Published in final edited form as:

Labour Econ. 2016 December ; 43: 42–54. doi:10.1016/j.labeco.2016.04.001.

Racial and Ethnic Infant Mortality Gaps and the Role of Socio-Economic Status

Todd E. Elder, John H. Goddeeris, and Steven J. Haider

Michigan State University

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, we examine mortality gaps of infants born to white, black, Mexican, Puerto Rican, Asian, and Native American mothers. We find that between-group mortality gaps are strongly and consistently (except for Mexican infants) associated with maternal marital status, education, and age, and that these same characteristics are powerful predictors of income and poverty for new mothers in U.S. Census data. Despite these similarities, we document a fundamental difference in the mortality gap for the three high mortality groups: whereas the black-white and Puerto Rican-white mortality gaps mainly occur at low birth weights, the Native American-white gap occurs almost exclusively at higher birth weights. We further examine the one group whose IMR is anomalous compared to the other groups: infants of Mexican mothers die at relatively low rates given their socio-economic disadvantage. We find that this anomaly is driven by lower infant mortality among foreign-born mothers, a pattern found within many racial/ethnic groups. Overall, we conclude that the infant mortality gaps for our six racial/ethnic groups exhibit many commonalities, and these commonalities suggest a prominent role for socio-economic differences.

Keywords

infant mortality; infant health; disparities

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 racial and ethnic groups, the IMRs among American Indians/Alaska Natives (8.28) and Puerto Ricans (8.01)

Publisher's Disclaimer: This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final citable form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

JEL Classification: J31, J15, J16

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, richer data could possibly support an SES explanation for much of the black-white gap. As another example, the absence of a Hispanic-white mortality gap also fails to support a large role for SES because Hispanics are relatively disadvantaged compared to whites. However, evaluating the Hispanic-white disparity is complicated because of the larger “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 using the reweighting approach developed in Elder, Goddeeris and Haider (2011) to study the black-white gap. The extension to study multiple racial and ethnic groups is important because 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. In addition, these other racial and ethnic IMR gaps are interesting in their own right, in part because of shifting demographics in the U.S.²

Our primary substantive findings are as follows. First, for the IMR gaps for blacks, Puerto Ricans, Asians, and Native Americans (all relative to whites), we find that three characteristics – maternal education, maternal marital status, and maternal age – are the primary drivers of the predictable gaps. We also find that these three key predictors are strongly related to poverty and income for new mothers.

Second, we further probe the IMR gaps among the high-IMR groups and find that the Native American gap is fundamentally different from the black and Puerto Rican gaps in that it emerges at much higher birth weights. Despite this difference, we further find that the part of the IMR gap that is predictable for all three groups is the part that emerges at higher birth weights.

Third, we find that infants born to Mexican mothers are not as different from the other groups as they initially seem. Specifically, large numbers of Mexican infants have foreign-born mothers, and infants of foreign-born mothers display substantial mortality advantages

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

²Between 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).

across several racial/ethnic groups. Although this finding raises the question of why such a foreign-born advantage exists, it also suggests that the Hispanic paradox is at least partially driven by mechanisms that are not unique to Hispanics. Moreover, we provide some evidence that the foreign-born advantage is linked in an interesting way to two of our socio-economic variables, maternal marital status and maternal education.

Overall, we conclude that the infant mortality gaps for our six racial/ethnic groups exhibit many similarities, and these similarities suggest that socio-economic differences play a prominent role for explaining the IMR differences and even some apparent anomalies that exist.

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

Although infant health undoubtedly has a strong genetic component (e.g., Currie and Moretti 2007), there has been a burgeoning of studies in recent years 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 Filipowski 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 (2015), who exploit variation in income arising from the expansion of the Earned Income Tax Credit (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 Elder, Goddeeris, and Haider (2011). 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; Elder, Goddeeris, and Haider (2011) uses the same 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.

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, defined as the first 28 days after birth and the remainder of the first year, respectively. 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, and 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 (2013) finds

³Sometimes 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. We do not do in this paper because both are themselves indicators of infant health.

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

To examine how background characteristics affect IMR gaps and their temporal components, we use inverse probability weighting to create counterfactual objects.⁴ This method allows us to use a common framework to examine both simple objects like IMR gaps and more complex objects like distribution functions (discussed below). 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 one group to match the distribution of characteristics in another group. Such a method, of course, can only align groups on observable characteristics, implying that unobservable characteristics could still be different between the groups, so that the usual concerns about inferring causality in the face of unobservable differences remain.

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

$$f(y|g) = \int_x f(y|g, x) dF(x|g) \equiv f(y; g_y|x, g_x), \quad (1)$$

expressing $f(y|g)$ 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

$$f(y; g_y|x = A, g_x = B) \equiv \int_x f(y|g = A, x) dF(x|g = B) \quad (2)$$

as the distribution of outcomes that would result if group A retained its own mapping from characteristics to outcomes ($g_y|x = A$) but had the group B distribution of characteristics ($g_x = B$).

The counterfactual density in (2) can be estimated as a weighted function of the actual group A data, with weights that are simple to construct. Specifically,

⁴Our 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).

$$f(y; g_y|_x=A, g_x=B) \equiv \int_x f(y|g=A, x) \psi_{A \rightarrow B}(x) dF(x|g=A), \quad (3)$$

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

$$\psi_{A \rightarrow B}(x) \equiv \frac{dF(x|g=B)}{dF(x|g=A)} = \frac{\Pr(g=B|x)}{\Pr(g=A|x)} \times \frac{\Pr(g=A)}{\Pr(g=B)}. \quad (4)$$

The last equality in (4) 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 baseline empirical analysis, 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 (4) for each observation in the white population. With the reweighted white population (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 also present results that use other reference groups to explore the robustness of our results.

