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PLACE EFFECTS AND GEOGRAPHIC INEQUALITY IN HEALTH AT BIRTH

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ABSTRACT

This paper uses birth records from California and mothers who move to quantify the absolute and relative importance of birth location in early-life health. Using a model that includes mother and location fixed effects, we find that moving from a below- to an above-median birth weight location leads to a 19-gram increase in average birth weight. These causal place effects explain 16 percent of geographic variation in birth weight, with family-specific factors accounting for the remaining 84 percent. Place effects are more influential for children of non-college-educated mothers, and 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, and could have a small, lasting effect on long-run outcomes.

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1 Introduction

Although the United States strives to be a land of equal opportunity, geographic disparities in the outcomes of children appear as early as birth. For example, children born in the Midwestern cities of Detroit and Cleveland are more than twice as likely to be born with low birth weight (below 2500 grams) compared to those born in coastal cities of San Diego and Seattle (Kids Count, 2021). Because of the link between birth weight and later-life success, this raises the potential concern that disparities in the quality of a child's birth location may translate into gaps in economic success and upward mobility.[1] However, it remains unclear to what extent these disparities in early life reflect the causal impact of place rather than the non-random sorting of families.

This paper provides new evidence on the role of place in determining early life outcomes. Using birth records from California that span three decades, we follow "mover" mothers that relocate across neighborhoods (Zip codes) and compare the birth weight of children born post-move relative to previous births to identify causal place effects. Our within-mother estimates capture the total effect of place, including the impacts of hard-to-measure characteristics, such as the degree of social capital, and more salient features such as pollution and climate. We use the estimated place effects to quantify the impact of moving to higher-quality neighborhoods and decompose spatial gaps in early-life health into a causal, place-based component and a selection, family-based component.

Our first main result is that the quality of an infant's birth location (as measured by the outcomes of other infants born there) is influential for birth weight. Mothers who move from a below- to above-median area experience a 19-gram improvement in their own child's birth weight. This compares favorably with the impact of policies that target pregnant women's health, such as providing access to Food Stamps and Medicaid (Almond, Hoynes

[1]See Black, Devereux and Salvanes (2007); Chetty et al. (2014); Bharadwaj, Lundborg and Rooth (2017).

and Schanzenbach, 2011; East et al., 2021) or reducing smoking (Permutt and Hebel, 1989). Place effects are symmetric for increases and decreases in the quality of location, suggesting that mothers are sensitive to both the health benefits and the health costs of locations. We also find small improvements in other outcomes, including a 1.7 percent decline in being low birth weight and a 0.64 day increase in gestational age.

Our second main finding comes from our decomposition analysis which shows that place explains 16 percent of the 116-gram difference in birth weight between above and below-median areas, with the remaining 84 percent of the variation due to sorting on mother-specific factors. This implies that equalizing location-specific amenities would eliminate roughly one-sixth of the spatial gap in infant health. We find similar shares when we decompose the gap between the top and bottom quartiles or deciles, as well as when we decompose the cross-Zip variance in birth weight.

However, not all groups are equally affected by place; we find much larger effects for mothers without a college degree. Moving from a below-median to an above-median area improves child birth weight for non-college educated mothers by three times as much as for college-educated mothers (24 grams vs. 8 grams). In turn, place explains significantly more of the spatial gap in outcomes for non-college-educated mothers (21 vs. 7 percent). These results add to an emerging body of evidence that contextual factors such as pollution may have stronger impacts on disadvantaged populations (e.g., Currie and Walker, 2011).

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 pollution, and particularly the local level of ozone, is the strongest correlate of place effects. This suggests that one of the primary ways that place affects fetal development is by shaping the level of maternal exposure to pollutants. Consistent with this, we find that longer-distance moves, which are likely to entail a larger change in the environment, have a greater effect on birth outcomes. Correlations between place effects and 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.

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 of a mother's location. We address potential threats to this assumption in three ways. First, we use an event study approach to rule out pre-trends and show that changes in birth weight only appear for the children born after a move. Second, we provide an upper bound on 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 (some of which may be influenced by place). Our results suggest that changes in these characteristics explain less than 10 percent of the place effect. Third, we show that our results are similar if we instrument for the quality of a mother's destination using the location choices of *other* mover mothers in her origin.

