Family- and Place-based Determinants of Early-Life Health*

Eric Chyn and Na'ama Shenhav

September 28, 2021

Abstract

This paper uses birth records and mothers who move to quantify the importance of place- and family-based determinants of early-life health. We find that causal place effects explain 16 percent of geographic variation in birth weight, with family-specific factors accounting for the remaining 84 percent. These place effects are most strongly correlated with local levels of pollution. The improvement in birth weight from moving to a higher-quality area compares favorably to policies that target maternal health. However, we project limited effects of these birth weight improvements on long-run outcomes, suggesting that lasting impacts of place operate primarily through post-birth channels.

Keywords: Health, Birth Weight, Children, Neighborhood Effects, Pollution.
JEL Codes: J13, I1, I14, R23, H51, Q53.

*Chyn: Department of Economics, Dartmouth College, 6106 Rockefeller Center, Hanover, NH 03755, and the National Bureau of Economic Research, eric.t.chyn@dartmouth.edu. **Shenhav:** Department of Economics, Dartmouth College, 6106 Rockefeller Center, Hanover, NH 03755, the Federal Reserve Bank of San Francisco, and the National Bureau of Economic Research, Naama.Shenhav@dartmouth.edu. We are thankful for helpful comments from Doug Miller, Jon Skinner, and Doug Staiger. We received excellent research assistance from Marcus Sander. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of San Francisco, or the Board of Governors of the Federal Reserve System.

1 Introduction

Infant health outcomes vary significantly within the United States. For example, the share of infants born with low birth weight in Detroit is more than twice as high as the share in Seattle (14 versus 6 percent; Kids Count, 2021). Given the link between outcomes at birth and later-life outcomes, these early-life disparities across place may contribute to spatial inequities in economic success and upward mobility (Black, Devereux and Salvanes, 2007; Chetty et al., 2014; Bharadwaj, Lundborg and Rooth, 2017).

A key challenge to understanding how location at birth might contribute to long-run spatial inequities is identifying the relative importance of various sources of these early-life disparities. On the one hand, these differences appear to reflect *contextual* factors, such as pollution, heat, or crime rates, which could be targeted by place-based policies. On the other hand, research suggests that these gaps also reflect household sorting on *family-specific* factors, including parental education, financial resources, or maternal stress. Because these factors are often studied in isolation, there is no comparison of the importance of family- and place-based inputs that can be used to weigh policies that aim to reduce inequality.

This paper uses a unified framework to decompose spatial gaps in early-life health into family- and place-based components. Using birth records from California that span three decades, we follow mothers (hereafter "movers") that relocate across neighborhoods, studying whether and to what extent their child's birth weight adjusts relative to their previous births. Specifically, we estimate a model of birth weight that includes both mother and location (Zip code) fixed effects, which is identified due to the presence of mothers who give birth in multiple locations. Intuitively, the size of adjustment in birth weight after a move provides an estimate of the importance of location-specific factors. This approach is based on Finkelstein, Gentzkow and Williams (2016) who studied patient migration and health care utilization in the over-65 Medicare population.

Our main finding is that the causal impact of location explains 16 percent of the variation in birth weight between above and below-median areas, with the remaining 84 percent of the variation due to mother-specific factors (i.e., sorting). We find similar results when we focus on the difference between the top and bottom quartiles or deciles. An alternative decomposition that estimates the share of cross-Zip variance in birth weight that is due to mother and location factors also yields a similar conclusion. That said, we estimate a 19-gram improvement in birth weight from moving from a below- to above-median area, which compares favorably with the impact of specific policies targeting maternal health. For example, it is up to 7, 10, and 20 times as large as the impacts of maternal access to WIC, Food Stamps, and Medicaid, respectively (Hoynes, Page and Stevens, 2011; Rossin-Slater, 2013; Almond, Hoynes and Schanzenbach, 2011; East et al., 2021).

We extend the decomposition results by exploring heterogeneity in the effects of location. Our analysis shows that place effects explain more of the share of variation in child health for non-college-educated mothers, and this result holds for both white and non-white mothers. These results are consistent with prior evidence that contextual factors such as pollution may have stronger impacts on disadvantaged populations (Almond, Currie and Duque, 2018).

These results rely on the key assumption that changes in the family-based determinants of birth weight do not correlate systematically with the improvement in the quality (as proxied by birth weight) of a mother's location. We address potential threats to this assumption in three ways. First, we use an event study approach to study pre-trends and moves to higher quality areas. The results show a sharp change in birth weight after a move, with no significant trend in birth weight for children born before a move. Second, we examine the role of confounding changes by estimating the impact of a move on *predicted* birth weight, which we construct from a large number of time-varying maternal and paternal characteristics (including proxies for economic status). Our results strongly suggest that changes in partner choice or economic circumstances do not drive our place effect estimates. Third, we show that the impact of a move is similar for moves from low-to-high and high-to-low birth weight areas. This provides support for the additive separability of mother and place effects assumed in our model.

Finally, to shed light on the mechanisms behind the impacts of place, we study the area-level correlates of our estimates of causal place effects. We find that the local level of ozone is the strongest correlate of place effects in our setting. This finding broadly aligns with studies of the causal impacts of pollution exposure on children. Correlations with the supply of prenatal care and average maternal education are smaller, but meaningful, suggesting potential roles for improved access to health care and the preferences of local residents.

Our study makes three contributions to the literature. First, we quantify the determinants of infant health using a unified model that separately identifies the contributions of place and family factors. In contrast, prior research focuses on estimating the impacts of *specific* contextual or maternal (family) characteristics on early-life health. For example, a large environmental literature estimates the effects of exposure to pollution or higher temperatures on child outcomes and infant mortality (Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie, Neidell and Schmieder, 2009; Deschenes, Greenstone and Guryan, 2009; Currie and Walker, 2011; Currie et al., 2015; Knittel, Miller and Sanders, 2016; Alexander and Currie, 2017; Alexander and Schwandt, 2019). Similarly, a number of studies identify the effects of particular maternal traits, such as a mother's highest level of completed education (McCrary and Royer, 2011; Currie and Moretti, 2003), nutrition intake (Hoynes, Page and Stevens, 2011; Almond, Hoynes and Schanzenbach, 2011; Rossin-Slater, 2013), or financial resources (Dehejia and Lleras-Muney, 2004; Lindo, 2011; Hoynes, Miller and Simon, 2015) on birth outcomes. These prior results cannot be easily aggregated to assess the *overall* effects of families or place (e.g., due to unknown covariances between these factors).

Second, we add to a growing literature studying children and neighborhood effects. Previous work has shown that living in a better neighborhood during childhood and adolescence leads to significant improvements in adult labor market activity, criminal behavior and education (Damm and Dustmann, 2014; Chetty, Hendren and Katz, 2016; Chyn, 2018; Chetty and Hendren, 2018; Chetty et al., 2020*a*,*b*; Laliberte, 2021). To our knowledge, we are the first to estimate place effects for birth weight, a key measure of early-life health. This fills an important gap in earlier findings, which have been limited to measuring the impacts of place on other outcomes during older ages. The projected effects on earnings from our estimates suggest that the impact of neighborhoods on long-run outcomes primarily operates through post-birth exposure, rather than through in-utero development. Hence, prior evidence that neighborhood exposure effects taper at younger ages likely also extends to the critical prenatal period (Deutscher, 2020; Chetty et al., 2020*a*,*b*; Chetty and Hendren, 2018).

Finally, our results complement previous studies of the causal impact of place on health spending and mortality outcomes for the elderly (Finkelstein, Gentzkow and Williams, 2016, 2021; Deryugina and Molitor, 2020). Relative to prior estimates, our findings suggest that the share of geographic disparities in early-life health explained by place-based factors is much smaller than the share for health spending (Finkelstein, Gentzkow and Williams, 2016) but similar to the share for over-65 mortality (Finkelstein, Gentzkow and Williams, 2021). This is consistent with a hypothesis in which location has a larger influence over inputs to health capital relative to the stock of health capital. Methodologically, our analysis is closely related to Finkelstein, Gentzkow and Williams (2016), who also use a decomposition approach to study effects on health care spending. One advantage of our data is that it allows us to uniquely test for and rule out potential confounds related to changes in family circumstances or maternal income that occur after a move. This provides additional support for using a mover-based design in this context and may extend to other settings as well.

2 Empirical Model

The primary goal of our analysis is to estimate the shares of the differences in early-life health across areas that stem from contextual (place-specific) factors or family characteristics. To account for unobserved heterogeneity in families across places, we use a model of child outcomes that allows for a fixed family-level component together with a fixed location component. This model of place effects and our subsequent decomposition analysis are similar to prior research on the determinants of medical spending among the elderly (Finkelstein, Gentzkow and Williams, 2016).[1]

Specifically, we assume the following model for child outcomes:

$$y^c_{mjkt} = \alpha_m + \gamma_j + \theta_k + \tau_t + \rho_{r(m,k)} + x_{mk}\beta + \epsilon^c_{mjkt}, \tag{1}$$

where y^c_{mjkt} is the birth outcome for child c (e.g., birth weight) for the k^{th} birth of mother m who lives in location j in year t. The terms α_m, γ_j, θ_k, and τ_t represent mother (i.e., family), location, birth order, and calendar year fixed effects, respectively. For mothers who move across areas, $r(m,k) = k - k^*$ is an index that tracks the birth order relative to the first post-move birth k^*. For example, $r(m,k) = 0$ if k is the first birth that occurs in a new mother's new location, and $r(m,k) = -1$ if k is the last birth that preceded a move.[2] The term $\rho_{r(m,k)}$ is a fixed effect for this index. For mothers who never move, we assume $\rho_{r(m,k)} = 0$. We also include fixed effects for the sex of the child, x_{mk}. Finally, ϵ_{mjkt} is an error term that we assume is conditionally mean zero: $\mathbb{E}(\epsilon_{mjkt}|m, j, k, t, x_{mk}) = 0$.

We use estimates from Equation 1 to decompose the difference in the average birth weight across areas into family- and location-specific components. To define this formally,

[1]Two recent studies use similar approaches to study consumer financial health (Keys, Mahoney and Yang, 2020) and the voting behavior of adults (Cantoni and Pons, 2019).

[2]Because we observe few mothers either three births before a move ($r(m,k) = -3$) or three births after a move ($r(m,k) = 2$), we group $r(m,k) = -3$ with $r(m,k) = -2$ and $r(m,k) = 2$ with $r(m,k) = 1$.

let $\overline{y}_j$ denote the expectation of y^c_{mjkt} across mothers living in location j. Also, let $\overline{y}^m_j$ denote the expectation of the part of child outcomes that is only attributable to family (mother) characteristics. This includes the influence of all fixed traits for a given mother (i.e., α_m), as well as predictable changes in outcomes that occur across children within a mother, such as from increasing birth order (i.e., $\theta_k + \tau_t + \rho_{r(m,k)} + x_{mk}\beta$ in our model). Using this notation, Equation 1 implies that $\overline{y}_j = \overline{y}^m_j + \gamma_j$.

Applying these definitions, the difference in average child outcomes between locations j and j' is:

$$\overline{y}_j - \overline{y}_{j'} = (\gamma_j - \gamma_{j'}) + (\overline{y}^m_j - \overline{y}^m_{j'}). \tag{2}$$

Equation 2 shows that the difference in average child outcomes between locations j and j' is the sum of two components. The first is the place-specific component given by the difference $\gamma_j - \gamma_{j'}$. The second is a family-specific component given by $\overline{y}^m_j - \overline{y}^m_{j'}$. It follows that our key empirical quantity of interest, the share of the difference in outcomes between locations j and j' attributable to place, is:

$$S_{place}(j, j') = \frac{\gamma_j - \gamma_{j'}}{\overline{y}_j - \overline{y}_{j'}}. \tag{3}$$

Analogously, the share attributable to family (mother) factors is:

$$S_{mom}(j, j') = \frac{\overline{y}^m_j - \overline{y}^{m'}_{j'}}{\overline{y}_j - \overline{y}_{j'}}. \tag{4}$$

By construction, the sum of these place- and family-specific shares, $S_{place}(j, j')$ and $S_{mom}(j, j')$, is equal to 1.