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 (2015). 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 by comparing the group A population with this newly reweighted population.

We use weights of the following form:

$$\psi_{A \rightarrow B}^z(z, x_{-z}) = \frac{dF(z|j=B) - dF(z|j=A) + dF(z|x_{-z}, j=A)}{dF(z|x_{-z}, j=A)}. \quad (5)$$

We calculate the weights using sample analogs of the objects on the right-hand-side of (5). For further details see Elder, Goddeeris and Haider (2015).

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.

4. The Racial/Ethnic Mortality Gaps

We discuss our two primary sources of data, the Vital Statistics data and Census data, show the mortality gaps that are the focus of our study, and then provide a detailed discussion of the observable characteristics we consider.

4.1. Our 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 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. 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 further limit our analysis to births that occur in the fifty U.S. states or the District of Columbia to mothers who reside in the U.S.⁵

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.⁶ 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.⁷ 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,

⁵We pool across the years 2000–04 because the mortality rates were relatively constant during these years and NCHS withholds state identifiers in the publicly available linked files starting in 2005. The data include a weight variable to adjust for unlinked deaths by state, but we do not apply these weights because we include state fixed effects in our key analysis. The definition of residing in the U.S. is not based on an official U.S. Citizen and Immigration Services definition, but rather on a simple question regarding where the mother actually resides; because of this broader definition of residence, this exclusion affects very few individuals – less than 0.1 percent of the U.S. population and less than 0.5 percent of each of the racial/ethnic groups we study.

⁶Most 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.

⁷In 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.

and Native Americans/Alaska Natives. For simplicity, we refer to these groups as whites, blacks, Mexicans, Puerto Ricans (abbreviated “PR”), Asians, and Native Americans/Alaskan Natives (abbreviated “NA/AN”), respectively.

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.

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 socioeconomic status of the families. To supplement our analysis, we also use an extract from the 2000 U.S. 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 than two years old and code the available background characteristics to match our VS sample as closely as possible. Of course, this method of constructing our sample of mothers necessarily excludes those mothers whose child has already died; to the extent that infant mortality is related to SES, as our findings suggest, this exclusion means that the most disadvantaged mothers are absent from our data.

4.2. The Mortality and Income/Poverty Gaps

Table 1 presents descriptive statistics from the VS data for our infant mortality measures and background characteristics. 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.

Table 1 also shows 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 matters: 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). However, Mexicans are an important anomaly: they are a low-IMR group, but have mean household income that is similar to the high-IMR groups (\$40,919). If we instead examine the deep poverty measure, defined as family income being less than one-half of the official poverty line, this anomalous pattern somewhat diminishes: 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)—albeit a rate still substantially higher than the two other low-IMR groups (whites and Asians at 0.05).

4.3. Defining Background Characteristics

Because income is not directly observable on birth certificate data, we instead must rely on other background characteristics to infer the role of income and, more generally, SES. 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—such as household income—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.⁸ 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 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.⁹

Unlike most previous studies, 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

⁸In the VS data, 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 (1st, 2nd/3rd, >3rd). We use single indicators for whether the infant is male, whether the birth was plural, whether the mother was married, and whether the mother experienced a previous pregnancy loss. We include observations where background characteristics were imputed, but exclude those observations where background characteristics were missing. Similarly, in the U.S. Censuses, we include identical measures for maternal education, maternal age, the gender of the infant, and whether the mother is married. In the Census, we are not able to include any covariates related to prenatal care and whether there was previous loss.

⁹Bachu (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.

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, thereby abstracting from all such differences at the state level. We have also estimated models in which we instead include indicators for county (or county groupings for less-populated counties), which allow us to abstract from all county-level differences as well. The results (available in an unpublished appendix) changed very little compared to those using state indicators.

5. 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. The first column of Table 2 shows an OLS regression to demonstrate the predictive power of these characteristics for infant death within the white population. All background characteristics are indicator variables, so each coefficient can be interpreted as the mortality difference compared 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.

5.1. The Combined Role of All Background Characteristics

We use the reweighting methods described in Section 3 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.¹⁰ We refer to the IMR gaps between whites and these

¹⁰Appendix Table A1 shows summary statistics for whites and these counterfactual populations. The counterfactual quantities are based on weights computed from, for example, a logit for whether an individual is black or white, according to equation 4. 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 across the various groups.

counterfactual populations as “predicted gaps”. We show the point estimates and standard errors in Table 3 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.¹¹

Several interesting findings emerge when comparing the gaps across groups. 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 ($-1.16/-1.01$).

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 in calculating predicted gaps.

Figure 1 reveals that the two different predicted gaps are quite similar for all racial/ethnic groups but Mexicans, implying that our conclusions about predicted gaps are generally insensitive to which group’s mapping is used.¹² Moreover, the differences in the predicted gaps for Mexicans shed additional light on the Hispanic paradox. Namely, it appears that the overall low mortality rate observed among Mexicans is accompanied by a compression of mortality differences across the background characteristics we study. In other words, background characteristics appear to matter less for mortality among Mexicans than they do among whites. We return to consider the Hispanic paradox directly in Section 7.