Our study makes three contributions to the literature. First, we are the first to quantify the *total* role of place-based factors in infant health. In contrast, prior research focuses on estimating the impacts of specific contextual characteristics on early-life health, such as the effects of exposure to pollution or higher temperatures on infant health at birth or child 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; Hansen-Lewis and Marcus, 2022).[2] Moreover, our data is unique in allowing us to follow the same mother over time, rather than following a panel of counties (or similar

[2] Our analysis of determinants of infant outcomes also complements research estimating the effects of the role of family background in early life health, such as the effect of 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), insurance coverage (Currie and Gruber, 1996; East et al., 2021; Miller and Wherry, 2022), or financial resources (Dehejia and Lleras-Muney, 2004; Lindo, 2011; Hoynes, Miller and Simon, 2015) on birth outcomes.

geographic units). This allows us to rule out changes in the sample composition as a possible source of confounding variation for the effect of place.

Second, our results complement previous studies of the causal impact of place on health-related behaviors and mortality outcomes for adults (Finkelstein, Gentzkow and Williams, 2016, 2021; Deryugina and Molitor, 2020; Hinnosaar and Liu, 2022). 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) and alcohol consumption (Hinnosaar and Liu, 2022), 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 most 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 study is that the data allow 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.

Finally, 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 later-life 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; Baran, Chyn and Stuart, 2022). To our knowledge, we are the first to estimate place effects for outcomes at birth. This fills a gap in earlier findings, which measure the impacts of place on other outcomes during older ages. The projected effects on earnings from our estimates suggest that moving to a higher quality neighborhood could have a small impact on later-life outcomes by improving health at birth. An implication of this finding is that the previously documented impacts of neighborhoods on long-run outcomes are likely to primarily operate 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).

2 Empirical Model

Our analysis consists of two main exercises. In the first exercise, we use a mover design to estimate the causal effect of place (Zip) on early life health. Second, we use the estimated place effects to decompose the difference in infant outcomes across areas into contextual (place-specific) factors *or* family characteristics. The 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).[3]

2.1 Causal Place Effects

We estimate the impact of birth location on early life health using 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 Zip 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

[3]Other studies use similar approaches to examine non-health-related behavior, such as consumer financial health (Keys, Mahoney and Yang, 2020), voting (Cantoni and Pons, 2019), and workers' earnings (Card, Rothstein and Yi, 2021).

mother's new location, and $r(m,k) = -1$ if k is the last birth that preceded a move.[4] 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^c_{mjkt} is an error term that we assume is conditionally mean zero: $\mathbb{E}(\epsilon^c_{mjkt}|m, j, k, t, x_{mk}) = 0$.

The key parameters of interest are the location fixed effects, γ_j. These are identified only if the estimation sample includes "mover" mothers who relocate between births. Otherwise, if all mothers gave birth in the same location, we could not separately identify the impact of location (γ_j) from the unobserved heterogeneity across families (α_m). As discussed in Section 4, we include both mover and non-mover mothers in our sample to enable us to identify the birth order fixed effects (which are collinear with $\rho_{r(m,k)}$ for movers); but our results are unchanged if we drop non-movers.

In order to interpret γ_j as the *causal* impact of place, we require that changes in unobserved, family-based 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. This would lead us to attribute some of the mother-specific adverse shock to the effect of moving, and thus overstate the place effect. We discuss the testable implications of this assumption in Section 3.

2.2 Decomposition

We use the model from Equation 1 to guide our decomposition of geographic disparities in infant outcomes. To define this formally, 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

[4] 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 $r(m,k) = 1$.

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 $\overline{y}_j = \overline{y}_j^m + \gamma_j$.