To obtain our main estimates of interest, we apply these formulas to decompose average outcomes in *groups* of locations, R and R'. We define the shares for these groups as

$S_{place}(R, R')$ and $S_{mom}(R, R')$, which we compute by replacing the j- and j'-level inputs in the equations above with averages within R and R', respectively. We obtain standard errors for our estimates as the standard deviation of the quantity of interest across 50 bootstrapped samples.

As an alternative to the additive decomposition, we decompose the variance in birth weight across Zip codes. Here, we study the share of cross-Zip variance in birth weight that would be eliminated in a counterfactual where average maternal characteristics were equalized across Zips. This quantity is:

$$S_{mom}^{var} = 1 - \frac{Var(\gamma_j)}{Var(\overline{y}_j)}$$

Similarly, the change if place (Zip) fixed effects were equalized is:

$$S_{place}^{var} = 1 - \frac{Var(\overline{y}_j^m)}{Var(\overline{y}_j)}$$

Note that the sum of S_{mom}^{var} and S_{place}^{var} will not equal one as long as $cov(\overline{y}_j^m, \gamma_j)$ is nonzero. We use a split-sample approach to estimate the variances and covariances in the above equations, as well as to generate bootstrapped standard errors for the estimated shares.[3]

3 Estimation and Identification

The model in Equation 1 is identified only if the estimation sample includes movers. If all mothers gave birth in only one location (i.e., were "non-movers"), we would not be able to separately identify the location fixed effect γ_j from the unobserved heterogeneity across families α_m. Intuitively, the key to separating these components is to observe the change in child outcomes after a mother's move.

[3]Details on the split-sample approach are provided in the notes for the variance decomposition results in Table 2.

Moreover, in order to interpret γ_j as the *causal* impact of place, we require that changes in unobserved determinants of early-life outcomes are not correlated with the difference in the average outcomes between the destination and origin chosen by a mother. For example, this assumption would be violated if mothers who receive negative shocks (that are correlated with child outcomes) respond by moving to areas that have worse place effects. In such a case, we would attribute some of the mother-specific adverse shock to the effect of moving, and thus overstate the role of place relative to family (mother) characteristics.

Although we cannot directly rule out all violations of our identifying assumption, we implement two tests to look for evidence of potential violations. First, we use an event-study approach to test for differences in child outcomes *prior* to a move. This addresses potential concerns that pre-existing trends in infant outcomes could bias our results. To implement this test, we rely on the following event-study model:

$$y^c_{mjkt} = \alpha_m + \sum_{r=-2}^{1} \theta_{r(m,k)} \hat{\delta}_m + \omega_k + \nu_t + x_{mk}\eta + \varepsilon^c_{mjkt}, \tag{5}$$

where $\hat{\delta}_m$ is the difference in average birth weight between the mother's origin $o(m)$ and destination $d(m)$.[4] The main parameters of interest are the relative birth coefficients $\theta_{r(m,k)}$. These parameters represent the change in the outcome y^c_{mjkt} in the years around the move scaled relative to the local area differences in birth weights $\hat{\delta}_m$. For instance, a positive value of $\theta_{r(m,k)}$ implies that moving to location that has better birth outcomes is associated with improvements in the birth outcomes of one's own children in relative year $r(m,k)$. We estimate the event study using all mover mothers (although the results are the same when including all mothers). For inference, we cluster standard errors at the mother-identifier level.

The pattern of estimated effects from Equation 5 provides an indirect test of our main identifying assumption. If move-induced changes in place characteristics cause changes in

[4]We measure $\hat{\delta_m} = \hat{\bar{y}}_{d(m)} - \hat{\bar{y}}_{o(m)}$ using leave-one-out means for our estimation sample that omit the outcomes of mother m.

child outcomes, then we should observe two patterns. First, the relative quality of one's destination should not be predictive of the birth outcomes of one's own children until *after* a move. This implies that the estimate of $\theta_{r(m,k)}$ should be statistically indistinguishable from zero in any period preceding a move, i.e., $r(m,k) < 0$. Second, the estimates for $\theta_{r(m,k)}$ should be nonzero for all periods following a move. The magnitude of the discontinuity in the level of $\theta_{r(m,k)}$ after a move measures how much place-specific factors influence child outcomes.[5]

As a second test, we examine the extent to which changes in observable characteristics of mothers after a move predict post-move changes in birth weight. This analysis provides more direct evidence for the role of coinciding shocks with a move, although we are limited to studying aspects of a mother's life that we observe in our data. We discuss this exercise in Section 5.4.

4 Data

Our primary data source is confidential individual birth records from California from 1989–2017. The data are compiled from forms completed at birth and contain approximately 15.6 million records. For each birth, the data include infant outcomes such as birth weight and length of gestation. In addition, the records contain information on the identity of the mother, her residential address, and demographic characteristics such as her place of birth, race, date of birth, educational background, and proxies for economic status (e.g., type of insurance).

Our main outcome of interest is birth weight (measured in grams), a key measure of early-life health that has been widely studied (Almond and Currie, 2011). Previous research links birth weight to a range of long-run outcomes, including education, adult health, and earnings (Black, Devereux and Salvanes, 2007; Royer, 2009; Figlio et al., 2014; Bharadwaj,

[5] We do not observe the precise timing of moves and cannot pinpoint when the first birth occurs after a move. Based on the average spacing between births before and after a move, a mother could be expected to reside in a destination Zip for up to 4.5 years.

Eberhard and Neilson, 2017). We focus on birth weight because other outcomes, such as very-low birth weight status, are rare, particularly at fine levels of geography.

To study the role of place, we use residential Zip code (ZIP-5's) as the geographic unit.[6] This unit was created by the U.S. Postal Service and represents small geographic areas (typically with populations less than 10,000). Using this fine level of geography allows us to capture nuanced differences across neighborhoods, such as the diffusion of knowledge about public programs (Chetty, Friedman and Saez, 2013). Our estimation sample includes 1,689 Zip codes.

4.1 Sample

Two main restrictions define the sample of mothers for our analysis. First, we focus on mothers who are California residents at the time of childbirth and who we observe having two-to-four births during the period covered by our records. The restriction to mothers with multiple children is necessary so that we have multiple observations with which to infer the mobility of mothers over time. We define a non-mover as a mother who is observed in the same Zip code for all her births. A mover is a mother who changes Zips exactly once; we drop mothers with multiple moves.[7] Second, to reduce noise in our estimates, the sample is restricted to mothers who live in Zip codes that contain at least 25 movers.

Appendix Table A1 reports summary statistics for all births and our estimation sample. Columns 1 and 2 show that the births in our estimation sample have broadly similar birth weight and demographic characteristics relative to all births in California.[8] Our estimation sample includes roughly 3.7 million mothers with a total of 8.5 million births. Among this

[6] In Section 5.4, we show that our main conclusions remain the same if we focus on county as the geography of interest.

[7] Mothers with more than four births account for 3 percent of births in our sample. Mothers with multiple moves are 13 percent of the sample. The results in Appendix Table B4 show that our estimates are similar if we include mothers with multiple moves.

[8] Appendix Figure A1 shows that the distributions of birth weight for all births in California and in our estimation sample are not meaningfully different.

sample, 51 and 49 percent of births are to non-mover and mover mothers, respectively. Columns 3 and 4 show that movers and non-movers are substantively similar in terms of infant birth weight and ethno-racial demographics, although movers have less education and are younger.

Appendix Figure A2 provides a Zip-level map of birth weight. The average birth weight in the median Zip code is 3,349 grams, and the standard deviation across Zips is 59 grams. We also find a similar distribution when we aggregate the birth records to the county level: the mean birth weight in the median county is 3,361 grams, and the standard deviation across counties is 55 grams.

How do these statistics for California compare more broadly? Based on birth records from the National Center for Health Statistics (NCHS) in 2004, which is roughly the median year of our data, the mean birth weight in the U.S. is 3,291 grams, which is 1 percent less than what we find for California (National Center for Health Statistics, 2004).[9] The average within-state standard deviation of birth weight across counties nationally is 43 grams, which is 9 grams (21 percent) lower than our estimate for California. Overall, we interpret these small differences as reassuring in that our setting is not particularly unusual relative to other states.

Finally, Appendix Table A2 provides details on the types of moves in the estimation sample. The average and median distances moved are 32.5 and 8.9 miles, respectively. Roughly 28 percent of moves cross county boundaries. At the Zip level, movers' destinations receive an average of 7,982 mothers at some point after their first birth.

[9]We calculate these statistics using the 2004 NCHS National Vital Statistics System birth files, which include the universe of U.S. birth records and contain identifiers for counties with populations over 100,000. The 2004 records are the last year to include county identifiers.

5 Main Results

5.1 Evidence on Identifying Assumptions from an Event Study

To support the causal interpretation of our estimated place effects, we examine how birth weight evolves around the time of a move as a function of the quality of the destination. Given our interest in early-life health, we proxy for destination quality using birth weight. We first present non-parametric, descriptive evidence and then present the results from our event study model.

Throughout this analysis, we characterize moves in terms of $\hat{\delta}_m$, the estimated difference in average birth weight between the mother's origin and destination locations. Appendix Figure A3 shows the distribution of $\hat{\delta}_m$ in our sample. The average for $\hat{\delta}_m$ is close to zero, and the distribution is roughly symmetric, indicating that mothers are equally likely to move to a better or worse location (based on average birth weight). The standard deviation is 25 grams, which is equivalent to moving from the median Zip to the 65^{th} percentile Zip.

As an initial exploration of the effect of moving to a new area, we plot the post-move change in birth weight for children of movers against $\hat{\delta}_m$. The slope of this graph can be interpreted as the extent to which moving to a location with higher average birth weight generates improvements in the early-life health outcomes of one's own children. If all geographic variation is due to the impact of place, we expect this plot to have a slope of 1. Alternatively, if individual factors explain all variation in birth weight, this plot should have a slope of 0.

The results in Panel (a) of Figure 1 suggest that moving to a better location influences child birth weight but to a limited degree. The slope of the fitted line is 0.11, implying that family and maternal-specific factors explain 89 percent of the geographic variation in our measure of early-life health. Notably, the pattern in the figure is symmetric around zero and and appears to be linear. These findings support the assumptions of additive separability in

Equation 1 and of a linear relationship between birth weight and $\hat{\delta}_m$ in Equation 5.

Next, Panel (b) of Figure 1 reports event study results, where we plot estimates of the relative birth coefficients $\theta_{r(m,k)}$. For ease of presentation, we scale the coefficients $\theta_{r(m,k)}$ to represent the impact of moving to a destination Zip that has a 100-gram higher average birth weight than one's origin Zip ($\delta_m = 100$). The omitted category is the relative period $\theta_{r(m,k)} = -1$.

The figure shows a statistically significant jump in weight for the first birth after a move. The coefficient suggests that moving to a destination with a 100-gram higher average birth weight leads to an 11-gram improvement in the weight of one's *own* child, or that roughly 11 percent of the origin-destination difference is due to the causal impact of place. Intuitively, this effect is close to the slope in Panel (a). Moreover, the coefficient is essentially the same for the second birth after a move, indicating that the impact of a place is relatively constant. This pattern is contrary to the hypothesis that moving to a better location increases birth weight by improving health behaviors, which could be expected to lead to gradual improvement in children's outcomes (Finkelstein, Gentzkow and Williams, 2021).

