's. Thus, the Hispanic paradox largely arises during the post-neonatal period.

6.2. The Roles of Individual Characteristics

We next turn to the roles of individual background characteristics in predicting IMR differences across groups, using the reweighting methods described in Section 3.2. Figure 2 displays our main results graphically, and Appendix Table A2 presents detailed estimates and standard errors. The standard errors are relatively small, ranging from less than 0.01 to 0.12. The figure shows the contribution of each background characteristic to the overall predicted racial / ethnic IMR gap with whites. The sum of the bars for each racial / ethnic group approximately equals the overall predicted IMR gap displayed in Figure 1. To illustrate, consider the set of bars labeled "education" in Figure 2. They show that if white mothers had the distribution of education of black mothers while retaining their own distribution of all other characteristics, there would be roughly 0.56 more deaths per 1000 live births among whites. Similarly, if white mothers had the distribution of education found among Mexican mothers, the white IMR would increase by 1.15.

If we concentrate on the relatively low SES groups (blacks, Mexicans, Puerto Ricans, and Native Americans), Figure 2 shows that three factors – maternal education, marital status, and age – are primarily responsible for the positive predicted gaps. If whites had the distribution of these three characteristics of these other groups, we would predict that their IMR would be substantially higher.[14] For example, convergence in these three characteristics alone would reduce the IMR gap by 1.95 for blacks, 1.83 for Puerto Ricans, and 1.93 for Native Americans. Oaxaca-Blinder methods yield very similar results: the contributions for the three variables are

[14] Because Asians tend to have more favorable distributions of these three variables compared to whites (mothers are more likely to be married, be older, and have more education), the predicted effect is negative.

1.80, 1.74 and 1.85 for blacks, Puerto Ricans and Native Americans, respectively.[15] Although there is some indication in Figure 2 of a positive effect of two other characteristics, prenatal care and birth order, these positive effects are much smaller in magnitude.

In contrast, two characteristics, state and plural birth, tend to predict a negative racial / ethnic IMR gap with whites. In other words, for these characteristics, our results suggest that the white IMR would decrease if whites had the characteristics of the disadvantaged groups. For example, the results suggest that the Puerto Rican / white IMR gap would increase by over 0.5 if white births were distributed across states in the same way Puerto Rican births are. To illustrate, 51 percent of Puerto Rican births occur in three states – New York, Florida and New Jersey – and the white IMR is 13 percent lower in these states as compared to the rest of the United States; however, only 8.7 percent of white births occurred in these three states. Similarly, whites have the highest share of plural births, and plural births are more likely to result in an infant death than is a single birth.

Our methods can also be used to analyze the temporal components through which each of the background characteristics operate (see Appendix Table A2). Briefly, these results suggest three findings. First, and not surprisingly, plurality differences generally operate through the birth weight component. Second, and much less obvious, maternal age operates almost exclusively through the post-neonatal component, whereas maternal education and marital status operate about two-thirds through the birth weight component and one-third through the post-neonatal

[15] These estimates combine the relevant coefficients from the infant death regression in Table 3 with the differences in the corresponding population characteristics from Table 1.

component. Third, while the state of residence effect can be important, its temporal patterns are not consistent across groups.

6.3. How Strongly Are The Vital Statistics Covariates Related to SES?

Our results indicate that the bulk of the positive IMR gap that can be predicted is due to three covariates: maternal education, marital status, and age. To provide direct evidence about the extent to which these variables are related to income differences, we turn to our Census sample of new mothers. Table 4 shows how these variables are related to three measures of SES, household income, the poverty rate, and the deep poverty rate, both adjusting and not adjusting for other covariates. For example, consider the results for household income. The column labeled "unadjusted" shows the results from three regressions for household income, one that only includes the married indicator, one that only includes maternal education indicators, and one that only includes the maternal age indicators. The column labeled "adjusted" shows the results from a single regression for household income in which all the available covariates (married indicator, maternal education indicators, maternal age indicators, sibling indicators, state indicators, and racial/ethnic group indicators) are included.

Turning to the household income results, the three covariates that predict much of the IMR gap are associated with large income differences. Married mothers have $30,932 more household income than non-married mothers, and mothers with a college degree have $63,737 more household income than mothers who have not completed high school. Large gaps remain even after adjusting for the other covariates: married mothers have $11,937 more household income than non-married mothers, and mothers with a college degree have $46,624 more household income than mothers who have not completed high school. Interestingly, age of the mother is also strongly related to income differences. Comparing the lowest income group to the highest income group using the adjusted results, mothers aged 35 and above have $26,588 more income than mothers aged 20 to 24; the size of this income gap by age is even bigger than the income gap by marriage.[16] These results suggest that all three of the main predictors of infant mortality are highly related to household income.

In the remaining columns, we show a comparable set of results for the poverty rate and the deep poverty rate. All three of the main predictors of IMR are also associated with these poverty measures, both before adjusting and after adjusting for the other covariates. Perhaps the one qualitative difference is that the effect of age, while still very large (a 10 percentage-point difference between mothers aged 35 and above when compared to mothers aged 20 to 24 in the adjusted poverty regression), is smaller than the poverty gaps associated with marriage and maternal education.

7. Extensions

In this section, we provide further analyses to extend our understanding of our results in several important dimensions.

7.1. Is More Detailed Information on Geography Important?

We included state indicators above because racial and ethnic groups are distributed very differently across states, as are many important factors for the production of healthy infants. Our findings suggest that these differences in distribution matter: overall, blacks tend to live in states

[16] As is clear from the table, age effects are non-monotonic. One explanation for this non-monotonicity is that the youngest mothers are more likely to live with her parents or other adults.

with a higher white IMR, whereas Mexicans, Asians and particularly Puerto Ricans live in states with a lower white IMR. However, there could still be important geographic differences within states. If this is the case, then including only state indicators would mask these important additional geographic differences.

To examine this possibility, we make use of the fact that our data provide the county of birth for those births that occur in counties with more than 250,000 residents. Specifically, we create county indicators for births that occur in these populous counties and an additional indicator for each state that groups together the births from the less populous counties. We then substitute these county indicators for the state indicators used in the previous section. This change increases the number of geographic indicators from 51 to 284. If important inputs vary by county within states and if disadvantaged minorities tend to live in counties where outcomes are poorer for all groups, then we would expect that predicted IMR gaps would be higher for disadvantaged groups when these additional geographic indicators are included.