5.2. 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. 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

¹¹Elder, Goddeeris and Haider (2011) explored the robustness of the predictability of the black-white IMR gap to several 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. Results were qualitatively similar in every case.

¹²Technically, groups cannot be reweighted to look like each other unless there is “sufficient overlap” in background characteristics. In Appendix Table A3, we show that the estimates are very similar if the samples are restricted to eliminate concerns about lack of overlap.

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 high-IMR groups (blacks, 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 found in the high-IMR groups, we would predict that their IMR would be substantially higher.¹³ 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.¹⁴ 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, our results suggest that the white IMR would decrease if whites had the characteristics found among the disadvantaged groups. For example, the white IMR would decrease by over 0.5 if white births were distributed across states in the same way Puerto Rican births are. To illustrate why this is the case, note that 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.

5.3. The Relationship between Background Characteristics and SES

Our results indicate that much 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 use our Census sample of new mothers to assess 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 the other covariates.¹⁵ The results are presented in Table 4.

Starting with the household income results that do not adjust for other covariates, the three background characteristics that predict much of the IMR gap are associated with large income differences. Married mothers have \$30,932 more household income than non-

¹³Because 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.

¹⁴Oaxaca-Blinder methods yield very similar results: the contributions for the three variables are 1.80, 1.74 and 1.85 for blacks,

Puerto Ricans and Native Americans, respectively. These estimates are calculated as $\beta'_A(\bar{z}_B - \bar{z}_A)$, where $\bar{z}_g$ is a vector of sample means from Table 1 and β_A is the corresponding vector of coefficients from a regression of y on x among whites from Table 2.

¹⁵Specifically, the columns labeled “unadjusted” show 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 columns labeled “adjusted” show 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.

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 background characteristics: 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, maternal age 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 strongly related to household income. Similar patterns are apparent for the poverty and deep poverty rate results shown in the rest of the table.

While these results suggest an important role for SES through these three observable characteristics, would the role of socio-economic status be even larger if birth certificates included income itself? 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, we construct a set of actual, predicted, and unpredicted deep poverty gaps for each racial/ethnic group.¹⁷ We focus on deep poverty due to the 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 3 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 3 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 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 using much smaller datasets that finds that income matters for birth outcomes even when controlling for other indicators of SES (Finch 2003, Nepomnyaschy 2009).

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

¹⁷Using 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.

6. Why Are Some Gaps More Predictable than Others?

As pointed out above, the fractions of the black and Puerto Rican gaps that are predictable are substantially less than the fraction of the Native American gap that is predictable (36 percent, 44 percent, and 70 percent, respectively, based on the results reweighting whites—see Table 3). We also see in Table 1 that the gap in average birth weight, another infant outcome that is highly related to infant mortality, is larger for blacks and Puerto Ricans than for Native Americans.

To examine how differences in IMR and birth weight are related, the top panel of Figure 4 shows the cumulative IMR gap for the three groups with the highest mortality rates – blacks, Puerto Ricans, and Native Americans – across the distribution of birth weight. Specifically, each curve is constructed by calculating the number of infant deaths that occur for birth weights less than or equal to a given weight per 1000 total births, and then subtracting the corresponding number for whites. For example, the rightmost endpoint of the curve labeled “Black” in the top panel has a height of 6.9, which is the overall black-white IMR gap.¹⁸ The height of the black curve at 1000 grams is roughly 4.8, meaning that roughly 70 percent (4.8/6.9) of the black-white gap is accounted for by deaths among infants weighing less than 1000 grams.

Comparing the cumulative lines for the three high mortality rate groups shown in the figure, we see that the black-white and Puerto Rican-white IMR gaps are fairly similar, in that much of the overall gaps emerge by 1000 grams. In contrast, very little of the Native American gap emerges at birth weights below 2000 grams. The comparison of the Native American and Puerto Rican curves is especially striking: despite these groups having very similar mortality gaps with whites (the endpoints are close), the mortality gaps arise in much different parts of the birth weight distribution (below 1000 grams for Puerto Ricans and above 2000 grams for Native Americans).

The bottom panel of the figure shows cumulative curves analogous to the top panel, but based on predicted IMR gaps. Comparing the right endpoints of the corresponding curves in the two panels replicates the findings from Table 2: a relatively small share of the full black-white gap is predictable, much of the Native American-white gap is predictable, and the Puerto Rican-white gap represents an intermediate case. The important feature of the predicted IMR gap curves, though, is their similarities: much of the overall increase in the cumulative predicted IMR gaps occurs between 2000 and 4000 grams. Thus, to the extent that IMR gaps can be predicted, it is the gaps that occur in the middle of the birth weight distribution.

Taken together, these results suggest both important differences and similarities between the high-IMR groups. On the one hand, the IMR gap for Native Americans is different from the gap for blacks and Puerto Ricans because the Native American gap emerges at higher birth weights. On the other hand, the predicted IMR gaps for the three groups are similar in that they emerge among those births between 2000 and 4000 grams. Thus, the Native American

¹⁸The black-white IMR gap reported in Table 2 is 7.0. The difference between that gap and the 6.9 end-point of the figure is that the figure necessarily drops those observations with missing birth weight.

gap is more predictable than the other two gaps because it emerges in portion of the birth weight distribution that tends to be predictable.¹⁹

7. Why is the Mexican Gap So Different?

The predicted mortality gap for Mexicans falls between the mortality gaps of Native Americans and Puerto Ricans, yet the actual mortality gap for Mexicans is much smaller. 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 is the crux of the Hispanic paradox. Consistent with previous studies, we found that the paradox exists for Mexicans, but not for Puerto Ricans.²⁰

In this section, we examine the extent to which the (more aptly named) Mexican 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). As in previous sections, we concentrate on whether our findings are consistent across various racial/ethnic groups.