Finally, a key estimate of interest is the coefficient for the birth that occurs in relative period $\theta_{r(m,k)} = -2$, which constitutes our main test for the existence of pre-trends in birth weight. We do not find detectable evidence of differential trends. The point estimate is -2.2 and is statistically insignificant.

5.2 Decomposition Results

Our main analysis centers on a decomposition that uses the Zip-level place effect estimates obtained from Equation 1.[10] These estimates exploit variation in birth weight across children of movers, as in the event study results. In what follows, we study two types of

[10]Appendix Figure A4 maps the estimated γ_j's, which are standardized effects relative to an excluded Zip (90019). The estimates are roughly half positive and half negative, indicating that the omitted Zip effect is around median.

decompositions.

First, Table 1 presents an additive decomposition of the difference in child birth weight between areas with "high" and "low" birth weight. We vary the definition of high and low and report results for different definitions in each column. Within each column, we report the difference in place effects across areas (i.e., $\hat{\gamma}_R - \hat{\gamma}_{R'}$) and the share of the total difference in birth weight attributable to place- or family- (mother) specific factors (i.e., $S_{place}(R, R') = \frac{\gamma_R - \gamma_{R'}}{\bar{y}_R - \bar{y}_{R'}}$ for groups R and R').

Column 1 decomposes the 117-gram difference in birth weight between above- and below-median Zips. We find that 16.2 percent (19 grams) of the variation is due to place, with the remaining 83.8 percent being due to family (maternal) factors. The standard error on our estimate implies that we can reject a role for place that exceeds 21 percent or falls below 12 percent.

The remaining columns show similar but smaller shares attributable to place when we examine alternative definitions of high and low birth weight locations. We consider a range of alternatives, including comparisons of the top and bottom 25, 10, 5 and 1 percent of Zips. Moving across columns, the difference in average birth weight increases substantially, from 193 to 725 grams. The estimated role of place is stable, ranging from 13.9 to 9 percent. Hence, the majority of geographic differences in birth weight appears to reflect *sorting* of mothers, rather than exposure to place-specific features.

How should we think about the magnitudes of these results and the potential impacts on other outcomes of children? The raw difference in average birth weight between the top and bottom 10-percent of locations amounts to a 10-percent gain in infant birth weight. Previous studies based on twin-comparisons suggest that a weight gap this large would translate into a 5-percent of standard deviation gap in test scores and a 1-percent gap in long-run earnings in adulthood (Black, Devereux and Salvanes, 2007; Figlio et al., 2014). In contrast, the estimated 38-gram gain from causal place effects between top and bottom 10-percent locations (Column 4 of Table 1), a 1.2 percent increase relative to the mean birth weight, would be expected to lead to improvements in test scores and earnings of 0.6 percent of a standard deviation and 0.12 percent, respectively. This is a meaningfully smaller impact than would be implied by the raw differences across Zips. However, this gain in birth weight compares favorably with other policies targeting maternal health, including core safety net programs. For example, our 38-gram estimate is at least 8 times as large as the impact of access to Food Stamps during pregnancy (Almond, Hoynes and Schanzenbach, 2011).[11]

Second, Table 2 presents a decomposition of the variance in birth weight across Zip codes. The bottom of the table reports results for two scenarios: (i) the share of cross-Zip variance in birth weight that would be eliminated if average maternal characteristics were equalized across Zips, and (ii) the share of cross-Zip variance that would be eliminated if place fixed effects were equalized.

The analysis shows that 89 percent of the variance in birth weight would be eliminated if maternal characteristics were equalized. Only 15 percent of the variance would be eliminated if place effects were equalized. There is also a small, positive correlation between $\overline{y}_j^m$ and γ_j, indicating that mothers with more advantaged characteristics (in terms of infant birth weight) tend to sort into areas that have slightly more beneficial place effects on child health.

5.3 Heterogeneity

This section expands on our prior analysis by summarizing decomposition results for subgroups of mothers defined by socioeconomic background and race. Our analysis is motivated by previous research documenting that contextual factors such as pollution may have stronger impacts on more-disadvantaged populations (Almond, Currie and Duque, 2018; Currie and Walker, 2011). Detailed discussion is provided in Appendix B1.

The most notable pattern across these subgroups is that the relative importance of place

[11]Similarly, the 19-gram increase in birth weight from moving from a below- to an above-median place is 4 to 10 times as large as the estimated increase from access to Food Stamps.

is larger for mothers with less than a college education. The role of place is also similar for white and non-white mothers. This finding for white mothers is interesting given their higher levels of education (Kane, 2004). This suggests that the pattern of results by education is unlikely to be driven by a higher minority share among less-educated mothers.

5.4 Robustness Exercises

This section summarizes the results from several exercises that we undertake to support our key identifying assumption and the robustness of our results. Appendix B2 provides details for these analyses. First, we test for shocks that could be correlated with location quality by examining whether moves are associated with changes in partner choice, financial resources, or delivery complications that could account for the post-move impacts on birth weight. Specifically, we regress infant birth weight on covariates from each of these three categories and create a "predicted birth weight" for each infant. We find there is little change in predicted birth weight after a move. Second, we obtain qualitatively similar results when we study place effects at the county-level (rather than at the Zip-level). Third, we show our conclusions are robust to changes in the functional form of our model (logs or levels). Finally, we rule out two forms of selection issues related to our sample definition. Our results do not change when we expand the sample to include mothers that move multiple times. We also find no evidence that fertility is correlated with a mother's destination.

6 Mechanisms: Correlates of Place Effects

This section provides a descriptive analysis to study the specific factors that drive the place effects on birth weight that we have documented. Specifically, we estimate the correlation of the estimates $\hat{\gamma}_j$ from Equation 1 and proxies for four types of contextual factors that have been analyzed in prior studies of infant health: (1) demographic and economic measures, such as racial composition and household income; (2) crime rates, to capture communitystress, the potential for exposure to in-utero violence, and social capital; (3) proxies for access to general health and prenatal care, such as the number of hospital beds per capita and obstetrician-gynecologists (OB-GYNs) per capita; and (4) environmental measures such as temperature and pollution (particulate matter and ozone). We standardize each measure to have a mean zero and standard deviation of 1. Note that each of these place factors is either measured at the Zip- or county-level depending on data availability. Appendix C provides details on each measure and the underlying data sources.

Figure 2 summarizes our correlational results for place effects.[12] It plots the bivariate correlation (and 95-percent confidence interval) between the Zip-level place effect estimates and each place characteristic. The most striking result from this graph is that the level of pollution in an area has a significant and large correlation with its estimated place effect. The correlation for ozone is particularly sizable at -0.35. While the correlation for particular matter ($PM_{2.5}$) is smaller, it is still among the largest magnitude correlations. Zip codes that have higher crime rates also have less beneficial place effects. In terms of health care access, the number of OB-GYNs per capita has a significant positive correlation that is relatively large at 0.17. Finally, demographic, economic, and temperature measures tend to have smaller correlations.[13] Of these, the largest coefficient is for maternal education (the share of mothers with a college degree), which may reflect the fact that higher-educated women have higher levels of civic engagement and greater support for progressive policies (Milligan, Moretti and Oreopoulos, 2004; Gillion, Ladd and Meredith, 2020).

[12]We also explore correlations between our Zip-level estimates of mother effects (i.e., $\overline{y}_j^m$) and means for specific maternal characteristics. Appendix Figure A5 shows that family (mother) effects on birth weight is moderately correlated with the share of mothers (-0.30 correlation). Correlations are smaller in magnitude for the remaining characteristics. Appendix Table A3 reports results from a decomposition exercise that suggests observable maternal characteristics explain a small share of the difference in birth weight between above and below median Zips.

[13]While we find smaller correlations for factors outside of pollution and OB-GYN access, many of these correlations are larger than those used to explain variation in health spending place effects in Finkelstein, Gentzkow and Williams (2016) (which are typically below 0.05).

7 Discussion and Conclusion

This paper uses birth records and a movers-based research design to estimate the relative importance of place- and family-based determinants of early-life health. We find that place accounts for the minority of geographic disparities in birth weight. Even so, the gain in birth weight from moving to a higher-quality location (as proxied by higher average birth weight) compares favorably with other policies targeting maternal health, including core safety net programs. A descriptive analysis suggests that causal place effects are most related to the presence of airborne pollutants, particularly ozone; the availability of prenatal care; and the level of maternal education.

Overall, our main finding that place accounts for a relatively small share of the variation in early-child health provides two contributions to the literature. First, relative to past estimates of the role of place in health, our estimate is at the lower end of the spectrum. At the higher end, Finkelstein, Gentzkow and Williams (2016) find that place effects account for at least 54 percent of the gap in seniors' health care utilization across Hospital Referral Regions (large collections of Zip codes). On the lower end, Finkelstein, Gentzkow and Williams (2021) find that 15 percent of the variance in elderly mortality across commuting zones would be eliminated by equalizing place effects. Our estimates suggest that the share of birth weight explained by place is one-third as large as the share for health care utilization and the same as the share for mortality. This is consistent with an intuitive hypothesis that place is more influential for *flows* of health inputs than for *stocks* of health capital.

Second, our results complement prior studies that estimate the effects of exposure to higher-quality neighborhoods at older ages. This literature finds a large role for neighborhood effects on long-run outcomes. For example, Chetty et al. (2020*a*) find that 62 percent of the variance in the expected income rank of children across areas is due to causal place effects.[14] However, the majority of prior place-based benefits appears to accrue during adolescence, with smaller impacts during early-childhood (Deutscher, 2020; Chetty et al., 2020*b*). Consistent with this, our back-of-the-envelope calculation indicates that in-utero exposure to place likely exerts a relatively limited influence on long-run outcomes. Collectively, these results suggest that childhood place effects on long-run outcomes operate primarily through post-birth mechanisms, such as schools or neighborhood peer effects.

Finally, one caveat for comparing our work to previous studies is that we study a single state, while others estimate place effects using national data. This may lead us to estimate smaller place effects if, for example, maternal health policies differ more across-states than within-states. This could be relevant for California, which has implemented several initiatives to standardize maternal health care (Main, Markow and Gould, 2018). However, the fact that the standard deviation of county birth weight in California (34 grams) is similar to the national average (43 grams), may make this less of a concern.

[14]Similarly, Baran, Chyn and Stuart (2020) study education in 1940 and find that equalizing place effects would reduce the variance of schooling for Black children across counties by half.

References

Alexander, Diane, and Hannes Schwandt. 2019. "The Impact of Car Pollution on Infant and Child Health: Evidence from Emissions Cheating." Federal Reserve Bank of Chicago.

Alexander, Diane, and Janet Currie. 2017. "Is it who you are or where you live? Residential segregation and racial gaps in childhood asthma." *Journal of Health Economics*, 55: 186–200.

Almond, Douglas, and Janet Currie. 2011. "Killing Me Softly: The Fetal Origins Hypothesis." *Journal of Economic Perspectives*, 25(3): 153–172.

Almond, Douglas, Hilary W. Hoynes, and Diane Whitmore Schanzenbach. 2011. "Inside the War on Poverty: The Impact of Food Stamps on Birth Outcomes." *Review of Economics and Statistics*, 93(2): 387–403.

Almond, Douglas, Janet Currie, and Valentina Duque. 2018. "Childhood Circumstances and Adult Outcomes: Act II." *Journal of Economic Literature*.