We present the results in Table 5. The top panel uses the full sample of births used in the previous section, with the first two rows repeating the unadjusted gaps and the predicted gaps using the state indicators presented in Table 2. The third row repeats the predictive exercise, but instead uses the 284 county indicators to adjust for differences in the geographic distribution of births. Despite the inclusion of 233 additional geographic indicators, we find that the predicted IMR changes very little or perhaps even declines. Thus, we have no evidence that our state results are aggregating over important geographic heterogeneity.

There is, however, an important caveat to this analysis. The addition of county indicators results in much worse “support” problems. In other words, models with county indicators results in many observations in the minority populations whose characteristics are not exactly matched in the white population, and vice-versa.[17] As Imbens (2004) describes, this lack of overlap in support may cause our reweighting methods, and propensity score methods more generally, to generate unreliable estimates (see also Fortin, Lemieux and Firpo 2011). As a straightforward solution, Imbens (2004) proposes limiting inferences to “common support” samples, which use just those observations in both groups that have an exact covariate match.

The bottom panel of Table 5 presents results based on these common support samples. Specifically, the estimates under the “Black” column are based on the samples of blacks and whites whose characteristics (including county indicators) are exactly matched in both samples, and the estimates in the “Mexican” column are based on the samples of Mexicans and whites whose characteristics are exactly matched in both samples. As was the case for the full sample, the predicted IMR gaps are smaller in all cases when the county indicators are included than when only the state indicators are included.

7.2. Why is there a Hispanic Paradox?

[17] While the models with state indicators do produce some observations with characteristics that are not exactly matched across populations, the lack of overlap is much worse in models that also include county indicators. For example, among blacks, 98.3 percent of observations in the state specification have an exact match in the white population, compared to 89.9 percent in the county specification. The corresponding numbers are 99.3 percent and 91.4 percent for Mexicans, 98.9 percent and 88.3 percent for Puerto Ricans, 99.1 percent and 95.1 percent for Asians, and 96.9 percent and 93.6 percent for Native Americans.

A striking result found above and in previous studies is the Hispanic paradox: the consistent finding that Hispanics do much better on health outcomes than would be predicted based on their observable characteristics. Consistent with previous studies, we found that the Hispanic paradox exists for Mexicans, but not for Puerto Ricans.[18] In this section, we examine the extent to which the paradox depends on whether or not the mother is foreign-born, which has also been found to be important in numerous studies (e.g., Singh and Yu 1996; David and Collins 1997; and Pallotto, Collins and David 2000).

The top row of Table 6 provides information about the size of the foreign-born group for each of the racial / ethnic groups. The share of mothers born outside the U.S. varies widely across groups, with particularly large shares for Asians, Mexicans and Puerto Ricans. The middle panel shows that the IMR is lower for foreign-born mothers than for U.S.-born mothers in every group, although after adjusting for background characteristics, the advantages are statistically significant only for whites, blacks, and Mexicans.

In the bottom panel of Table 6, we repeat the reweighting analysis from Table 2, adding the "foreign-born mother" indicator to the set of covariates. Because small numbers of observations are necessarily dropped due to missing data on the birthplace of the mother, we first show the actual IMR gaps and the predicted IMR gaps using the baseline characteristics and the new samples; these gaps differ only slightly from those shown in Table 2. When the foreign-born indicator is added, the predicted gap for blacks and Native Americans, groups with few foreign-

[18] In an unpublished appendix, we show results for Cubans and Central / South Americans that mimic the results for Mexicans: they have negative actual IMR gaps, these actual gaps are much smaller than their predicted gaps, and the inclusion of a foreign-born indicator reduces the difference between the actual and predicted gaps.

born mothers, change relatively little, from 2.54 to 2.40 and 2.06 to 2.05, respectively. For the other three groups, the predicted IMR gaps fall much more: from 1.63 to 0.21 for Mexicans, 1.01 to 0.38 for Puerto Ricans, and -1.16 to -2.50 for Asians.

Compared to the baseline results, the estimates of Table 6 produce a more nuanced picture about the Hispanic paradox. Once we account for the systematic relationship between being foreign-born and IMR among whites (recall that our reweighting procedure always uses the white mapping from characteristics to outcomes), the paradox largely disappears even for Mexicans: the predicted IMR gap is no longer substantially greater than the actual IMR gap. Of course, these results beg the question of why foreign-born mothers do so much better than U.S.-born mothers.

7.3. Do the Results Vary if Other Mappings Are Used?

All of the specifications thus far have reweighted whites to have the background characteristics of the other groups, implying that we have been assessing the role of predicted gaps based on the mapping between background characteristics and infant mortality for whites. One way to examine the generality of our results is to instead reweight other groups to have the background characteristics of whites, thereby using the mappings of the other groups.

Figure 3 presents the results from such an analysis. Specifically, for each group, we graph three bars: the unadjusted gap between a particular group and whites, the predicted gap between the two groups using the white mapping (e.g., reweighting whites to have the background characteristics of blacks, which are the results studied in previous sections), and the predicted gap using the other group’s mapping (e.g., reweighting blacks to have the background characteristics of whites).[19] The figure reveals that the two different predicted gaps are quite similar for all racial/ethnic groups, except for Mexicans. Thus, our conclusions about predicted gaps are not very sensitive to which group's mapping is used. Moreover, this result sheds additional light on the Hispanic Paradox. Namely, the overall low mortality rate observed among Mexicans is accompanied by a compression of mortality differences across the background characteristics we study. It appears that background characteristics matter less for mortality among Mexicans than they do among whites.

The role of individual covariates is also broadly similar across different mappings. For example, as reported above, the three background characteristics maternal education, marital status, and age jointly account for much of the predictable differences between groups and are strongly associated with socioeconomic status: based on the mapping of whites, the convergence in these three characteristics would reduce the IMR gap by 1.95 for blacks, 1.83 for Puerto Ricans, and 1.93 for Native Americans. If we instead used the mapping of the other group in each pair, then convergence in these three characteristics would reduce the IMR gap by 1.88 for blacks, 1.40 for Puerto Ricans, and 1.93 for Native Americans.[20]

7.4. Would More Detailed Information on Socio-Economic Status Help?

[19] In Appendix Table A3, the results from Figure 3 are presented along with analogous results using the "common support" sample approach from Table 5. The results are very similar.

[20] An Oaxaca-Blinder approach using the other group's mapping also yields similar results: the previously reported Oaxaca-Blinder results using the white mapping were 1.80 for blacks, 1.74 for Puerto Ricans, and 1.85 for Native Americans, whereas the analogous estimates based on the other group's mapping are 1.63, 1.33 and 1.79, respectively.