The top row of Table 5 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 next set of rows of Table 5 shows the difference in IMR for foreign-born mothers versus U.S.-born mothers for each of our racial/ethnic groups, both with and without adjusting for our other background characteristics. In every case, we find that the IMR is lower for foreign-born mothers, although the advantage for foreign-born mothers is statistically significant only for whites, blacks, and Mexicans when adjust we adjust for background characteristics. Even so, it is clear from these results that the advantage of foreign-born mothers is a phenomenon that goes beyond Mexican-born mothers.

In the lower panel of Table 5, we repeat the reweighting analysis from Table 3 in two ways to demonstrate the importance of foreign-born mothers to our analysis. The first way simply adds a “foreign-born mother” indicator to the set of covariates. Because a small number 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 3, and the crux of the Hispanic paradox is still apparent: Mexicans are unique in that the actual IMR gap is much smaller than the predicted IMR gap. When the foreign-born indicator is added, the predicted IMR gap falls from 1.63 to 0.21 for Mexicans. Thus, once we account for the systematic relationship between being foreign-born and IMR among whites (recall that our

¹⁹In an unpublished appendix, we decompose the mortality gaps into three distinct temporal components – a birth weight component, a neonatal component, and a post-neonatal component – and assess predictability of each component with similar methods. The results verify that mortality differences due to birth weight distribution differences are relatively unpredictable. In addition, we show that the results are similar if gestational age is used as a measure of fitness at birth rather than birth weight.

²⁰In 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.

preferred results use the white mapping from characteristics to outcomes), much of the paradox disappears for Mexicans: the predicted IMR gap (0.21) is now much closer to the actual IMR gap (−0.29).

Our second analysis instead drops all foreign-born mothers in each racial/ethnic group and then repeats the reweighting analysis.²¹ We first show the actual IMR gaps and then show the predicted gaps based on reweighting white mothers to have the characteristics of the U.S.-born mothers in the various racial/ethnic groups. As in the previous analysis, much of the paradox disappears: whereas the difference between the predicted and actual IMR gaps was 1.92 when all Mexican mothers were included (the difference between 1.63 and −0.29 in the previous panel), the same difference when just U.S.-born mothers are used is 0.78 (the difference between 1.34 and 0.56). Moreover, these additional results show that much of the closing of the gap comes from U.S.-born Mexican mothers being less advantaged as foreign-born Mexican mothers with respect to mortality (an actual IMR gap of 0.56 vs. −0.29). A smaller fraction of the closing of the gap between predicted and actual IMR results from U.S.-born Mexican mothers having better observable characteristics than foreign-born Mexican mothers (a predicted IMR gap of 1.34 vs. 1.63).

Of course, these results raise the questions of (1) what is the source of the foreign-born advantage and (2) what is the source of the remaining Mexican paradox? To shed light on these remaining questions, we return to Table 2 and examine the relationships between background characteristics and infant mortality for white mothers, US-born Mexican mothers, and foreign-born Mexican mothers. These comparisons reveal that the differences arise with respect to two of the background characteristics that have been the focus of our study, maternal marital status and maternal education. For example, the infant mortality rate is 1.92 lower for married white mothers than for single white mothers, but there is essentially no difference between married and single foreign-born Mexican mothers (the difference is −0.03); the difference between married and single U.S.-born Mexican mothers lies between these two quantities (−1.22). Similarly, the gradient with respect to education is smaller for foreign-born Mexican mothers than for white mothers; for example, the IMR is 4.01 lower for college educated white women than for white women who have not completed high school, while the same gap is only 1.38 for foreign-born Mexican mothers and takes on an intermediate value for U.S.-born Mexican mothers (2.29).

Taken together, these results suggest that the source of both the foreign-born advantage and the Mexican advantage appear to be related to two factors that emerged as being important in the previous section: the IMR disadvantage for infants born to single mothers and less-educated mothers is smaller for both U.S.-born and foreign-born Mexican mothers than it is for white mothers.²² Importantly, Hummer, Powers, et al. (2007) conclude that a common hypothesis that might partially explain the general Hispanic paradox, and one that would relate more generally to the foreign-born advantage, is not relevant for IMR: return

²¹We retain all foreign-born white mothers for this additional analysis so that all changes between this analysis and the previously reported analysis are due to dropping the foreign-born mothers in the racial/ethnic group being studied.

²²In results available from the authors, the results are similar for Asian mothers: The effect of education on IMR is much less for foreign-born Asian mothers and takes on an intermediate values for U.S.-born Asian mothers. This finding supports our interpretation that the patterns are informative about the foreign-born advantage more generally.

migration of the least healthy is unlikely to be relevant for IMR because (a) the majority of infant deaths occur in the first week of life and these infants are unlikely to travel and (b) the Mexican advantage occurs even for the 1-hour and 1-day mortality rate. Our results suggest that the explanation for the Mexican paradox instead stems from much smaller IMR disadvantages for being single or low-educated compared to whites. The sources of these smaller disadvantages are unclear, but perhaps Mexican mothers have access to better support networks to compensate for these disadvantages; alternatively, these characteristics might be less indicative of skill or labor market opportunities than they are for natives. The latter explanation might reflect a “healthy immigrant” phenomenon, whereby Mexican-born mothers giving birth in the U.S. have better unobserved characteristics than their SES would suggest.