Baran, Cavit, Eric Chyn, and Bryan A Stuart. 2020. "The Great Migration and Educational Opportunity." Working Paper.

Bharadwaj, Prashant, Juan Pedro Eberhard, and Christopher A. Neilson. 2017. "Health at Birth, Parental Investments, and Academic Outcomes." *Journal of Labor Economics*, 36(2): 349–394.

Bharadwaj, Prashant, Petter Lundborg, and Dan-Olof Rooth. 2017. "Birth Weight in the Long Run." *Journal of Human Resources*, 0715. Publisher: University of Wisconsin Press.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. 2007. "From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes." *The Quarterly Journal of Economics*, 122(1): 409–439.

Cantoni, Enrico, and Vincent Pons. 2019. "Does Context Trump Individual Drivers of Voting Behavior? Evidence from U.S. Movers." 94.

Chay, Kenneth Y., and Michael Greenstone. 2003. "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession*." *The Quarterly Journal of Economics*, 118(3): 1121–1167.

Chetty, Raj, and Nathaniel Hendren. 2018. "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects*." *The Quarterly Journal of Economics*.

Chetty, Raj, John Friedman, Nathaniel Hendren, Maggie Jones, and Sonya Porter. 2020*a*. "The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility." Opportunity Insights, Harvard University, January.

Chetty, Raj, John N. Friedman, and Emmanuel Saez. 2013. "Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings." *American Economic Review*, 103(7): 2683–2721.

Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment." *American Economic Review*, 106(4): 855–902.

Chetty, Raj, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2020*b*. "Race and Economic Opportunity in the United States: an Intergenerational Perspective." *The Quarterly Journal of Economics*, 135(2): 711–783. Publisher: Oxford Academic.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *The Quarterly Journal of Economics*, 129(4): 1553–1623.

Chyn, Eric. 2018. "Moved to Opportunity: The Long-Run Effects of Public Housing Demolition on Children." *The American Economic Review*, 108(10): 3028–3056.

Currie, Janet, and Enrico Moretti. 2003. "Mother's Education and the Intergenerational Transmission of Human Capital: Evidence from College Openings." *The Quarterly Journal of Economics*, 118(4): 1495–1532.

Currie, Janet, and Matthew Neidell. 2005. "Air Pollution and Infant Health: What Can We Learn from California's Recent Experience?*." *The Quarterly Journal of Economics*, 120(3): 1003–1030.

Currie, Janet, and Reed Walker. 2011. "Traffic Congestion and Infant Health: Evidence from E-ZPass." *American Economic Journal: Applied Economics*, 3(1): 65–90.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings." *American Economic Review*, 105(2): 678–709.

Currie, Janet, Matthew Neidell, and Johannes F. Schmieder. 2009. "Air pollution and infant health: Lessons from New Jersey." *Journal of Health Economics*, 28(3): 688–703.

Damm, Anna Piil, and Christian Dustmann. 2014. "Does Growing Up in a High Crime Neighborhood Affect Youth Criminal Behavior?" *American Economic Review*, 104(6): 1806–1832.

Dehejia, Rajeev, and Adriana Lleras-Muney. 2004. "Booms, Busts, and Babies' Health." *The Quarterly Journal of Economics*, 119(3): 1091–1130.

Deryugina, Tatyana, and David Molitor. 2020. "Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina." *American Economic Review*, 110(11): 3602–3633.

Deschenes, Olivier, Michael Greenstone, and Jonathan Guryan. 2009. "Climate Change and Birth Weight." *American Economic Review*, 99(2): 211–17.

Deutscher, Nathan. 2020. "Place, Peers, and the Teenage Years: Long-Run Neighborhood Effects in Australia." *American Economic Journal: Applied Economics*, 12(2): 220–249.

East, Chloe N, Sarah Miller, Marianne Page, and Laura R Wherry. 2021. "Multi-generational Impacts of Childhood Access to the Safety Net: Early Life Exposure to Medicaid and the Next Generation's Health." National Bureau of Economic Research Working Paper 23810.

Figlio, David, Jonathan Guryan, Krzysztof Karbownik, and Jeffrey Roth. 2014. "The Effects of Poor Neonatal Health on Children's Cognitive Development." *American Economic Review*, 104(12): 3921–3955.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams. 2016. "Sources of Geographic Variation in Health Care: Evidence From Patient Migration*." *The Quarterly Journal of Economics*, 131(4): 1681–1726.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams. 2021. "Place-Based Drivers of Mortality: Evidence from Migration." *American Economic Review*, 111(8): 2697–2735.

Gillion, Daniel Q., Jonathan M. Ladd, and Marc Meredith. 2020. "Party Polarization, Ideological Sorting and the Emergence of the US Partisan Gender Gap." *British Journal of Political Science*, 50(4): 1217–1243.

Hoynes, Hilary, Doug Miller, and David Simon. 2015. "Income, the Earned Income Tax Credit, and Infant Health." *American Economic Journal: Economic Policy*, 7(1): 172–211.

Hoynes, Hilary, Marianne Page, and Ann Huff Stevens. 2011. "Can targeted transfers improve birth outcomes?: Evidence from the introduction of the WIC program." *Journal of Public Economics*, 95(7): 813–827.

Kane, Thomas. 2004. "College-Going and Inequality." In *Social Inequality.* ed. Kathryn Neckerman. Russell Sage Foundation.

Keys, Benjamin J., Neale Mahoney, and Hanbin Yang. 2020. "What Determines Consumer Financial Distress? Place- and Person-Based Factors." National Bureau of Economic Research w26808.

Kids Count. 2021. "Low birth-weight babies in the United States." *https://datacenter.kidscount.org/data/tables/5425-low-birth-weight-babies*, Accessed: 2021-07-13.

Knittel, Christopher R., Douglas L. Miller, and Nicholas J. Sanders. 2016. "Caution, Drivers! Children Present: Traffic, Pollution, and Infant Health." *The Review of Economics and Statistics*, 98(2): 350–366.

Laliberte, Jean-William. 2021. "Long-term Contextual Effects in Education: Schools and Neighborhoods." *American Economic Journal: Economic Policy*, 13(2): 336–377.

Lindo, Jason M. 2011. "Parental job loss and infant health." *Journal of Health Economics*, 30(5): 869–879.

Main, Elliott K., Cathie Markow, and Jeff Gould. 2018. "Addressing Maternal Mortality And Morbidity In California Through Public-Private Partnerships." *Health Affairs (Project Hope)*, 37(9): 1484–1493.

Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. 2021. "National Historical Geographic Information System: Version 16.0 [dataset]."

McCrary, Justin, and Heather Royer. 2011. "The Effect of Female Education on Fertility and Infant Health: Evidence from School Entry Policies Using Exact Date of Birth." *The American Economic Review*, 101(1): 158–195.

Miller, Douglas L, Na'ama Shenhav, and Michel Z Grosz. 2021. "Selection into Identification in Fixed Effects Models, with Application to Head Start." Working Paper, Dartmouth College.

Milligan, Kevin, Enrico Moretti, and Philip Oreopoulos. 2004. "Does education improve citizenship? Evidence from the United States and the United Kingdom." *Journal of Public Economics*, 88(9): 1667–1695.

National Center for Health Statistics. 2004. "Vital Statistics Natality Birth Data."

Rossin-Slater, Maya. 2013. "WIC in your neighborhood: New evidence on the impacts of geographic access to clinics." *Journal of Public Economics*, 102: 51–69.

Royer, Heather. 2009. "Separated at Girth: US Twin Estimates of the Effects of Birth Weight." *American Economic Journal: Applied Economics*, 1(1): 49–85.

8 Figures and Tables

Table 1: Additive Decomposition of Geographic Differences in Birth Weight

	(1) Top vs. Bottom 50%	(2) Top vs. Bottom 25%	(3) Top vs. Bottom 10%	(4) Top vs. Bottom 5%	(5) Top vs. Bottom 1%
Diff. in avg. birth weight (grams):					
Overall	116.890	193.478	295.756	387.602	725.233
Due to place	18.897	26.982	37.832	40.676	64.949
Due to family (mother)	97.993	166.496	257.923	346.926	660.284
Share of difference due to:					
Share due to place	0.162	0.139	0.128	0.105	0.090
	(0.023)	(0.024)	(0.027)	(0.032)	(0.038)
Share due to family (mother)	0.838	0.861	0.872	0.895	0.910

Notes: This table presents additive decomposition results. All results are based estimates of Equation 1, where the dependent variable is birth weight (in grams). Each column defines a set of areas R and R'. The first row reports estimates of the difference in average birth weight between two areas (i.e., $\overline{y}_R - \overline{y}_{R'}$). The second row reports the estimated difference due to place effects (i.e., $\gamma_R - \gamma_{R'}$). The third row reports the estimated difference due to family (mother) characteristics (i.e., $\overline{y}^m_R - \overline{y}^m_{R'}$). Standard errors (in parentheses) are calculated using a mother-level bootstrap approach that has 50 repetitions.

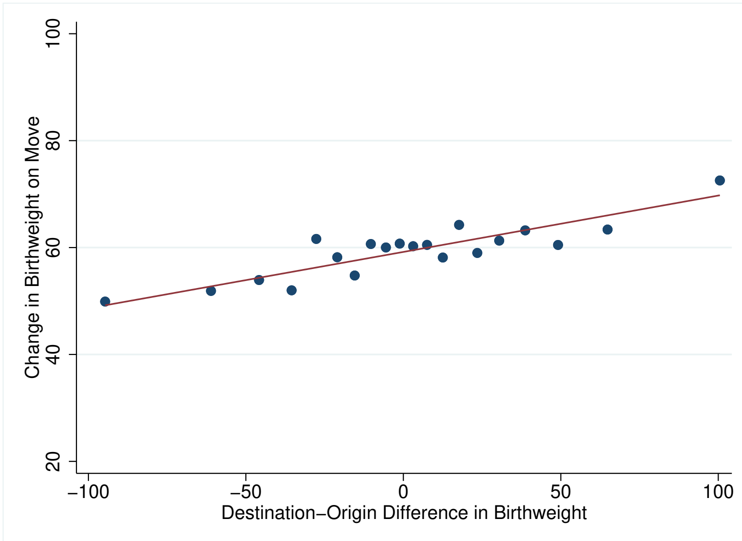
Table 2: Variance Decomposition of Geographic Differences in Birth Weight

	(1) Estimates
Variances of birth weight (grams):	
Birth weight	8,984.977
Place effects	963.706
Family (mother) effects	7,666.727
Corr. of average place and family effects	0.065
	(0.069)
Share of variance reduced if:	
Family (mother) effects were made equal	0.893
	(0.080)
Place effects were made equal	0.147
	(0.132)

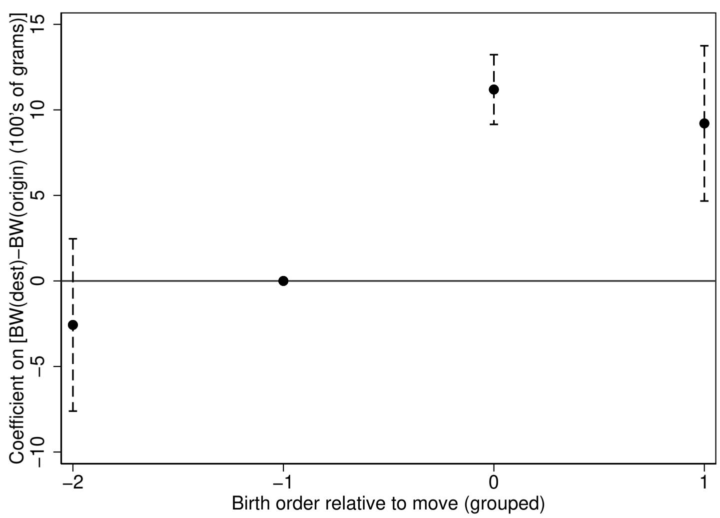
Notes: This table presents variance decomposition results. All results are based estimates of Equation 1, where the dependent variable is birth weight (in grams). We use a split-sample approach to estimate variances and covariances. As in Finkelstein, Gentzkow and Williams (2016), we randomly assign movers within each origin-destination pair and non-movers within each Zip code to two approximately equal-sized subsamples, and estimate Equation 1 on each subsample. We estimate the variance of γ_j and $\overline{y}_j^m$ as the covariance between the estimates of γ_j and $\overline{y}_j^m$ from the two subsamples. The estimated correlation between γ_j and $\overline{y}_j^m$ is based on the estimated variance of γ_j and $\overline{y}_j^m$ and the covariance of γ_j and $\overline{y}_j^m$, which we compute as the average of the covariances between the estimates of γ_j from one subsample and $\overline{y}_j^m$ from the other subsample. The first row reports the variance of zip-code average birth weight (i.e., $\overline{y}_j$). The second, third and fourth rows report the variance of place effects (i.e., γ_j), variance of family (mother) effects (i.e., $\overline{y}_j^m$), and the correlation of place effects and family effects. The final two rows report the shares of the variance in birth weight that would be reduced if zip-level place effects were made equal and if family (mother) effects were made equal, respectively. Standard errors (in parentheses) are calculated using a mother-level bootstrap approach that has 50 repetitions.