While our results thus far suggest an important role for three variables that are highly related to socio-economic status – maternal marital status, education, and age – direct measures of income and wealth are still absent from our analysis of birth certificate data. Would the role of socio-economic status be even larger if we had such direct measures? We explore this question by applying the methods developed in this paper to examine racial / ethnic gaps in poverty. Specifically, using our 2000 Census sample of new mothers and a set of background characteristics that are intended to be comparable to the baseline analysis from Section 6, we then construct a set of actual, predicted, and unpredicted deep poverty gaps for each racial/ethnic group.[21] We focus on deep poverty due to a host of suggestive evidence that infant mortality is disproportionately concentrated among the very poor, but the results are similar for poverty and household income.

The top panel of Figure 4 presents actual and predicted deep poverty gaps for the racial / ethnic groups defined above, following the structure used in Figure 1. The three high-IMR groups all have large deep poverty gaps, and, as was the case for IMR, these gaps are only partially predicted by differences in background characteristics. Although Mexicans also have a sizeable deep poverty gap, almost all of it is predicted.

The bottom panel of Figure 4 shows a scatter plot of the unpredicted IMR gap against the unpredicted deep poverty gap. Clearly, larger unpredicted IMR gaps are associated with larger unpredicted resource gaps. While we are wary of inferring too much from an analysis based on five data points, the plot is at least suggestive that the measured effect of SES based on

[21] Using the IPUMS version of the 5% 2000 Census, we include the gender of the infant, 5 maternal age categories, 4 maternal education categories, an indicator for whether the mother is married, 3 indicators for the number of siblings, and 51 geography indicators.

characteristics on the birth certificate is an underestimate of the true effect of SES. Specifically, because the covariates we have been using to study the IMR gaps leave much of the deep poverty gaps unpredicted, the inclusion of deep poverty in models of IMR could reduce the unpredicted IMR gaps we have documented. Such a conclusion is consistent with prior work that finds income matters for birth outcomes even when controlling for other indicators of SES, although with much smaller samples (Finch 2003, Nepomnyaschy 2009).

8. Discussion and Conclusions

We used micro-level U.S. Vital Statistics data from 2000 to 2004 to examine differences in infant mortality across several racial and ethnic groups. Based on the approach of EGH, we decomposed mortality disparities into three temporal components – fitness at birth, conditional neonatal mortality, and conditional post-neonatal mortality – and estimated the extent to which infant mortality and these components are predictable based on differences in background characteristics. We additionally showed several supplementary analyses using Census data to shed additional light on the extent to which the differences are related to SES differences.

Our analyses revealed several important findings. First, there are important differences in the mortality gaps across race. Among the high-IMR groups, the black and Puerto Rican gaps were largely apparent at the time of birth, but the Native American gap primarily emerged during the neonatal period. In addition, as prior research has also shown, Mexicans were not among the high-IMR groups despite having similar levels of poverty and income to the high-IMR groups.

Second, despite these distinctions, the gaps also had much in common. Although the majority of infant deaths occur during the neonatal period, the conditional neonatal mortality component of the gaps tended to be quite small. In addition, the same three covariates tended to predict much of the gap that exists: maternal marital status, education, and age. Moreover, across all groups, the post-neonatal mortality gaps tend to be predictable – thus, shedding light on why the Native American gap and Asian gap are more predictable than the black and Puerto Rican gap. Finally, we show that even the Hispanic paradox can be largely accounted for by a common finding across race/ethnic groups: foreign-born citizens generally have lower infant mortality than do their domestic-born counterparts.

Third, despite the fact that much of the mortality gaps are not predictable by background characteristics, we demonstrate that there appears to be a substantial role for SES. Each of the three covariates that predict much of the differences between groups – maternal marital status, education and age – is strongly related to income and poverty. If whites had the distribution of these three characteristics found among the high-IMR groups, then the white infant mortality rate would increase by about 1.9. This estimate represents a substantial fraction of the IMR for whites (5.4) and the IMR gap for blacks (7.0), Native Americans (3.0), and Puerto Ricans (2.3). Moreover, an additional analysis that compared the unpredicted IMR gaps to the unpredicted deep poverty gaps suggests that an even larger role for SES might be uncovered if more comprehensive measures of SES were available on birth certificates.