8. Discussion and Conclusions

We used micro-level U.S. Vital Statistics data from 2000 to 2004 and U.S. Census data from 2000 to examine differences in infant mortality rates across several racial and ethnic groups, and we examined the extent to which these differences are related to SES differences. In addition, we directly examined why the infant mortality gap for Mexican mothers is so different than the infant mortality gap for the other groups, and we provided additional insight into the nature of the unexplained portion of the mortality gaps. These analyses led to several conclusions.

First, we conclude that there appears to be a substantial role for SES when we look across all groups. Each of the three covariates that consistently 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 of the IMR gaps 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, such as income, were available on birth certificates.

Second, we further probed the IMR gaps among the high-IMR groups and found that the Native American gap is fundamentally different from the black and Puerto Rican gap in that it emerges at much higher birth weights. Although the importance of low birth weight for the black-white gap is well-known, its importance for the Puerto Rican-white gap and its unimportance for the Native American-white gap are not. Despite these differences, we further found that much of the IMR gap that is predictable for all three groups is the part that emerges at high birth weights.

Third, we showed that even the Mexican paradox can be partially be accounted for by a common finding across various racial/ethnic groups: foreign-born mothers tend to have lower infant mortality than do their domestic-born counterparts. Further analysis then demonstrated that the differences for foreign-born and U.S.-born Mexican mothers relate to the association between infant death and maternal marital status and education, two of the

socioeconomic characteristics that arose as being important for the other racial/ethnic groups.

Overall, while our results echo findings in previous studies, they suggest that many of the previous findings are far more widely applicable: the SES variables contribute to substantial mortality gaps across numerous groups; the central importance of low birth weights for IMR gaps is not just a phenomenon among blacks, but also a phenomenon among Puerto Ricans; and the mortality benefit associated with the Hispanic paradox stems to a significant extent from a foreign-born advantage that is evident even among whites. Thus, our systematic comparisons of the racial/ethnic IMR gaps suggest that they are more similar than they might initially appear, and these similarities suggest that socio-economic differences play a prominent role for explaining the IMR differences. Furthermore, to the extent that SES differences are a driver of the IMR gaps, then income support and social service programs that alleviate the disadvantages associated with low SES would be more effective at reducing the gaps than perhaps previously understood.

Acknowledgments

*We thank Isaac Eberstein, Nigel Paneth, Gary Solon and seminar participants at Miami University, the University of California-Davis, the University of Chicago, the University of Florida, the University of Illinois-Chicago, the University of Louisville, the University of Michigan, and Western Michigan University for helpful comments. Earlier drafts were also presented at the 2012 Population Association of America and the 2010 American Society of Health Economists meetings. Research reported in this paper was supported by the Eunice Kennedy Shriver National Institute of Child Health and Human Development of the National Institutes of Health under award number R03HD073565.

Appendix

Table A1

Mortality and Background Characteristics for Reweighted Whites

	Whites Reweighted to Look Like:					
	Whites	Blacks	Mexicans	PR	Asians	NA/AN
<u>Mortality rates</u>						
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
<u>Background info.</u>						
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

	Whites Reweighted to Look Like:					
	Whites	Blacks	Mexicans	PR	Asians	NA/AN
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

	Black	Mexican	PR	Asian	NA/AN
Education	.56 (.05)	1.15 (.14)	.67 (.07)	-.22 (.02)	.71 (.06)
Age	.39 (.09)	.31 (.07)	.37 (.08)	-.10 (.02)	.40 (.09)
Marriage	1.00 (.09)	.42 (.04)	.79 (.07)	-.19 (.01)	.82 (.08)
Prenatal care	.15 (.03)	.15 (.02)	.11 (.02)	.04 (.01)	.21 (.04)
Previous loss	.04 (.00)	-.12 (.01)	.07 (.01)	-.06 (.01)	.00 (.00)
Male	-.01 (.00)	.00 (.00)	.00 (.00)	.00 (.00)	-.01 (.00)
Plurality	-.02 (.01)	-.34 (.01)	-.17 (.01)	-.24 (.01)	-.28 (.01)
Birth order	.10 (.03)	.07 (.02)	.05 (.01)	.01 (.01)	.15 (.04)
State of residence	.17 (.04)	-.21 (.07)	-.64 (.06)	-.38 (.08)	.08 (.12)

Table A3

Robustness of Predicted Gaps

	Black	Mexican	PR	Asian	NA/AN
<u>Full predicted gaps</u>					

	Black	Mexican	PR	Asian	NA/AN
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
<u>Gaps due to the three SES variables</u>					
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.

Unpublished Appendix Table U1

Actual and Predicted IMR Gaps by Racial/Ethnic Group

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

Notes: These decompositions are based on the same three-component decompositions reported in Elder, Goddeeris, Haider (2011). "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

References

Akerlof GA, Yellen JL, Katz ML. An Analysis of Out-of-Wedlock Childbearing in the United States. *Quarterly Journal of Economics*. 1996; 111(2):277-317.