Applying these definitions, the difference in average child outcomes between locations j and j' can be written as the sum of two components:

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

The first term in Equation 2 is a place-specific component given by the difference in location fixed effects, $\gamma_j - \gamma_{j'}$. This is the causal effect of moving from location j to j'. The second term is a family-specific component given by the difference in average maternal characteristics, $\overline{y}_j^m - \overline{y}_{j'}^m$. Rearranging terms, the share of the difference in outcomes between locations j and j' that is 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:

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

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

Empirically, we apply these formulas to decompose average outcomes in *groups* of locations, R and R', such as the top and bottom 50-percent of Zip codes. 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 above additive decomposition, we also 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 counterfactuals where either the average maternal characteristics or place (Zip) effects were equalized across Zips. These quantities are:

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

$$S^{var}_{place} = 1 - \frac{Var(\overline{y}^m_j)}{Var(\overline{y}_j)}.$$

Note that the sum of S^{var}_{mom} and S^{var}_{place} will not equal one as long as $cov(\overline{y}^m_j, \gamma_j)$ is nonzero. We use a split-sample approach to estimate this covariance as well as the variances in the above equations, as well as to generate bootstrapped standard errors for the estimated shares.[5]

3 Event Study and Tests of Identification

We implement three tests to study potential violations of the identifying assumption required for causal interpretation of our place effect estimates. Although we cannot directly rule out all violations of this assumption (i.e., that the improvement in the quality of a mother's location after a move is uncorrelated with family-based determinants of infant health), the exercises that we consider narrow the scope for potential concerns. This section previews these tests while Sections 5.1 and 7 provide results and discussion.

As one of our main tests, we use an event-study approach to test for differences in within-

[5]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 $\overline{y}^m_j$ as the covariance between the estimates of γ_j and $\overline{y}^m_j$ from the two subsamples. The estimated correlation between γ_j and $\overline{y}^m_j$ is based on the estimated variance of γ_j and $\overline{y}^m_j$ and the covariance of γ_j and $\overline{y}^m_j$, which we compute as the average of the covariances between the estimates of γ_j from one subsample and $\overline{y}^m_j$ from the other subsample.

mother changes in child outcomes between mothers who move to higher- and lower-quality destinations *prior* to a move. This addresses potential concerns about differential pre-trends, which could bias our results. To implement this test, we rely on the following event-study model:

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

where $\hat{\delta}_m$ is the difference in average birth weight between the mother's origin $o(m)$ and destination $d(m)$, which we use as a proxy for the change in the quality of a mother's destination.[6] 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 by 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 mothers (although the results are the same when we restrict the estimation sample to mover mothers). We include the same control variables as in our model of Zip effects (birth order, year, birth order relative to move, and sex of child). For inference, we cluster standard errors at the mother level.

If move-induced changes in place characteristics cause changes in child outcomes, then we should observe the following pattern. The relative quality of one's destination should not be predictive of the birth outcomes of one's children *before* a move, but should be predictive of outcomes *after* a move. This implies that the estimate of $\theta_{r(m,k)}$ should be statistically indistinguishable from zero for any birth preceding a move, i.e., $r(m,k) < 0$, and nonzero for all births following a move. The magnitude of the discontinuity in the level of $\theta_{r(m,k)}$ after a

[6] 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.

move measures how much place-specific factors influence child outcomes.[7]

Next, we conduct two additional tests to further rule out potential sources of endogeneity. The first of these tests is motivated by the potential concern that the timing of a move may be correlated with shocks to maternal and household outcomes that affect child health. To address this, we study the extent to which changes in observable characteristics of mothers after a move predict can predict any post-move changes in birth weight. This exercise provides evidence for the potential role of coinciding shocks with a move, although we are limited to studying aspects of a mother's life that we observe in our birth records.

The second test addresses the potential concern that the choice of destination may be endogenous. We use an instrumental variable (IV) approach to isolate variation arising from the average change in location quality for individuals from a given origin. The power of the instrument comes from a regression-to-the-mean-type logic: individuals that begin in worse origins are more likely to move to a relatively better destination, and individuals that begin in better origins are more likely to move to a relatively better destination. This idea is similar to the IV approaches in Chetty and Hendren (2018) and Abaluck et al. (2021).

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

[7]Due to data limitations, 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 observed in birth records, a mother could be expected to reside in a destination Zip for up to 4.5 years.

insurance).[8]

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

To study the role of place, we use residential Zip code (ZIP-5's) as the geographic unit.[9] 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.[10] Second, to reduce noise in our estimates, the sample is restricted to mothers who live in Zip codes that contain at least 25 movers.