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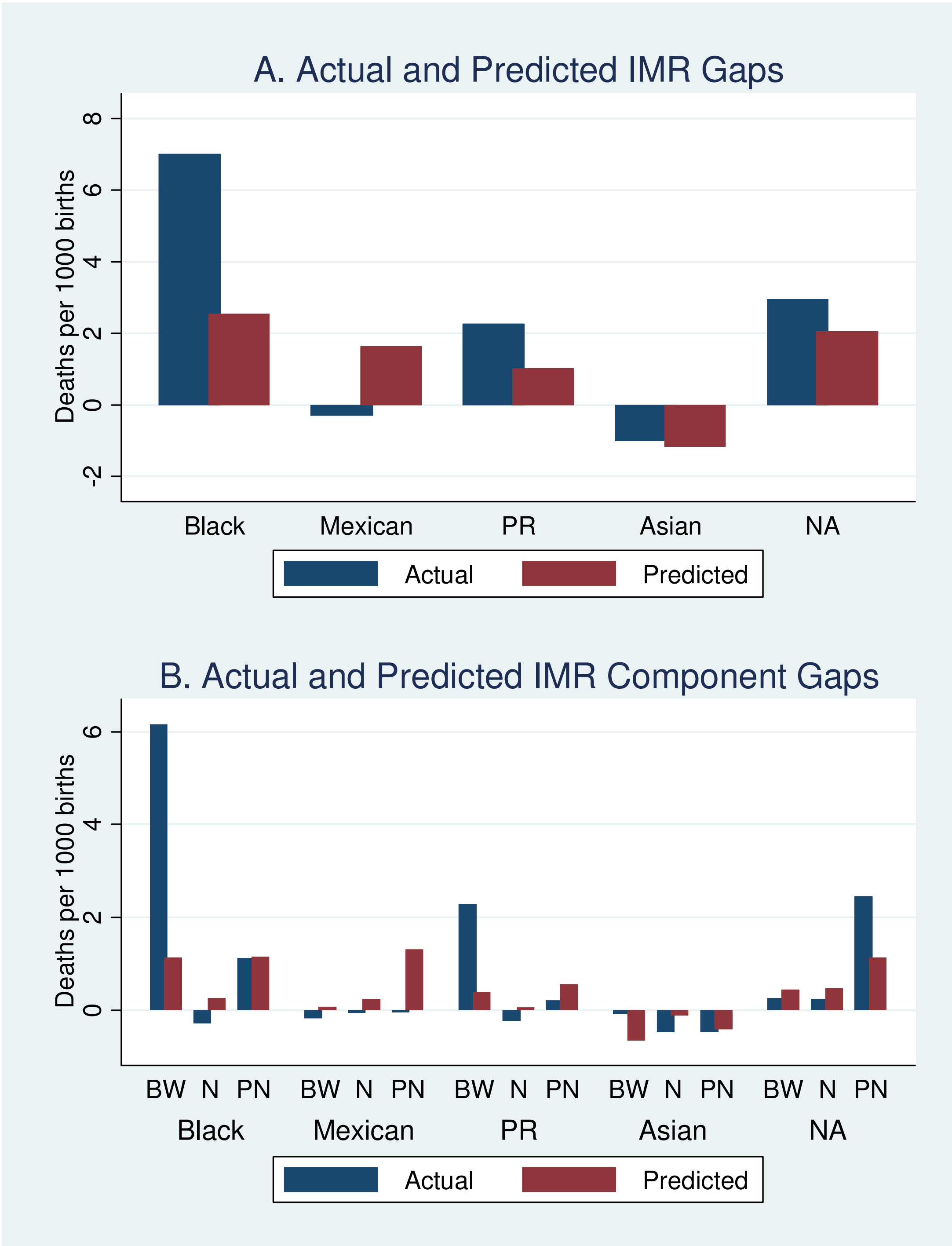
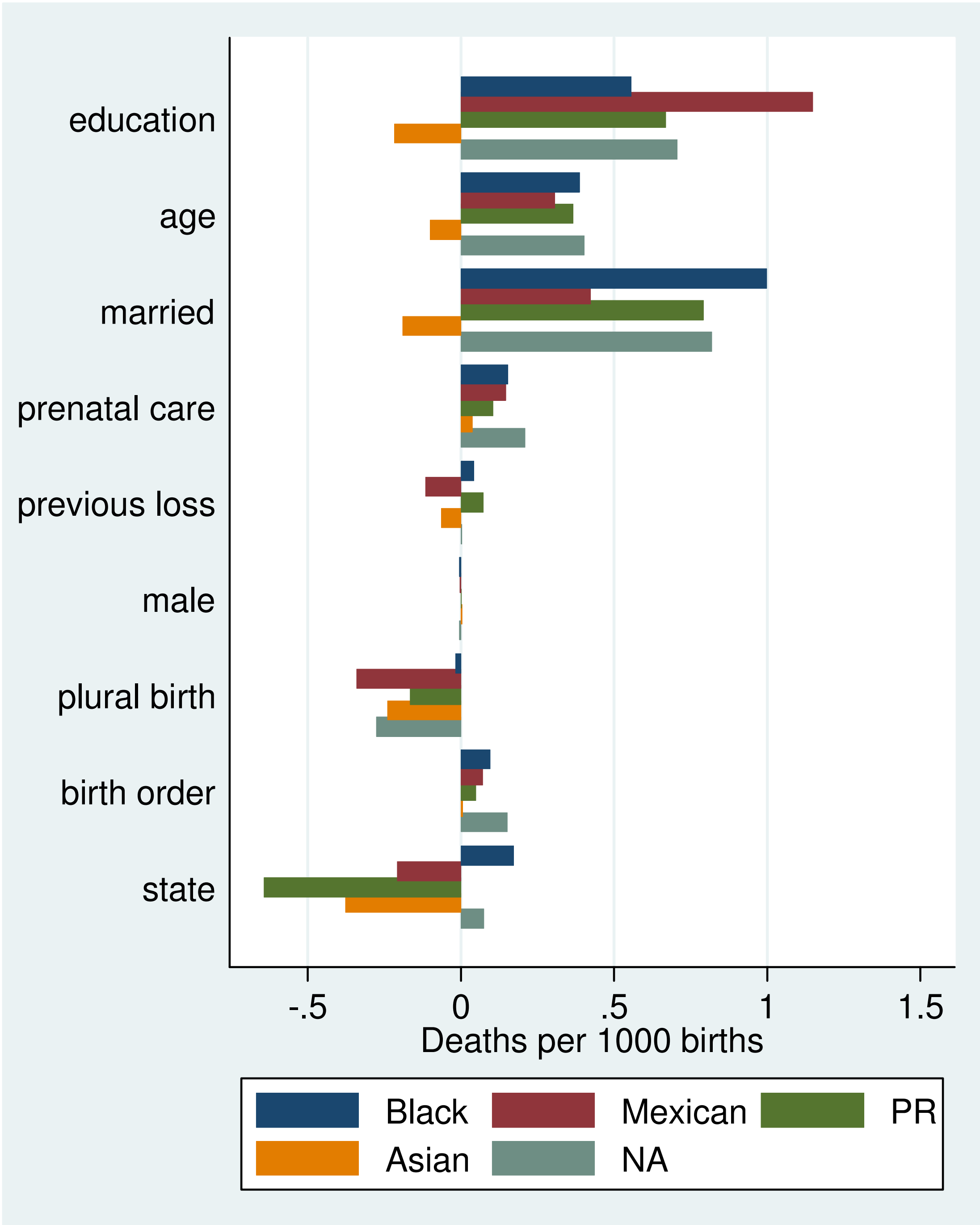
Figure 1: Actual and Predicted IMR Gaps by Racial / Ethnic Group