- Alexander GR, Wingate MS, Bader D, Kogan MD. The Increasing Racial Disparity in Infant Mortality Rates: Composition and Contributors to Recent US Trends. *American Journal of Obstetrics and Gynecology*. 2008; 198:51.e1–51.e9. [PubMed: 17870043]
- Almond D, Chay KY, Greenstone M. Civil Rights, the War on Poverty, and Black-White Convergence of Infant Mortality in the Rural South and Mississippi. MIT Working Paper. 2006
- Almond D, Hoynes HW, Schanzenbach DW. Inside the War on Poverty: The Impact of Food Stamps on Birth Outcomes. *Review of Economics and Statistics*. 2011; 93(2):387–403.
- Bachu, A. Current Population Reports P23–197. Washington, DC: U.S. Census Bureau; 1999. Trends in Premarital Childbearing: 1930 to 1994.
- Busso M, DiNardo J, McCrary J. New Evidence on the Finite Sample Properties of Propensity Score Matching and Reweighting Estimators. 2009 IZA Discussion Paper No 3998
- Carmichael SL, Iyasu S. Changes in the black-white infant mortality gap from 1983 to 1991 in the United States. *Am J Prev Med*. 1998; 15(3):220–7. [PubMed: 9791640]
- Case A, Lubotsky D, Paxson C. Economic Status and Health in Childhood: The Origins of the Gradient. *American Economic Review*. 2002; 92(5):1308–1334.
- Cole SR, Hernán MA. Adjusted survival curves with inverse probability weights. *Computer Methods and Programs in Biomedicine* 2004. 2004; 75(1):45.
- Cooksey E. Factors in the Resolution of Adolescent Premarital Pregnancies. *Demography*. 1990; 27(2): 207–18. [PubMed: 2332086]
- Chay KY, Greenstone M. The Convergence in Black-White Infant Mortality Rates during the 1960's. *American Economic Review*. 2000; 90(2):326–332.
- Chay KY, Greenstone M. The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession. *Quarterly Journal of Economics*. 2003; 118(3):1121–1167.
- Chay KY, Greenstone M. Does Air Quality Matter? Evidence from the Housing Market. *Journal of Political Economy*. 2005; 113(2):376–424.
- Currie J. Inequality at Birth: Some Causes and Consequences. *American Economic Review*. 2011; 101(2):1–22.
- Currie J. Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. *Journal of Economic Literature*. 2009; 47(1):87–122.
- Currie J, Greenstone M, Moretti E. Superfund Cleanups and Infant Health. *American Economic Review*. 2011; 101(3):435–441. [PubMed: 25152535]
- Currie J, Gruber J. Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women. *Journal of Political Economy*. 1996; 104(6):1263–96.
- Currie J, Moretti E. Biology as Destiny? Short- and Long- Run Determinants of Intergenerational Transmission of Birth Weight. *Journal of Labor Economics*. 2007; 25(2):231–63.
- Currie J, Neidell M. Air Pollution and Infant Health: What Can We Learn from California's Recent Experience? *Quarterly Journal of Economics*. 2005; 120(3):1003–30.
- Currie J, Neidell M, Schmieder JF. Air Pollution and Infant Health: Lessons from New Jersey. *Journal of Health Economics*. 2009; 28(3):688–703. [PubMed: 19328569]
- Currie J, Schmieder JF. Fetal Exposures to Toxic Releases and Infant Health. *American Economic Review*. 2009; 99(2):177–83. [PubMed: 19724661]
- Currie J, Walker R. Traffic Congestion and Infant Health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*. 2011; 3(1):65–90.
- David RD, Collins JW. Differing Birthweight among Infants of US-born Blacks, African-born Blacks, and US-born Whites. *N Engl J Med*. 1997; 337:1209–1214. [PubMed: 9337381]
- Dehejia R, Lleras-Muney A. Booms, Busts, and Babies' Health. *Quarterly Journal of Economics*. 2004; 119:1091–1130.
- DiNardo J, Fortin NM, Lemieux T. Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach. *Econometrica*. 1996; 64(5):1001–44.
- Eberstein IW, Nam CB, Hummer RA. Infant Mortality by Cause of Death: Main and Interaction Effects. *Demography*. 1990; 27(3):413–430. [PubMed: 2397820]