Figure 1: Evidence on Identifying Assumptions for Place Effects Estimates

(a) Destination-Origin Differences in Child Birth Weight

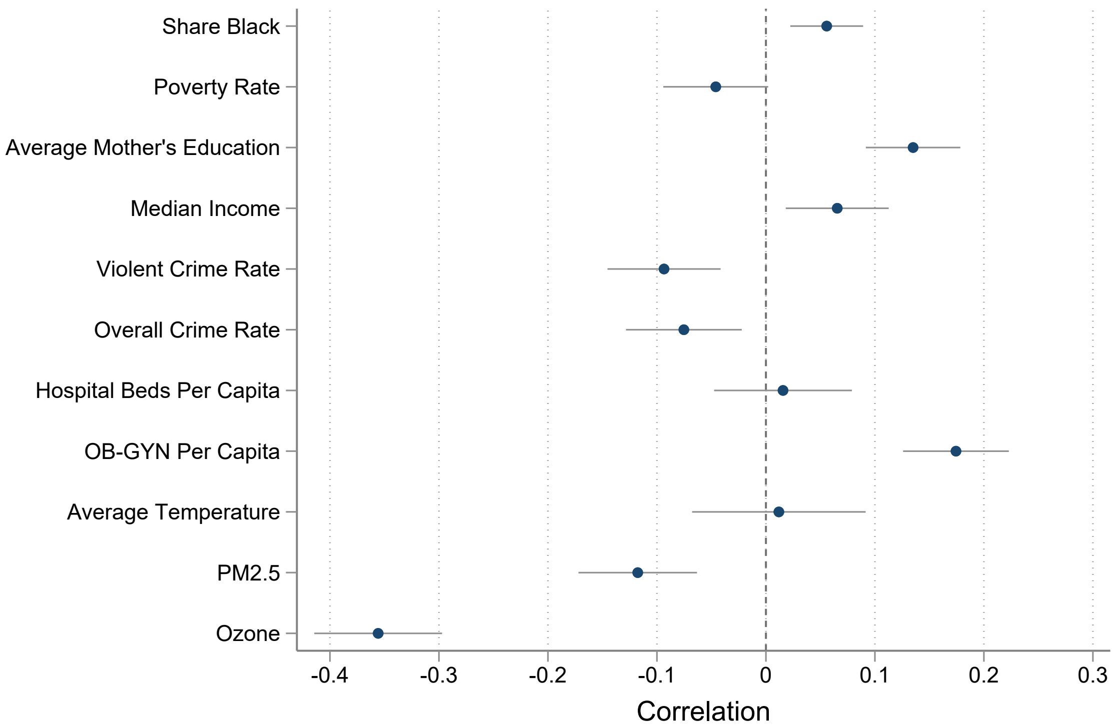


(b) Event Study Analysis of Child Birth Weight



Notes: Panel (a) shows the relationship between changes in birth weight before and after a move and the type of move that a mother experiences. For each mover, we calculate the difference $\hat{\delta}_m$ in average birth weight between their destination and origin zip codes and group the data into 20 bins. The x-axis displays the mean of $\hat{\delta}_m$. The y-axis reports binned averages of the change in birth weight for the children born before and after the move. The line of best fit is obtained from an OLS regression using the underlying mother-level sample. Panel (b) reports the coefficient estimates of $\hat{\theta}_{r(m,k)}$ from Equation 5. The coefficient for the birth that occurs immediately before the move is normalized to 0. The x-axis indicates the birth order relative to the mother's move, $r(m,k)$. Each dot is a point estimate and represents the impact on birth weight measured in grams. The dashed vertical lines surrounding each dot are estimates of the 95-percent confidence interval. To reduce noise in the figure, the coefficient shown at "-2" on the x-axis includes the second and third birth prior to a move (i.e., $r(m,k) = -2$ and $r(m,k) = -3$) and the coefficient shown at "1" on the x-axis includes the second and third birth births after a move (i.e., $r(m,k) = 1$ and $r(m,k) = 2$). Standard errors are clustered at the mother-identifier level.

Figure 2: Correlates of Spatial Variation in Place Effects on Birth Weight



Notes: This figure shows the correlation of estimates of place effects based on Equation 1 and place characteristics. For each characteristic listed on the y-axis, the dots report the point estimate of the correlation and the horizontal lines show the 95-percent confidence intervals based on robust standard errors. Details on each measure and the underlying data sources are provided in Appendix C.

Online Appendix

A Appendix Tables and Figures

Table A1: Summary Statistics

	(1)	(2)	(3)	(4)
	All:	Estimation sample:		
	All	All	Non-movers	Movers
Infant birthweight	3333.372	3334.398	3317.194	3352.445
	(577.5)	(582.8)	(599.7)	(563.9)
Black mother	0.063	0.054	0.040	0.068
	(0.244)	(0.226)	(0.196)	(0.252)
White, non-Hispanic mother	0.327	0.350	0.366	0.334
	(0.469)	(0.477)	(0.482)	(0.472)
Hispanic mother	0.482	0.471	0.461	0.480
	(0.500)	(0.499)	(0.499)	(0.500)
Asian mother	0.087	0.086	0.095	0.077
	(0.281)	(0.281)	(0.293)	(0.266)
Mother has HS degree	0.722	0.750	0.762	0.738
	(0.448)	(0.433)	(0.426)	(0.439)
Mother has college degree	0.226	0.257	0.296	0.216
	(0.418)	(0.437)	(0.457)	(0.412)
Maternal age	27.950	28.129	28.740	27.487
	(6.255)	(6.053)	(6.044)	(5.997)
Observations	15,318,718	8,458,047	4,330,242	4,127,805

Notes: This table presents summary statistics based on birth records from California (1989-2017). Column 1 provides statistics for all births. Columns 2-4 provide statistics for the estimation sample that we use for our main analysis.

Table A2: Distribution of Distance Between Origin and Destination

	(1)
Average Move Distance (mi.)	32.528
25th Percentile of Move Distance (mi.)	4.214
50th Percentile of Move Distance (mi.)	8.937
75th Percentile of Move Distance (mi.)	22.552
Share of Moves that Cross Counties	0.279
Observations	13,480,833

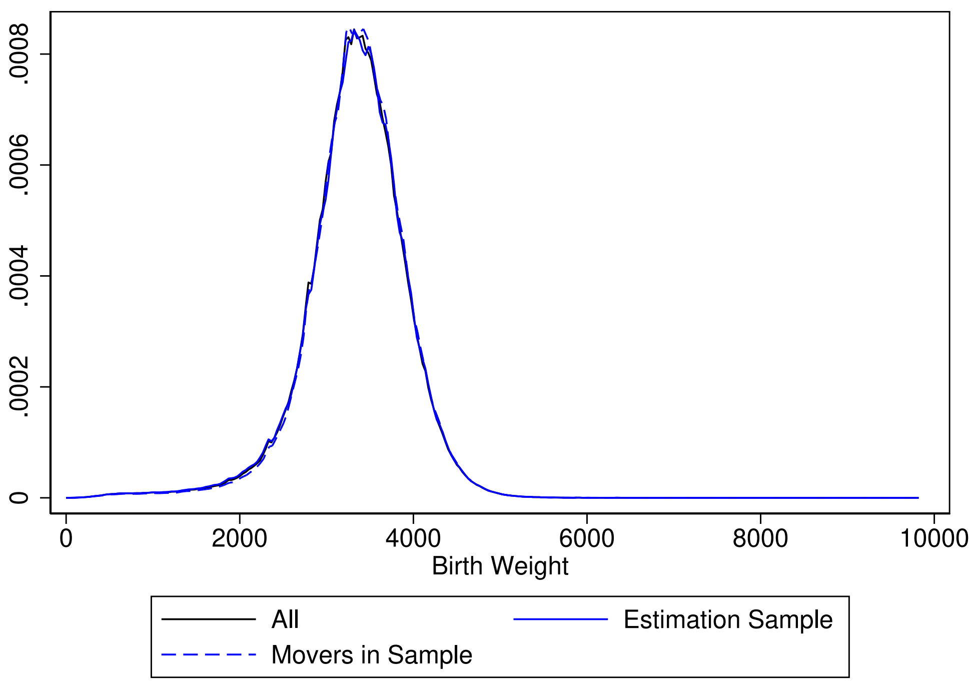
Notes: This table presents summary statistics for the average and percentiles of the distance of moves for movers in our estimation sample. Distance is measured as the miles between centroids of the origin and destination Zip codes for each mover.