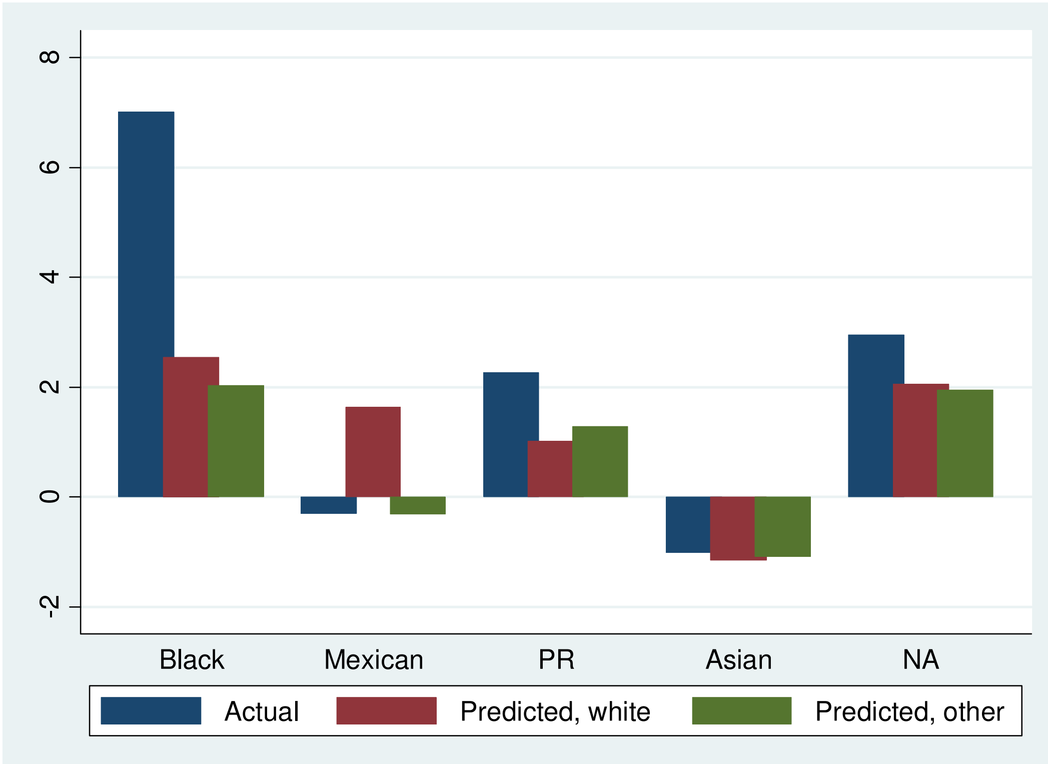
Notes: The bars denote the difference in the actual or predicted IMR between each of the labeled groups and whites. In Panel B, the three components are birth weight (BW), neonatal morality (N), and post-neonatal mortality (PN). The point estimates and their standard errors are provided in Table 2.

Figure 2: Predicted IMR Gaps by Background Characteristic and Racial / Ethnic Group



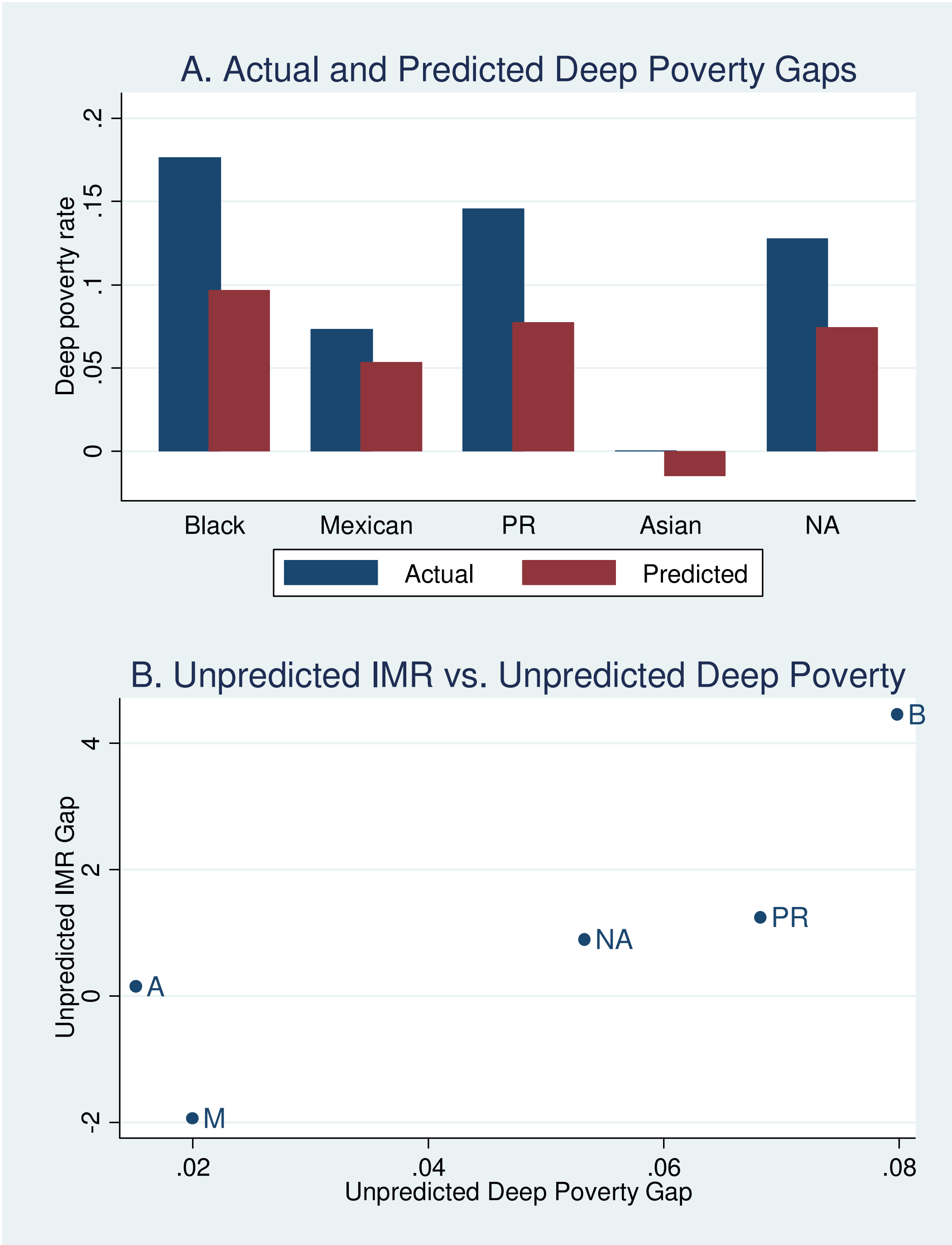
Notes: The bars denote the difference in the predicted IMR between each of the labeled groups and whites that is due to each of the listed covariates. The point estimates and their standard errors are provided in Table A2.

Figure 3: Actual and Predicted IMR Gaps by Racial / Ethnic Group



Notes: The "Actual" bars denote the actual IMR gap between each of the labeled groups and whites, the "Predicted, white" bars denote the predicted IMR gap based on the white mapping, and the "Predicted, other" bars denote the predicted IMR gap based on the other group's mapping (e.g., the black mapping for blacks and the Mexican mapping for Mexicans).