- Elder TE, Goddeeris JH, Haider SJ. A Deadly Disparity: A Unified Assessment of the Black-White Infant Mortality Gap. *B E Journal of Economic Analysis & Policy*. 2011; 11(1)
- Elder TE, Goddeeris JH, Haider SJ. Isolating the Role of Individual Covariates in Reweighting Estimation. *Journal of Applied Econometrics*. 2015; 30(7):1169–1191.
- Finch BK. Early origins of the gradient: The relationship between socioeconomic status and infant mortality in the United States. *Demography*. 2003; 40(4):675–699. [PubMed: 14686137]
- Fortin, N.; Lemieux, T.; Firpo, S. Decomposition Methods in Economics. In: Ashenfelter, O.; Card, D., editors. *Handbook of Labor Economics*. Vol. 4. Elsevier; 2011. p. 1-102.
- Franzini L, Ribble JC, Keddie AM. Understanding the Hispanic paradox. *Ethnic Disparities*. 2001; 11(3):496–518.
- Frisbie WP, Song S. Hispanic Pregnancy Outcomes: Differentials Over Time and Current Risk Factor Effects. *Policy Studies Journal*. 2003; 32:237–252.
- Frisbie WP, Song SE, et al. The Increasing Racial Disparity in Infant Mortality: Respiratory Distress Syndrome and Other Causes. *Demography*. 2004; 41(4):773–800. [PubMed: 15622954]
- Hirano K, Imbens GW, Ridder G. Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score. *Econometrica*. 2003; 71(4):1161–1189.
- Hoynes H, Miller D, Simon D. Income, the earned income tax credit, and infant health. *American Economic Journal: Economic Policy*. 2015; 7(1):172–211.
- Hoynes H, Page M, Stevens AH. Can targeted transfers improve birth outcomes? Evidence from the introduction of the WIC program. *Journal of Public Economics*. 2011; 95:813–827.
- Hummer RA, Biegler M, et al. Race/Ethnicity, Nativity, and Infant Mortality in the United States. *Social Forces*. 1999; 77(3):1083–118.
- Hummer RA, Powers DA, et al. Paradox Found (Again): Infant Mortality among the Mexican-origin Population in the United States. *Demography*. 2007; 44(3):441–457. [PubMed: 17913005]
- Iceland, J.; Weinberg, D.; Steinmetz, E. *Racial and Ethnic Residential Segregation in the United States: 1980–2000*. Washington, DC: U.S. Government Printing Office; 2002.
- Imbens G. Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *Review of Economics and Statistics*. 2004; 86(1):4–29.
- Leonard J, Mas A. Welfare reform, time limits, and infant health. *Journal of Health Economics*. 2008; 27(6):1551–1566. [PubMed: 18947892]
- Lee KS, Paneth N, et al. Neonatal mortality: an analysis of the recent improvement in the United States. *Am J Public Health*. 1980; 70(1):15–21. [PubMed: 7350819]
- Martin, JA.; Hamilton, BE.; Sutton, PD., et al. *National vital statistics reports*. Vol. 57. Hyattsville, MD: National Center for Health Statistics; 2009. Births: Final data for 2006.
- Mathews, TJ.; MacDorman, MF. *National vital statistics reports*. Vol. 58. Hyattsville, MD: National Center for Health Statistics; 2010. Infant mortality statistics from the 2006 period linked birth/infant death data set.
- Miller DL, Page ME, Stevens AH, Filipowski M. Why Are Recessions Good for Your Health? *American Economic Review*. 2009; 99(2):122–127.
- National Center for Health Statistics. *Technical Appendix from Vital Statistics of the United States 2003, Natality*. Hyattsville, MD: 2005.
- National Center for Health Statistics. *Health United States, 2009 With Special Feature on Medical Technology*. Hyattsville, MD: 2010.
- Nepomnyaschy L. Socioeconomic Gradients in Infant Health Across Race and Ethnicity. *Maternal and Child Health Journal*. 2009; 13(6):720–731. [PubMed: 19557507]
- Pallotto EK, Collins JW Jr, David RJ. Enigma of Maternal Race and Infant Birth Weight: a Population-based Study of US-born Black and Caribbean-born Black Women. *Am J Epidemiol*. 2000; 151:1080–1085. [PubMed: 10873132]
- Powers DA. Paradox Revisited: A Further Investigation of Race/Ethnic Differences in Infant Mortality by Maternal Age. *Demography*. 2013; 50(2):495–520. [PubMed: 23055238]
- Ruhm C. Are Recessions Good for Your Health? *Quarterly Journal of Economics*. 2000; 115:617–650.
- Schempf AH, Branum AM, et al. The contribution of preterm birth to the Black-White infant mortality gap, 1990 and 2000. *Am J Public Health*. 2007; 97(7):1255–60. [PubMed: 17538050]

- Singh GK, Yu SM. Adverse Pregnancy Outcomes: Differences Between U.S.- and Foreign-Born Women in Major U.S. Racial and Ethnic Groups. *Am J Public Health*. 1996; 86:837–43. [PubMed: 8659659]
- Tomashek KM, Qin C, Hsia J, Lyasu S, Barfield WD, Flowers LM. Infant mortality trends and differences between American Indian/Alaska native infants and white infants in the United States, 1989–1991 and 1998–2000. *Am J Public Health*. 2006; 96(12):2222–27. [PubMed: 17077400]
- United States Department of Agriculture. Building a Healthy America: A Profile of the Supplemental Nutrition Assistance Program. Alexandria, VA: 2012.
- Watson T. Public health investments and the infant mortality gap: Evidence from federal sanitation interventions on US Indian reservations. *Journal of Public Economics*. 2006; 90(8–9):1537–60.
- Wise PH. The Anatomy of a Disparity in Infant Mortality. *Annual Review of Public Health*. 2003; 24:341–62.
- Wooldridge J. Inverse probability weighted estimation for general missing data problems. *Journal of Econometrics*. 2007; 141(2):1281–130.

Highlights

- This paper studies the infant mortality rate (IMR) gaps between various racial/ethnic groups
- These IMR gaps are strongly associated with three SES characteristics: maternal age, education, and marital status
- The main anomaly, the Mexican-white gap, is associated with a common finding in other groups: an IMR advantage for foreign-born mothers
- Overall, much is learned by comparing the commonalities across groups

Figure 1. 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). The point estimates and their standard errors are provided in Table 3.

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. 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.

Figure 4. Actual and Predicted Cumulative IMR Gaps by Racial/Ethnic Group

Notes: The lines denote the predicted and actual cumulative IMR gap across the birth weight distribution between three racial/ethnic groups and whites.