Table A3: Share of Birth Weight Gaps Explained by Observable Maternal Characteristics

	(1) Avg. Mother's Education	(2) Avg. Mother's Age	(3) Share Non-white	(4) Share on Medi-Cal
Regression Coef.	-31.213	-3.886	-103.480	-1,110.806
Diff. in Mom Characteristic	-0.033	-0.307	-0.155	-0.000
Share	0.009	0.010	0.137	0.001

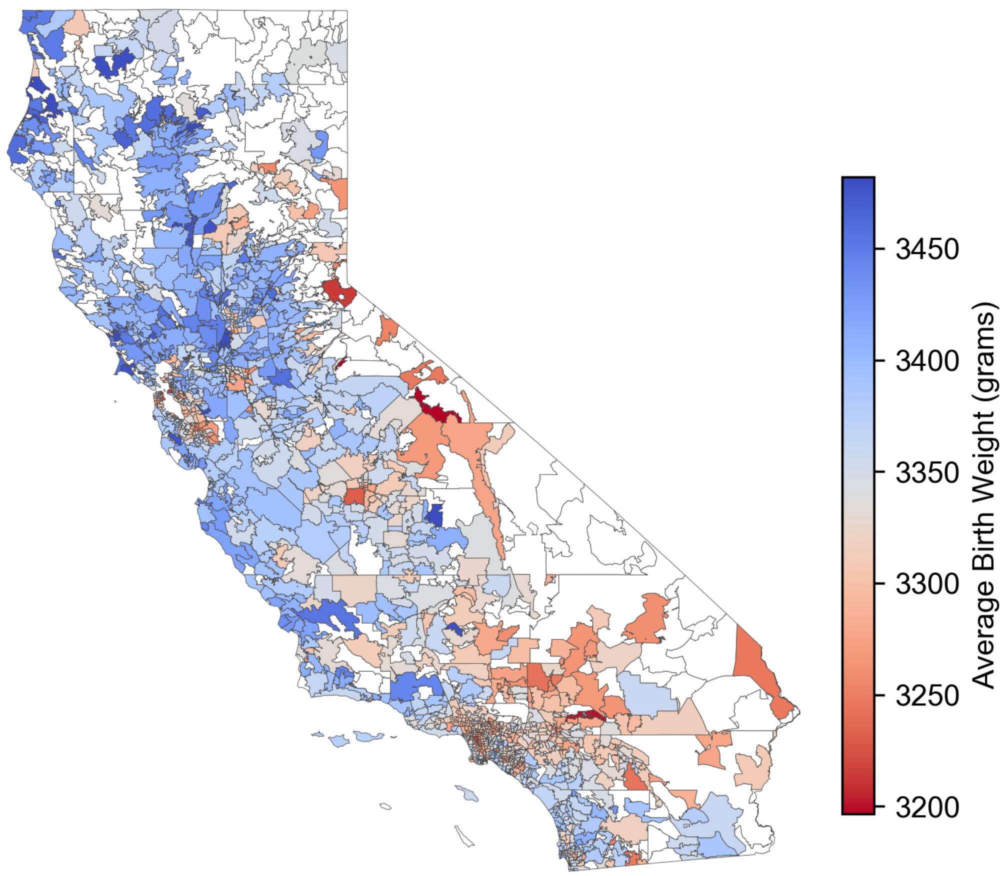
Notes: This table presents results for the difference in birth weight between areas that can be explained by differences in specific maternal characteristics. All results are based on dividing areas based on those that have above- and below-median birth weight. Each column provides results where the focus is on a specific Zip-level mean of a maternal characteristic observed in birth records. We estimate the role of a given maternal characteristic by regressing family (mother) effects (i.e., $\overline{y}_j^m$) on a Zip-level mean. These estimates are reported in the first row. The Zip-level differences in the given maternal characteristic are reported in the second row. The third row reports our estimate of the share explained by the given characteristic which is defined as the product of the first and second rows divided by the raw difference in birth weight between above and below median Zips, as in Finkelstein, Gentzkow and Williams (2016).

Figure A1: Distribution of Birth Weight for all Mothers and Estimation Sample



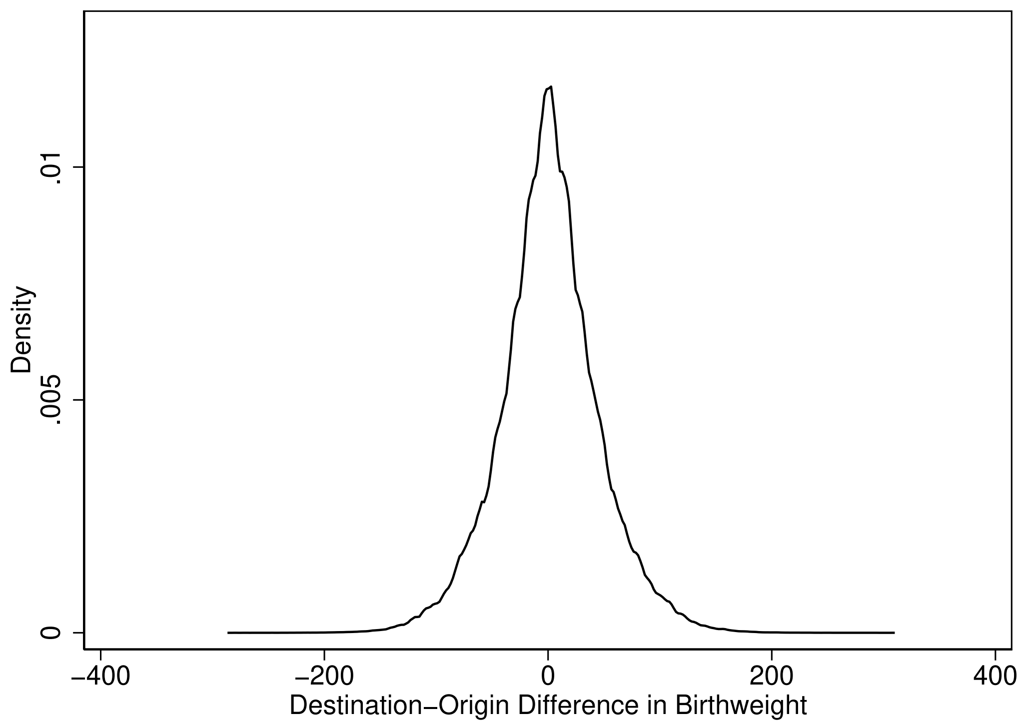
Notes: This figure shows the kernel densities for the birth weight of children born to all mothers in California (from 1989 to 2017), all mothers in our estimation sample, and mover mothers in our estimation sample.

Figure A2: Average Birth Weight by Zip Code



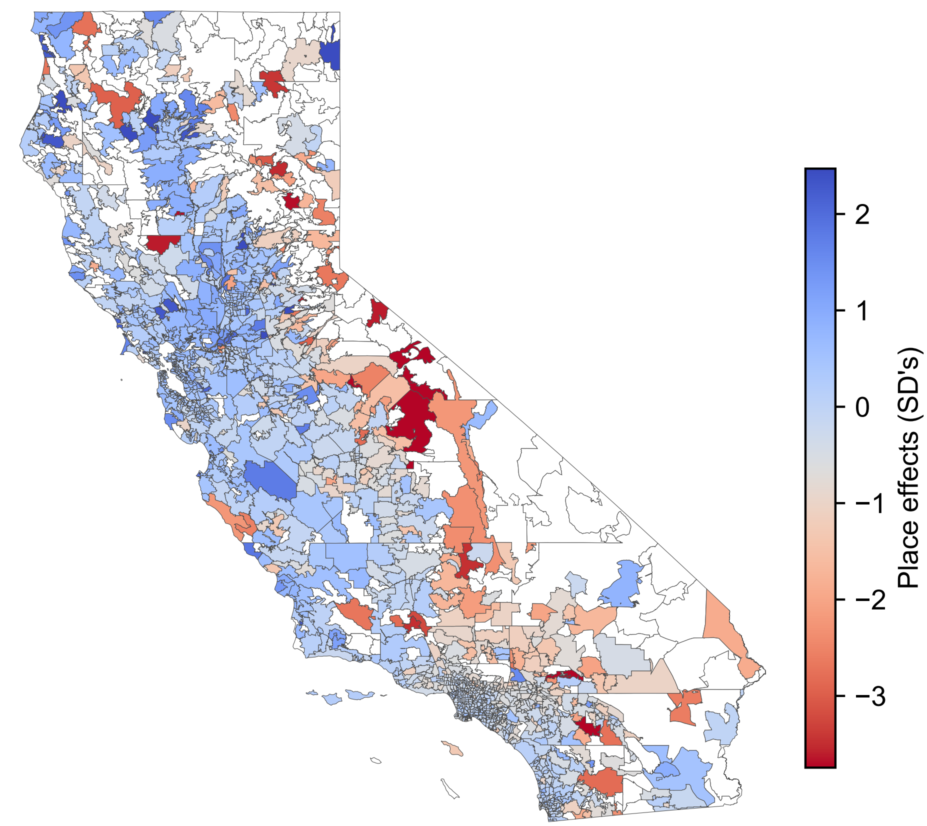
Notes: This figure provides a map of average birth weight (in grams) at the zip code level. The legend indicates the level of birth weight with dark blue and dark red colors indicating places with the highest and lowest birth weight, respectively. White areas are Zip codes where there are no mothers that meet our baseline sample criteria (always being in California; always being in a zip code with at least 25 movers; and either never moving or moving once across births). Note that average birth weight is winsorized at the 1 percent level to limit the influence of outliers.

Figure A3: Distribution of Destination-Origin Difference in Average Child Birth Weight



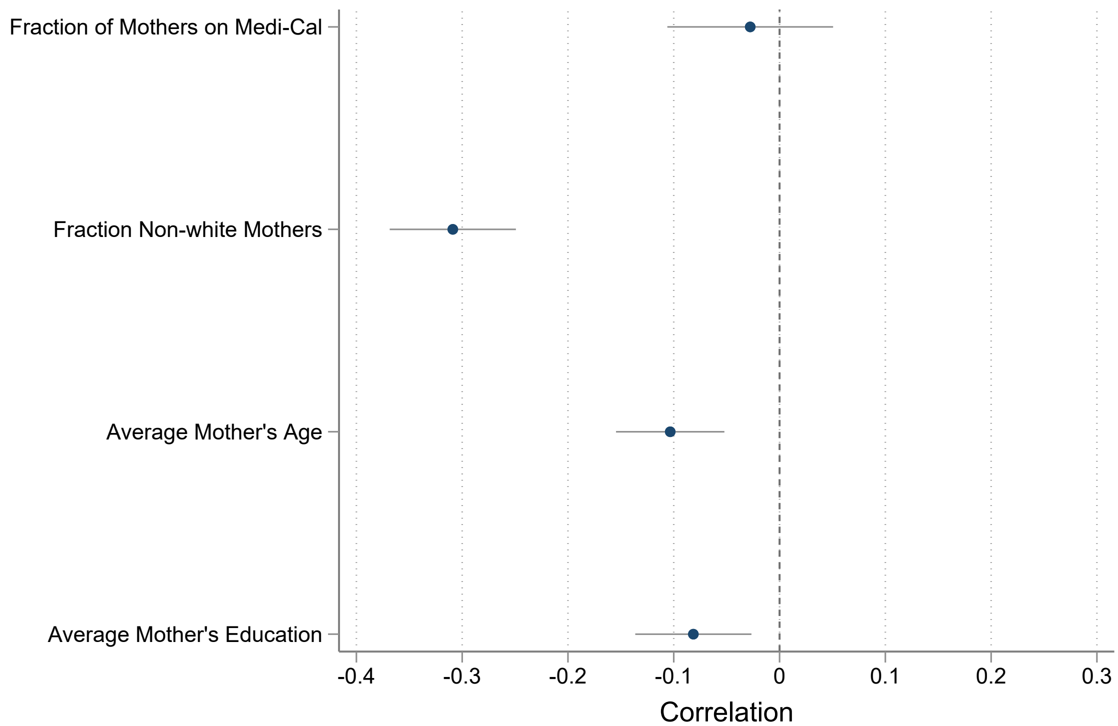
Notes: This figure shows the kernel density of the destination-origin difference in average child birth weight ($\hat{\delta_m}$) for mothers who move across zip codes.

Figure A4: Estimated Place Effects



Notes: This figure provides a map of the estimated Zip code place effects in standard deviation units. The legend indicates the level of birth weight with dark blue and dark red colors indicating zip codes with the highest and lowest estimated effects (relative to the omitted zip code, 90019), respectively. Zip codes with no color are not included in our estimation of zip code fixed effects. Note that the Zip code effects are winsorized at the 1 percent level to limit the influence of outliers.

Figure A5: Correlates of Spatial Variation in Family (Mother) Effects



Notes: This figure shows the correlation of estimates of family (mother) effects (i.e., $\overline{y}^m_j$) based on Equation 1 and Zip-level means of specific maternal characteristics observed in the birth records. For each characteristic listed on the y-axis, the dots report the point estimate of the correlation and the horizontal lines show the 95-percent confidence intervals based on robust standard errors. Details on each measure and the underlying data sources are provided in Appendix C.