Figure 4: Deep Poverty and IMR Gaps by Racial / Ethnic Group



Notes: Panel A graphs the actual and predicted deep poverty gaps, analogous to the actual and predicted IMR gaps in Figure 1. Panel B plots the unpredicted deep poverty gaps against the unpredicted IMR gaps.

Table 1: Descriptive Characteristics by Racial / Ethnic Group

	White	Black	Mexican	PR	Asian	NA
VS Data						
Observations	2,253,597	555,299	601,170	277,357	683,977	184,341
Infant MR	5.35	12.35	5.04	7.61	4.34	8.31
Neonatal MR	3.51	8.12	3.29	5.22	2.91	3.94
Post-neonatal MR	1.84	4.23	1.75	2.39	1.43	4.36
Mother married	0.77	0.31	0.58	0.41	0.86	0.40
Maternal education						
<12	0.12	0.24	0.54	0.32	0.10	0.30
12	0.30	0.39	0.29	0.34	0.23	0.40
13-15	0.24	0.24	0.11	0.23	0.21	0.22
16 +	0.34	0.13	0.06	0.12	0.47	0.09
Maternal age						
<20	0.08	0.18	0.16	0.18	0.04	0.18
20-24	0.22	0.33	0.31	0.32	0.13	0.34
25-29	0.27	0.23	0.27	0.24	0.29	0.24
30-34	0.27	0.16	0.17	0.17	0.34	0.15
35 +	0.17	0.10	0.09	0.10	0.20	0.09
Birth weight (g)	3356	3099	3323	3216	3215	3351
Gestational age (w)	38.8	38.2	38.8	38.6	38.8	38.7
Plural birth	0.036	0.036	0.020	0.029	0.025	0.024
Populous County	0.49	0.69	0.77	0.87	0.85	0.35
Census region						
Northeast	0.18	0.16	0.03	0.59	0.21	0.04
Midwest	0.28	0.19	0.11	0.10	0.13	0.20
South	0.35	0.57	0.34	0.24	0.21	0.27
West	0.19	0.08	0.52	0.07	0.46	0.49
Census Data						
Observations	222,123	39,813	37,407	4,473	14,115	3,417
Mean HH income	64,839	36,402	40,919	41,951	77,212	37,649
Median HH income	50,360	26,000	31,400	31,000	60,000	30,200
Poverty rate	0.12	0.39	0.31	0.35	0.12	0.35
Deep poverty rate	0.05	0.23	0.13	0.20	0.05	0.18

Table 2: Actual and Predicted IMR Gaps by Racial / Ethnic Group

	Black	Mexican	PR	Asian	NA
Actual gaps					
Full	7.00	-0.30	2.27	-1.01	2.96
	(.17)	(.10)	(.16)	(.10)	(.22)
Birth weight	6.15	-0.18	2.29	-0.08	0.26
	(.12)	(.05)	(.12)	(.05)	(.09)
Neonatal	-0.27	-0.06	-0.24	-0.47	0.24
	(.07)	(.07)	(.08)	(.05)	(.12)
Post-neonatal	1.13	-0.06	0.21	-0.46	2.46
	9.08)	(.06)	(.09)	(.05)	(.14)
Predicted gaps					
Full	2.54	1.63	1.01	-1.16	2.06
	(.12)	(.20)	(.14)	(.09)	(.24)
Birth weight	1.13	0.08	0.39	-0.64	0.45
	(.07)	(.08)	(.07)	(.05)	(.11)
Neonatal	0.26	0.24	0.06	-0.11	0.48
	(.06)	(.10)	(.07)	(.08)	(.13)
Post-neonatal	1.15	1.32	0.56	-0.41	1.13
	(.07)	(.15)	(.09)	(.04)	(.13)

Notes: These three-component decompositions follow equation (2). The gaps are always listed with respect to white. Standard errors (in parentheses) are calculated from 100 bootstrapped replications.

Table 3: Infant Death and Birth Weight OLS Regressions for Whites

	Dependent Variable		
	Infant death (x1000)	Birth weight (grams)	Birth weight <1500g (x1000)
Mother married	-1.92	72.1	-3.5
	(0.14)	(1.0)	(0.2)
Maternal education			
<12	(excluded)	(excluded)	(excluded)
12	-2.01	82.7	-2.2
	(0.18)	(1.3)	(0.3)
13-15	-3.25	129.4	-4.0
	(0.20)	(1.5)	(0.3)
16 +	-4.01	162.2	-6.4
	(0.20)	(1.5)	(0.3)
Maternal age			
<20	(excluded)	(excluded)	(excluded)
20-24	-0.72	-20.6	-0.2
	(0.22)	(1.6)	(0.3)
25-29	-1.05	-14.5	1.0
	(0.24)	(1.8)	(0.3)
30-34	-1.25	-10.8	1.9
	(0.25)	(1.9)	(0.4)
35 +	-0.79	-32.0	3.4
	(0.26)	(2.0)	(0.4)
First trimester prenatal care	-1.65	27.9	-0.8
	(0.16)	(1.2)	(0.2)
Previous loss	1.25	-22.3	2.9
	(0.11)	(0.9)	(0.2)
Male	1.13	118.2	-0.1
	(0.10)	(0.7)	(0.1)
Plural birth	20.42	-1082.6	95.6
	(0.26)	(2.0)	(0.4)
Live birth order			
1^{st}	(excluded)	(excluded)	(excluded)
$2^{nd} – 3^{rd}$	-0.46	93.0	-6.1
	(0.11)	(0.8)	(0.2)
4^{th} +	0.58	116.2	-6.4
	(0.20)	(1.5)	(0.3)
State indicators	Yes	Yes	Yes
Dependent variable mean	5.35	3356	11.3
R^2	.004	.147	0.030
Observations	2,253,597	2,253,417	2,253,417

Notes: Standard errors (in parentheses) are the analytic standard errors.