Table 1

Descriptive Characteristics by Racial/Ethnic Group

<u>VS Data</u>	White	Black	Mexican	PR	Asian	NA/AN
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
<u>Census Data</u>						
Observations	222,123	39,813	37,407	4,473	14,115	3,417

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

	White	Black	Mexican	PR	Asian	NA/AN
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 2OLS Regressions of Infant Death ($\times 1000$) on Background Characteristics

	White mothers, All	Mexican mothers, US born	Mexican mothers, Foreign born
Mother married	-1.92 (0.14)	-1.22 (0.36)	-0.03 (0.24)
Maternal education			
<12	(excluded)	(excluded)	(excluded)
12	-2.01 (0.18)	-0.92 (0.41)	-0.64 (0.27)
13–15	-3.25 (0.20)	-0.95 (0.53)	-1.63 (0.45)
16 +	-4.01 (0.20)	-2.29 (0.73)	-1.38 (0.59)
Maternal age			
<20	(excluded)	(excluded)	(excluded)
20–24	-0.72 (0.22)	-1.11 (0.50)	-0.77 (0.39)
25–29	-1.05 (0.24)	-1.08 (0.60)	-0.97 (0.41)
30–34	-1.25 (0.25)	-0.95 (0.71)	-0.56 (0.45)
35 +	-0.79 (0.26)	-0.48 (0.86)	0.73 (0.53)
First trimester prenatal care	-1.65 (0.16)	-0.63 (0.41)	0.07 (0.25)
Previous loss	1.25 (0.11)	1.25 (0.42)	2.42 (0.31)
Male	1.13 (0.10)	1.02 (0.33)	0.57 (0.22)
Plural birth	20.42 (0.26)	23.18 (1.10)	19.08 (0.81)
Live birth order			
1 st	(excluded)	(excluded)	(excluded)
2 nd – 3 rd	-0.46 (0.11)	-0.81 (0.39)	-0.88 (0.27)
4 th +	0.58 (0.20)	0.45 (0.61)	-0.39 (0.39)
State indicators	Yes	Yes	Yes
Dependent variable mean	5.35	5.90	4.53
R ²	.004	.003	.002
Observations	2,253,597	221,395	379,177

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

Table 3

Actual and Predicted IMR Gaps by Racial/Ethnic Group

	Black	Mexican	PR	Asian	NA/AN
Actual gap	7.00 (0.16)	-0.30 (0.09)	2.27 (0.18)	-1.01 (0.09)	2.96 (0.22)
Predicted gap, reweighting whites	2.54 (0.13)	1.63 (0.20)	1.01 (0.13)	-1.16 (0.08)	2.06 (0.22)
Predicted gap, reweighting others	2.04 (0.29)	-0.32 (0.55)	1.29 (0.45)	-1.09 (0.12)	1.95 (0.57)

Notes: Standard errors (in parentheses) are calculated from 100 bootstrapped replications.

Table 4

Background Characteristics and Socio-economic Status

	HH Income		Poverty		Deep Poverty	
	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Married	30,932 (261)	11,937 (273)	-0.369 (0.002)	-0.282 (0.002)	-0.238 (0.001)	-0.190 (0.001)
Maternal education						
<12	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)
12	9,492 (298)	6,609 (306)	-0.190 (0.002)	-0.137 (0.002)	-0.100 (0.001)	-0.076 (0.002)
13-15	22,399 (296)	15,648 (320)	-0.315 (0.002)	-0.216 (0.002)	-0.169 (0.001)	-0.119 (0.002)
16 +	63,737 (306)	46,624 (352)	-0.406 (0.002)	-0.238 (0.002)	-0.207 (0.001)	-0.117 (0.002)
Maternal age						
<20	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)	(excluded)
20-24	-523 (467)	-10,023 (458)	-0.076 (0.003)	0.066 (0.003)	-0.051 (0.002)	0.039 (0.002)
25-29	13,994 (453)	-7547 (469)	-0.215 (0.003)	0.010 (0.003)	-0.129 (0.002)	0.012 (0.002)
30-34	33,856 (455)	3494 (487)	-0.272 (0.003)	-0.014 (0.003)	-0.156 (0.002)	0.003 (0.002)
35 +	46,950 (467)	16,358 (502)	-0.271 (0.003)	-0.033 (0.003)	-0.155 (0.002)	-0.007 (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

The Role of Foreign-Born Status

	White	Black	Mexican	PR	Asian	NA/AN
Percent foreign-born	5.6	11.4	63.1	34.0	84.2	3.4
<u>Foreign-born effect on IMR</u>						
Unadjusted	-1.7 (0.2)	-4.3 (0.5)	-1.4 (0.2)	-0.7 (0.4)	-1.6 (0.2)	-2.4 (1.2)
Regression adjusted	-0.9 (0.2)	-2.8 (0.5)	-1.6 (0.2)	-0.4 (0.4)	-0.2 (0.2)	-0.1 (1.3)
<u>IMR gaps relative to whites</u>						
<i>All racial/ethnic mothers</i>						
Actual		6.94	-0.29	2.27	-1.00	2.97
Predicted, baseline covariates		2.53	1.63	1.01	-1.16	2.07
Predicted, adding foreign-born		2.40	0.21	0.38	-2.50	2.05
<i>U.S.-born racial/ethnic mothers</i>						
Actual		7.41	0.56	2.49	0.32	3.03
Predicted, baseline covariates		2.88	1.34	1.14	-0.39	2.18

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.