B Additional Details for Analyses in Sections 5.3 and 5.4

B1 Appendix to Section 5.3: Heterogeneity

In this section, we provide further detail on the heterogeneity analysis described in Section 5.3. Appendix Table B1 presents the results, where the columns report the additive decomposition for selected groups of mothers. Column 1 reproduces our baseline estimate from Table 1 for comparison, while Columns 2-5 report results for mothers who are (i) non-college-educated, (ii) college-educated, (iii) white non-Hispanic, or (iv) not-white-non-Hispanic ("non-white"), respectively.

As highlighted in the main text, the key result of the table is that the relative importance of place is largest for mothers with less education. For mothers with a college education, Column 2 shows that less than 3 percent of the the birth weight gap between above and below median Zips can be attributed to place. In contrast, Column 3 shows that place effects account for nearly 20 percent of the variation for non-college-educated mothers.[15] In Columns 4-5, we find that the role of place is similar across white and non-white mothers. This is inconsistent with an alternative hypothesis in which the pattern of education results reflects the fact that mothers with less education are more likely to be minorities.

[15]Given that non-college-educated mothers are slightly over-represented among movers (Table A1), this suggests that our main effects may be an upper bound on the role of place in the population of California mothers. Consistent with this, Appendix Table B2 shows that reweighting our estimates to account for this imbalance between movers and non-movers (as in Miller, Shenhav and Grosz, 2021) reduces our estimated effect of place by about 25 percent.

Table B1: Additive Decomposition of Geographic Differences in Birth Weight, By Group

	(1) All	(2) College Educated	(3) Non-college Educated	(4) White	(5) Non-white
Diff. in avg. birth weight (grams):					
Overall	116.903	174.594	123.221	129.137	158.040
Due to place	18.897	4.567	23.994	23.730	9.042
Due to family (mother)	98.006	170.027	99.227	105.407	148.998
Share of difference due to:					
Share due to place	0.162	0.026	0.195	0.184	0.150
Share due to family (mother)	0.838	0.974	0.805	0.816	0.667

Notes: This table presents additive decomposition results for selected groups of mothers. All estimates are based on dividing areas based on those that have above and below median birth weight. For comparison, Column 1 reproduces our estimate for all mothers from Table 2. Columns 2-6 report results for college educated, non-college, white, and non-white mothers, respectively. All results are based estimates of Equation 1, where the dependent variable is birth weight (in grams). The first row reports estimates of the difference in average birth weight between two areas (i.e., $\overline{y}_R - \overline{y}_{R'}$). The second row reports the estimated difference due to place effects (i.e., $\gamma_R - \gamma_{R'}$). The third row reports the estimated difference due to family (mother) characteristics (i.e., $\overline{y}^m_R - \overline{y}^m_{R'}$).

Table B2: Impact of Reweighting Estimates of Place to Account for Covariate Imbalance Across Movers and Non-Movers

	(1) Baseline Model	(2) Reweighted
Dest-Origin Diff. in BW (100's of grams) x Post	11.228***	7.970***
	(1.033)	(2.605)
Observations	4,127,506	3,967,122

Notes: This table presents estimates of the within-mother change in birth weight around a move, scaled by the destination-origin change in quality, $\hat{\delta}_j$. We estimate the following equation: $y^c_{mjkt} = \alpha_m + \theta\hat{\delta}_m \times post_{mk} + \omega_k + \nu_t + x_{mk}\eta + \varepsilon^c_{mjkt}$, which replaces the relative birth order dummies in our event study model with $post_{mk}$, an indicator for the births that occur after a mother's move. The key coefficient of interest is θ, the parameter on $\hat{\delta}_m \times post_{mk}$. We estimate this equation without weights (Column 1), as in our main analysis, and applying weights to correct for imbalance in maternal covariates between movers and non-movers (Column 2). We follow Miller, Shenhav and Grosz (2021) and generate the weights as the product of (i) the inverse of the probability of being a mover (estimated from fitted values from a logit model that includes fixed effects for maternal race/ethnicity and maternal education, and a linear term in maternal age) and (ii) the inverse of the within-mother variance in $\hat{\delta}_m \times post_{mk}$. Standard errors are clustered at the mother-identifier level.

B2 Appendix to Section 5.4: Robustness Exercises

In this section, we describe the specifics of the robustness exercises summarized in Section 5.4. First, to test for potential shocks that could be correlated with location quality, we create a "predicted birth weight" for each infant as the fitted values from a regression of birth weight on a number of proxies for partner quality, financial resources, or delivery complications.[16] Appendix Figure B1 shows that there is little change in predicted birth weight after a move. This suggests that the vast majority of the change in birth weight after a move is due to place-based influences, rather than time-varying individual covariates.[17]

Second, another potential concern with using moves across Zip codes is that average birth weight may be noisily measured. Therefore, we conduct an analysis of place effects at the county-level, and summarize these results using our event study specification. Appendix Figure B3 shows that our qualitative results are quite robust when we focus on county moves. That said, these estimates are somewhat larger than our baseline effects, suggesting that the causal effect of place accounts for roughly 30 percent of geographic variation at the county level.[18]

Third, we examine whether our results are sensitive to changes in the functional form of our model (logs or levels). Estimating our model in logs allows for the possibility that there could be interactions between mother effects and place effects (i.e., that mothers that tend to have smaller infants (low α_i) may be benefited more by moving to a high-birth-weight Zip code than mothers that tend to have larger infants (high α_i)). Appendix Figure B4 shows that re-estimating our event-study model with log birth weight as an outcome and $\hat{\delta}_m$ defined in logs, produces very similar effects to our main effects.

Finally, we consider whether changes in our sample criteria or data construction might affect our estimates. To start, Appendix Table B4 demonstrates that our decomposition results are not meaningfully changed when we expand our sample to include mothers that move multiple times. Next, we address the potential concern that fertility is correlated with a mother's location choice. For example, if mothers are less likely to have a birth when they move to a lower-quality location (smaller $\hat{\delta}_m$) and the effects of place are heterogeneous across mothers, then the estimated post-move changes in birth weight could confound such differences in (unobserved) selection into having a birth across locations with the causal impacts of place. We examine these types of fertility responses by testing whether the quality of a mother's destination, $\hat{\delta}_m$, is a significant predictor of a total completed fertility (con-

[16] These covariates include an indicator for whether a father is present at the time of birth, father's age, indicators for whether the father completed high school and college, an indicator for having a c-section, an indicator for having no delivery complications, and indicators for public and private insurance. Missing father characteristics are imputed as the mean in a given calendar year.

[17] We find similarly small effects when we expand the index to include indicators for whether the mother worked in the last year and whether she received any WIC for the pregnancy, which are only available after 2007, and limit our analysis to 2007 and onward. See Appendix Figure B2.

[18] One possible explanation for these larger effects is that cross-county moves may cover longer-distances and entail larger shifts in the local environment. Consistent with this, Appendix Table B3 shows that longer-distance Zip-level moves, relative to shorter-distance moves, have larger impacts on birth weight.

trolling for fixed maternal characteristics).[19] Appendix Table B5 shows that an 100-gram increase in $\hat{\delta}_m$ is associated with a substantively small and statistically insignificant decline in completed fertility.[20] This provides strong evidence that selective fertility is not a factor in our estimates.

[19] Controls include fixed effects for mother race; whether a mother has a college education; the age of a mother's first birth; and the parity of the first child born after a move.

[20] The estimate is also economically small when controls are not included.

Table B3: Impacts of Place on Birth Weight by Distance of Move

	(1) Estimate
Dest-Origin Diff. in BW (100's of grams) x Post x Move 0-5 mi	5.797**
	(2.529)
Dest-Origin Diff. in BW (100's of grams) x Post x Move 5-10 mi	2.281
	(2.349)
Dest-Origin Diff. in BW (100's of grams) x Post x Move 10-25 mi	7.641***
	(2.105)
Dest-Origin Diff. in BW (100's of grams) x Post x Move at least 25 mi	22.812***
	(1.791)
Mean of outcome	3351.288
Individuals	4,027,112

Notes: This table presents estimates of the within-mother change in birth weight around a move, scaled by the destination-origin change in quality, $\hat{\delta}_j$, and allowing this effect to vary by the distance of the move. We estimate the following equation: $y^c_{mjkt} = \alpha_m + \theta_1\hat{\delta}_m \times post_{mk} \times Move05 + \theta_2\hat{\delta}_m \times post_{mk} \times Move510 + \theta_3\hat{\delta}_m \times post_{mk} \times Move1025 + \theta_4\hat{\delta}_m \times post_{mk} \times Move25pl + \omega_k + \nu_t + x_{mk}\eta + \varepsilon^c_{mjkt}$. This equation replaces the relative birth order dummies in our event study model with $post_{mk}$, an indicator for the births that occur after a mother's move, and allows the coefficient on the $\hat{\delta}_m \times post_{mk}$ interaction to vary for mothers that move (i) up to 5 miles, $Move05$; (ii) between 5-10 miles, $Move510$; (iii) between 10-25 miles, $Move1025$; or (iv) more than 25 miles, $Move25pl$. The key coefficients of interest are θ_1, θ_2, θ_3, and θ_4, the parameters on the interactions between $\hat{\delta}_m \times post_{mk}$ and each of the distance of move variables. Standard errors are clustered at the mother-identifier level

Table B4: Additive Decomposition of Geographic Differences in Birth Weight, Robustness to Including Multiple Movers

	(1)	(2)	(3)	(4)
	Main Estimation Sample		Including Multiple Movers	
	Top vs. Bottom 50%	Top vs. Bottom 25%	Top vs. Bottom 50%	Top vs. Bottom 25%
Diff. in avg. birth weight (grams):				
Overall	116.903	193.514	116.903	193.514
Due to place	18.897	26.982	22.184	33.651
Due to family (mother)	98.006	166.532	94.720	159.863
Share of difference due to:				
Share due to place	0.162	0.139	0.190	0.174
Share due to family (mother)	0.838	0.861	0.810	0.826

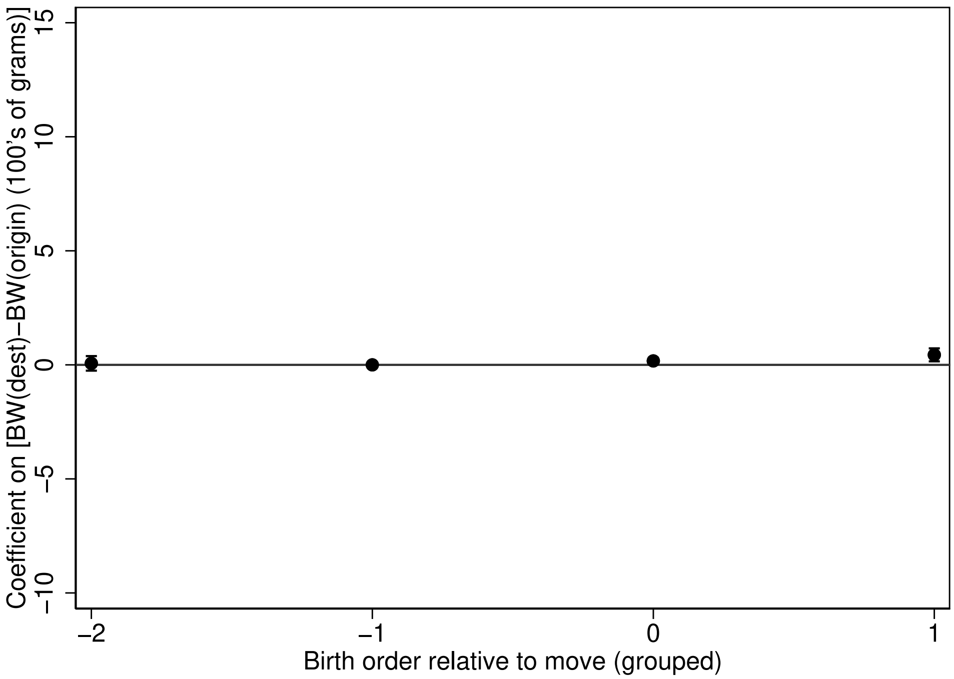
Notes: This table presents additive decomposition results for mothers. For comparison, Columns 1 and 2 reproduces our estimate for all mothers from Table 2. All results are based estimates of Equation 1, where the dependent variable is birth weight (in grams). Each column defines a set of areas R and R'. The first row reports estimates of the difference in average birth weight between two areas (i.e., $\overline{y}_R - \overline{y}_{R'}$). The second row reports the estimated difference due to place effects (i.e., $\gamma_R - \gamma_{R'}$). The third row reports the estimated difference due to family (mother) characteristics (i.e., $\overline{y}^m_R - \overline{y}^m_{R'}$).