Table 4: Background Characteristics and Socio-economic Status

	HH Income		Poverty		Deep Poverty	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Married	30,932	11,937	-0.369	-0.282	-0.238	-0.190
	(261)	(273)	(0.002)	(0.002)	(0.001)	(0.001)
Maternal education						
<12	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)
12	9,492	6,609	-0.190	-0.137	-0.100	-0.076
	(298)	(306)	(0.002)	(0.002)	(0.001)	(0.002)
13-15	22,399	15,648	-0.315	-0.216	-0.169	-0.119
	(296)	(320)	(0.002)	(0.002)	(0.001)	(0.002)
16 +	63,737	46,624	-0.406	-0.238	-0.207	-0.117
	(306)	(352)	(0.002)	(0.002)	(0.001)	(0.002)
Maternal age						
<20	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)
20-24	-523	-10,230	-0.076	0.066	-0.051	0.039
	(467)	(458)	(0.003)	(0.003)	(0.002)	(0.002)
25-29	13,994	-7547	-0.215	0.010	-0.129	0.012
	(453)	(469)	(0.003)	(0.003)	(0.002)	(0.002)
30-34	33,856	3494	-0.272	-0.014	-0.156	0.003
	(455)	(487)	(0.003)	(0.003)	(0.002)	(0.002)
35 +	46,950	16,358	-0.271	-0.033	-0.155	-0.007
	(467)	(502)	(0.003)	(0.003)	(0.002)	(0.002)

Note: The unadjusted column comes from separate regressions of the specified dependent variable on each set of regressors (e.g., household income on a married indicator, household income on the education indicators, etc.). The adjusted column comes from a single regression of the specified dependent variable on all of the background characteristics that are available in the Census data (i.e., married indicator, maternal education indicators, maternal age indicators, sibling indicators, and state indicators) and indicators for each of the racial/ethnic groups.

Table 5: IMR Gap Results Using State Indicators versus County Indicators

	Black	Mexican	PR	Asian	NA
Full sample					
White N	2,253,597	2,253,597	2,253,597	2,253,597	2,253,597
Minority group N	555,299	601,170	277,357	683,977	184,341
Actual IMR gap	7.00	-0.30	2.27	-1.01	2.96
Predicted IMR gap, state	2.54	1.63	1.01	-1.16	2.06
Predicted IMR gap, county	2.41	0.98	0.52	-1.38	1.80
Common support sample					
White N	1,781,609	1,524,977	1,530,973	1,900,143	1,446,965
Minority group N	499,304	549,727	244,810	650,622	172,607
Actual IMR gap	6.67	-0.02	2.52	-0.39	3.25
Predicted IMR gap, state	2.58	1.90	1.58	-0.51	2.52
Predicted IMR gap, county	2.47	1.44	1.20	-0.68	2.32

Note: The common support results use all observations for which the white population and the respective minority population have exact matches on background characteristics, including county indicators.

Table 6: The Role of Foreign-Born Status

	White	Black	Mexican	PR	Asian	NA
Percent foreign-born	5.6	11.5	63.1	34.0	84.2	3.4
<u>Foreign-born effect on IMR</u>						
Unadjusted	-1.7	-4.3	-1.4	-0.7	-1.6	-2.4
	(0.2)	(0.5)	(0.2)	(0.4)	(0.2)	(1.2)
Regression adjusted	-0.9	-2.8	-1.6	-0.4	-0.2	-0.1
	(0.2)	(0.5)	(0.2)	(0.4)	(0.2)	(1.3)
<u>IMR Gaps relative to whites</u>						
Actual, baseline		7.00	-0.30	2.27	-1.01	2.96
Predicted, baseline		2.54	1.63	1.01	-1.16	2.06
Predicted, adding foreign-born		2.40	0.21	0.38	-2.50	2.05

Notes: The unadjusted foreign-born effects are the mean difference in IMR between foreign-born and non-foreign mothers. The adjusted foreign-born effects are the coefficients on the foreign born indicator from group-specific regressions of IMR on the background characteristics used in the reweighting analysis and a foreign-born indicator variable.

Table A1: Mortality and Background Characteristics for Reweighted Whites

		Whites Reweighted to Look Like:				
	Whites	Blacks	Mexicans	PR	Asians	NA
Mortality rates						
Infant	5.35	7.89	6.98	6.37	4.19	7.41
Neonatal	3.51	4.65	3.70	3.89	2.84	4.31
Post-neonatal	1.84	3.24	3.28	2.48	1.34	3.10
Background info.						
Maternal ed. (years)						
<12	.12	.25	.55	.30	.09	.30
12	.30	.39	.28	.34	.22	.39
13-15	.24	.24	.11	.24	.20	.22
16 +	.34	.12	.05	.12	.49	.09
Maternal age						
<20	.08	.18	.18	.17	.03	.18
20-24	.22	.33	.35	.32	.13	.35
25-29	.27	.23	.26	.24	.29	.24
30-34	.27	.16	.15	.17	.34	.14
35 +	.17	.11	.07	.10	.21	.08
Mother married	.77	.31	.52	.43	.87	.41
First trimester care	.88	.74	.71	.79	.85	.70
Previous loss	.25	.30	.17	.31	.20	.26
Male	.51	.51	.51	.51	.52	.51
Plural birth	.036	.035	.019	.029	.025	.024
Live birth order						
1st	.41	.38	.36	.40	.48	.36
2^{nd} / 3^{rd}	.50	.47	.49	.48	.46	.46
4^{th} +	.09	.15	.15	.11	.06	.18
Census region						
Northeast	.18	.15	.02	.54	.20	.04
Midwest	.28	.19	.10	.10	.13	.19
South	.35	.58	.37	.28	.20	.30
West	.19	.08	.50	.08	.47	.47

Table A2: Estimates and Standard Errors for the Roles of Covariates Graphed in Figure 2

	Edu	Age	Mar	Prenat.	Prev.	Male	Plur	Order	State
Black									
Full	.56	.39	1.00	.15	.04	-.01	-.02	.10	.17
	(.05)	(.09)	(.09)	(.03)	(.00)	(.00)	(.01)	(.03)	(.04)
Birth Weight	.33	.01	.64	.04	.04	.00	-.02	-.04	.11
	(.02)	(.03)	(.06)	(.01)	(.00)	(.00)	(.01)	(.01)	(.02)
Neonatal	.08	.07	-.01	.04	.00	.00	.00	.03	.01
	(.03)	(.05)	(.04)	(.02)	(.00)	(.00)	(.00)	(.01)	(.02)
Post-neonatal	.15	.31	.37	.07	.01	.00	.00	.11	.06
	(.02)	(.06)	(.05)	(.02)	(.00)	(.00)	(.00)	(.02)	(.02)
Mexican									
Full	1.15	.31	.42	.15	-.12	.00	-.34	.07	-.21
	(.14)	(.07)	(.04)	(.02)	(.01)	(.00)	(.01)	(.02)	(.07)
Birth Weight	.70	.00	.27	.04	-.10	.00	-.43	-.10	-.17
	(.08)	(.02)	(.02)	(.01)	(.01)	(.00)	(.01)	(.01)	(.04)
Neonatal	.15	.05	.00	.04	-.01	.00	.06	.04	-.12
	(.08)	(.04)	(.02)	(.02)	(.01)	(.00)	(.01)	(.01)	(.05)
Post-neonatal	.31	.26	.16	.07	-.01	.00	.03	.12	.08
	(.07)	(.05)	(.02)	(.01)	(.01)	(.00)	(.00)	(.02)	(.04)
Puerto Rican									
Full	.67	.37	.79	.11	.07	.00	-.17	.05	-.64
	(.07)	(.08)	(.07)	(.02)	(.01)	(.00)	(.01)	(.01)	(.06)
Birth Weight	.40	.01	.51	.03	.06	.00	-.21	-.03	-.24
	(.04)	(.02)	(.05)	(.01)	(.00)	(.00)	(.01)	(.01)	(.03)
Neonatal	.09	.06	-.01	.03	.00	.00	.03	.02	-.12
	(.04)	(.05)	(.03)	(.01)	(.00)	(.00)	(.00)	(.01)	(.04)
Post-neonatal	.18	.29	.30	.05	.01	.00	.01	.06	-.28
	(.03)	(.06)	(.04)	(.01)	(.00)	(.00)	(.00)	(.01)	(.04)

Table A2 (continued)

Asian									
Full	-.22	-.10	-.19	.04	-.06	.00	-.24	.01	-.38
	(.02)	(.02)	(.01)	(.01)	(.01)	(.00)	(.01)	(.01)	(.08)
Birth Weight	-.13	.04	-.11	.01	-.05	.00	-.30	.11	-.22
	(.01)	(.01)	(.01)	(.00)	(.00)	(.00)	(.01)	(.00)	(.04)
Neonatal	-.03	-.01	.00	.01	.00	.00	.04	-.03	-.09
	(.01)	(.01)	(.01)	(.00)	(.00)	(.00)	(.00)	(.01)	(.06)
Post-neonatal	-.06	-.13	-.07	.02	-.01	.00	.02	-.07	-.07
	(.01)	(.01)	(.01)	(.00)	(.00)	(.00)	(.00)	(.00)	(.04)
Native American									
Full	.71	.40	.82	.21	.00	-.01	-.28	.15	.08
	(.06)	(.09)	(.08)	(.04)	(.00)	(.00)	(.01)	(.04)	(.12)
Birth Weight	.42	.01	.52	.06	.00	.00	-.35	-.08	-.05
	(.03)	(.03)	(.05)	(.02)	(.00)	(.00)	(.01)	(.02)	(.05)
Neonatal	.10	.07	-.01	.06	.00	.00	.05	.05	.08
	(.04)	(.05)	(.04)	(.02)	(.00)	(.00)	(.01)	(.02)	(.08)
Post-neonatal	.19	.32	.30	.09	.00	.00	.03	.18	.04
	(.03)	(.06)	(.04)	(.02)	(.00)	(.00)	(.00)	(.04)	(.07)

Table A3: Robustness of Predicted Gaps

	Black	Mexican	PR	Asian	NA
Full predicted gaps					
Figure 3 results, white mapping	2.54	1.63	1.02	-1.16	2.06
Figure 3 results, other group mapping	2.04	-0.32	1.29	-1.09	1.95
Common support, white mapping	2.65	2.15	1.56	-0.73	2.60
Common support, other group mapping	1.81	0.13	1.54	-0.91	2.26
Gaps due to the three SES variables					
Reweighting, white mapping	1.95		1.83		1.93
Reweighting, other group mapping	1.88		1.40		1.93

Notes: The common support results use all observations for which the white population and the respective minority population have exact matches on the baseline set of characteristics (i.e., including state but not county indicators).

Unpublished Appendix Table U1: Actual and Predicted IMR Gaps by Racial / Ethnic Group

	Black		Mexican		PR		Asian		NA	
Gap Type	Act.	Pred.	Act.	Pred.	Act.	Pred.	Act.	Pred.	Act.	Pred.
Overall	7.00	2.54	-0.30	1.63	2.27	1.02	-1.01	-1.16	2.96	2.06
	(.17)	(.12)	(.10)	(.20)	(.16)	(.14)	(.10)	(.09)	(.22)	(.24)
Fitness Measured by Birth Weight										
Fitness	6.15	1.13	-0.18	0.08	2.29	0.39	-0.08	-0.64	0.26	0.45
	(.12)	(.07)	(.05)	(.08)	(.12)	(.07)	(.05)	(.05)	(.09)	(.11)
Neonatal	-0.27	0.26	-0.06	0.24	-0.24	0.06	-0.47	-0.11	0.24	0.48
	(.07)	(.06)	(.07)	(.10)	(.08)	(.07)	(.05)	(.08)	(.12)	(.13)
Post-neonatal	1.13	1.15	-0.06	1.32	0.21	0.56	-0.46	-0.41	2.46	1.13
	(.08)	(.07)	(.06)	(.15)	(.09)	(.09)	(.05)	(.04)	(.14)	(.13)
Fitness Measured by Gestational Age										
Fitness	5.60	1.10	0.22	0.24	2.16	0.44	-0.24	-0.52	0.82	0.56
	(.11)	(.06)	(.05)	(.08)	(.11)	(.06)	(.05)	(.05)	(.09)	(.11)
Neonatal	-0.08	0.22	-0.39	0.06	-0.20	-0.00	-0.40	-0.19	-0.17	0.34
	(.07)	(.06)	(.06)	(.11)	(.09)	(.08)	(.06)	(.08)	(.13)	(.14)
Post-neonatal	1.48	1.23	-0.13	1.33	0.30	0.59	-0.38	-0.45	2.31	1.16
	(.09)	(.07)	(.06)	(.15)	(.08)	(.09)	(.05)	(.04)	(.14)	(.14)

Notes: These three-component decompositions follow equation (2). “Act.” refers actual gaps and their components, and “Pred.” refers to gaps that result when whites are compared with the white population reweighted to have the background characteristics of the relevant group. Standard errors (in parentheses) are calculated from 100 bootstrapped replications.

Unpublished Appendix Table U2: Results for other Hispanic Groups

	Mexican	Puerto Rican	Cuban	Central/South American
Sample size	601,170	277,357	69,794	610,117
Actual gap	-0.30	2.27	-1.21	-0.77
Predicted gap, baseline	1.63	1.01	-0.30	0.57
Predicted gap, baseline and adding foreign-born	0.21	0.38	-0.66	-1.12