Table B5: Test for Differences in Fertility by Destination-Origin Difference in Average Birth Weight

	(1)	(2)
	Controls added:	
	None	Mom Chars.
Dest-Origin Diff. in BW (100's of grams)	-0.008***	-0.001
	(0.001)	(0.001)
Mean of outcome	2.367	2.368
Observations	1,743,865	1,705,598

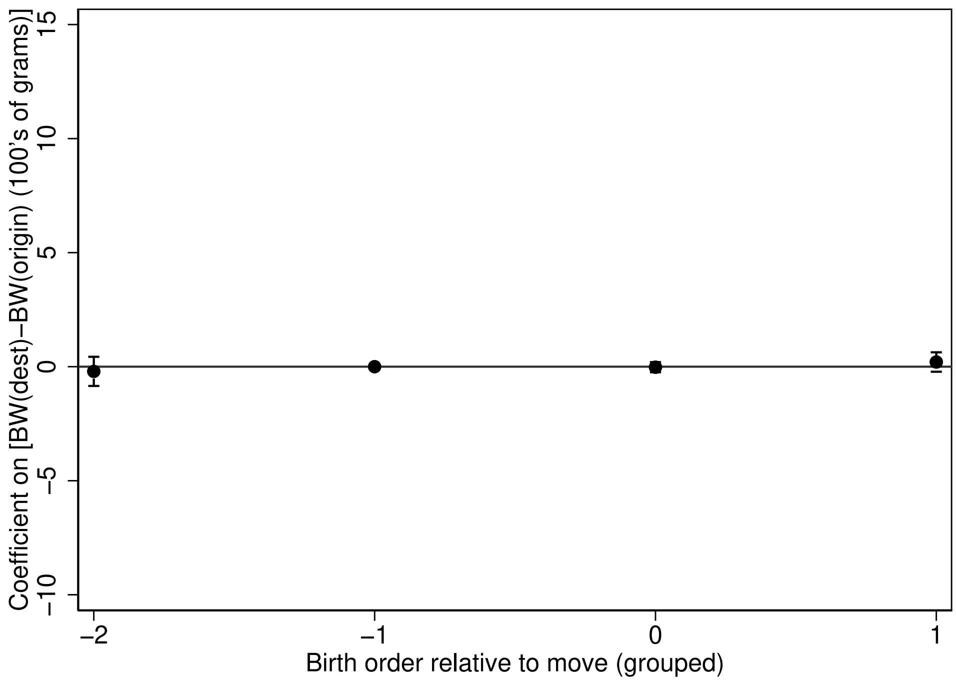
Notes: This table presents results from mother-level regressions where the outcome is the total completed fertility of each mother and the key regressor of interest is the destination-origin difference in average child birth weight ($\hat{\delta_m}$) for each mother. Column 1 includes no additional covariates; while Column 2 includes fixed effects for mother race, whether a mother has a college education, the age of a mother's first birth, and the parity of the first child born after a move. Robust standard errors are shown in parenthesis.

Figure B1: Predicted Infant Birth Weight Around a Move



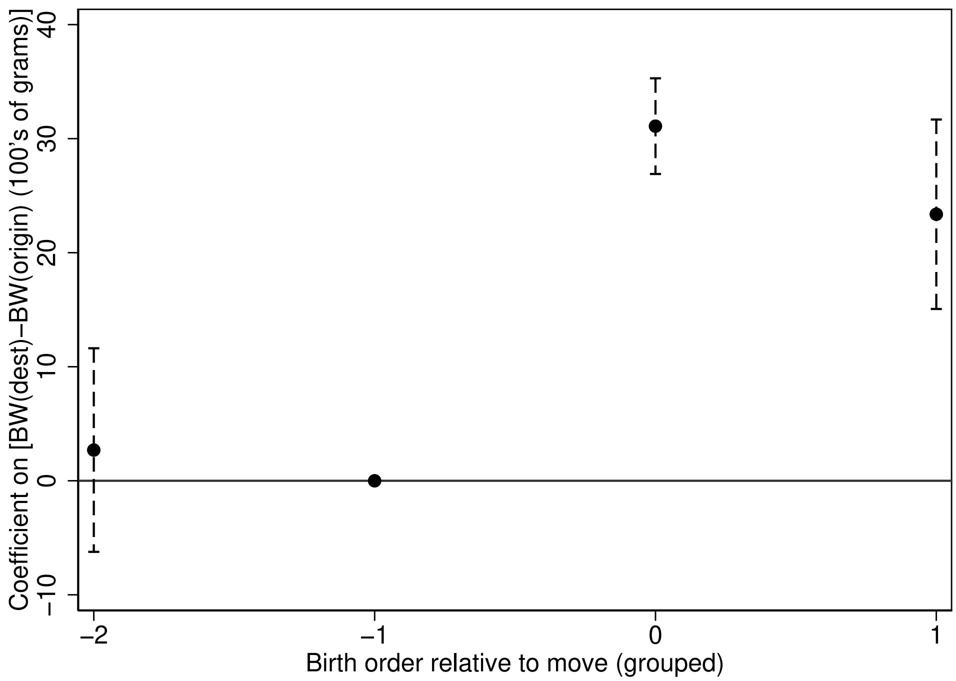
Notes: This figure shows coefficients from our event study model (Equation 5) in which the dependent variable is the *predicted* infant birth weight as an outcome. We generate predicted birth weight for each infant as the fitted value from a regression of birth weight on an indicator for whether a father is present at the time of birth, father's age, indicators for whether the father completed high school and college, an indicator for having a C-section, an indicator for no delivery complications during the birth, and indicators for public and private insurance. Missing father characteristics are imputed as the mean in a given calendar year. See the notes for Panel (b) Figure 1 for additional details about the interpretation of the estimates.

Figure B2: Predicted Infant Birth Weight Around a Move Using Additional Covariates (2007 on)



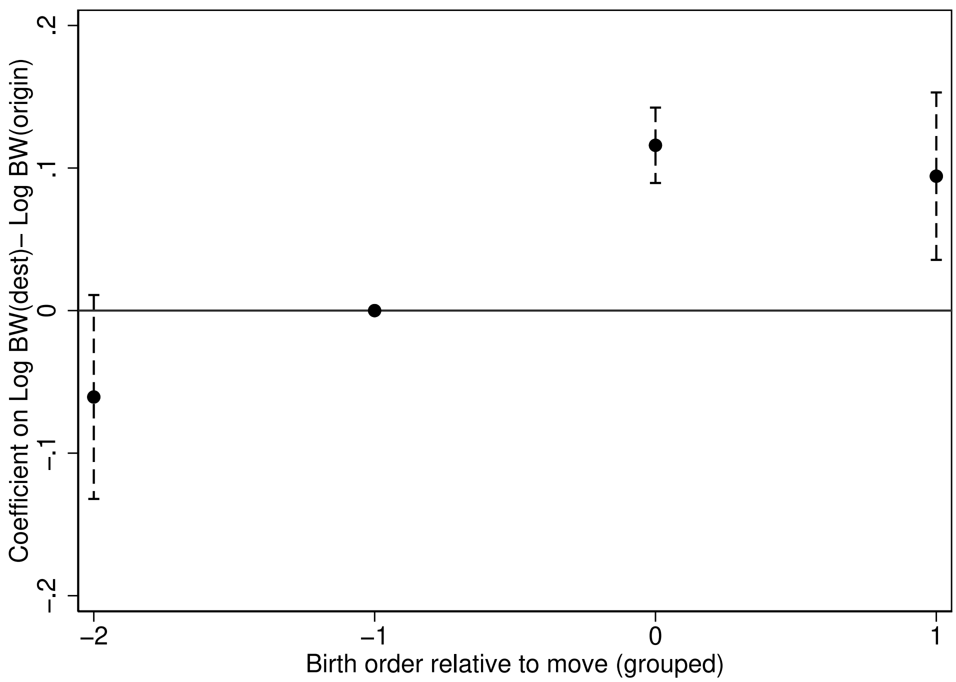
Notes: This figure shows coefficients from our event study model (Equation 5) when we use *predicted* infant birth weight as an outcome. We generate predicted birth weight using the baseline prediction model (described in the notes of Appendix Figure B1), augmented with additional covariates that include indicators for whether the mother worked in the last year and whether she received any WIC for the pregnancy. Because these additional covariates are only available after 2007, we restrict our analysis to the years 2007 to 2017. See the notes for Panel (b) of Figure 1 for additional details about the interpretation of the estimates.

Figure B3: Event Study of Birth Weight using Moves Across Counties



Notes: This figure reports the coefficient estimates of $\hat{\theta}_{r(m,k)}$ from Equation 5 where we define moves as a change in a mother's county of residence. See the notes for Panel (b) of Figure 1 for additional details about the interpretation of the estimates.

Figure B4: Event Study of Log Birth Weight



Notes: This figure shows coefficients from our event study model (Equation 5) in which we set log birth weight as the dependent variable. See the notes for Panel (b) of Figure 1 for additional details about the interpretation of the estimates.

C Additional Data Description

This appendix provides details on the data sources that we use to construct measures of place characteristics. We use measures at the Zip or county geographic levels to analyze the correlates of the causal place effects in Section 6.

1. **Pollution:** We rely on Zip-level measures of particular matter ($PM_{2.5}$) and ozone from the CalEnviroScreen (version 1.1) database. The CalEnviroScreen database was created by the California Office of Environmental and Health Hazard Assessment (OEHHA). The $PM_{2.5}$ measure is the annual mean concentration (average of quarterly means) over the three year period 2007-2009. The ozone measure is the portion of the daily maximum eight-hour ozone concentration over the federal eight-hour standard (0.075 ppm), averaged over the three year period 2007-2009.

2. **Criminal Justice:** We rely on county-level measures of arrests for violent and all types of crime per 100,000 persons. Arrest data are available from the California Department of Justice (DOJ) Criminal Justice Statistics Center (CJSC). We compute the average annual number of arrests for violent and all types of crime for the period 1990-2015. We use population statistics from the U.S. Census Bureau to calculate the number of arrests per 100,000 persons.

3. **Demographics and Economic Characteristics:** We rely on Zip-level measures of median income, the poverty share, and the share of Black residents from the 2000 Decennial Census. The Zip-level data was downloaded from the IPUMS National Historical Geographic Information System (NHGIS) (Manson et al., 2021). In addition, we also calculate the Zip-level share of mothers with a college degree using the birth records from California (1989-2017) for all of the mothers in our estimation sample.

4. **Health Care:** We rely on county-level measures of the per capita number of hospital beds and obstetrician-gynecologists (OB-GYNs) from the Area Health Resource Files (AHRF).