[8]We use this information to construct a unique identifier for each mother based on first name, maiden name, date of birth, and place of birth.

[9]In Section 7, we show that our main conclusions are similar if we focus on county as the geography of interest.

[10]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 A5 show that our estimates are similar if we include mothers with multiple moves.

Table 1 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.[11] Our estimation sample includes roughly 3.7 million mothers with a total of 8.5 million births. Among this 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.

Figure 1 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).[12] 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.[13] Overall, we interpret these small differences as reassuring in that our setting is not particularly unusual relative to other states.

Finally, we provide descriptive statistics on the types of moves in the estimation sample.

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

[12] 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.

[13] Note that the average within-state standard deviation (43 grams) is roughly three quarters of the unconditional standard deviation across counties, suggesting that the majority of across-county variation is within states.

Appendix Table A1 shows that 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. Figure 2 further characterizes moves in terms of the change in location quality. As in the event study, we measure the improvement in location quality using the difference in average birth weight between a mother's destination and origin ($\hat{\delta}_m$). The distribution of $\hat{\delta}_m$ is centered around zero and 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 the change experienced from moving from the median Zip to the 65^{th} percentile Zip.

5 Main Results

5.1 Initial Evidence on the Impact of Place

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 the change in quality of a mother's location, $\hat{\delta}_m$. 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 Figure 3 suggest that moving to a better location positively influences child birth weight. The slope of the fitted line is 0.11, which implies that place-based factors explain 11 percent of the geographic variation in birth weight. The relationship between the change in location quality and the improvement in birth weight in the figure is symmetric for positive and negative changes in location quality and appears to be linear. These findings indicate that mothers are prone to both the health costs and benefits of locations. They also support the assumption of a linear relationship between birth weight and $\hat{\delta}_m$ in Equation 5.[14,15]

Next, Figure 4 reports event study results by plotting the estimated coefficients on $\hat{\delta}_m$ from Equation 5 for each birth relative to a move. For ease of presentation, we scale the coefficients to represent the impact of moving to a destination Zip that has a 100-gram higher average birth weight than one's origin Zip (i.e., $\delta_m = 100$). The omitted category is the relative period $\theta_{r(m,k)} = -1$.

Our main estimates are plotted in solid grey triangle markers and show a statistically significant jump in weight for the first birth after a move. The magnitude of 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, consistent with the slope of Figure 3. Moreover, the coefficient is essentially the same for the second birth after a move, indicating that the impact of a place is relatively constant over time.

A key estimate of interest in Figure 4 is the coefficient for the birth that occurs in relative period $r(m, k) = -2$, 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.

As a point to consider for the interpretation of our results, it is worth noting that the main event study estimates rely on an unbalanced panel of mothers (i.e., we do not observe all mothers for two births before and two births after a move). This implies that the event time estimates are identified by distinct samples of mothers. We find similar estimates when we alternatively use balanced samples. The hollow blue markers in Figure 4 report results from separate event study specifications where the samples are defined based on three different balance subsample restrictions. These include (i) mothers that have two births with one

[14] It also supports the assumption of additive separability in Equation 1, which requires that the change in outcomes when an individual moves from j to j' is the same as when an individual moves from j' to j.

[15] In Figure 3, the change in birth weight is positive for all values of $\hat{\delta}_m$ (including when $\hat{\delta}_m = 0$) due to birth order effects. We include fixed effects for birth order in our decomposition and event study specifications to absorb this (level) effect.

birth occurring after a move; (ii) mothers that have three births with two births occurring after a move; and (iii) mothers that have three births with two births occurring before a move. Reassuringly, we estimate a very similar increase in birth weight post-move as in the main estimates (in the grey triangle markers) and continue to find no detectable evidence of pre-trends.

5.2 Impacts of Moving and Decomposition Results

Next, we exploit the variation in birth location around a move to estimate Equation 1. Appendix Figure A2 provides a map of the estimated $\hat{\gamma}_j$'s. These estimates are relative to the effect of an excluded Zip (90019, in Los Angeles County) as we must omit one fixed effect due to collinearity. The estimates are roughly half positive and half negative, indicating that the effect of the omitted Zip code is roughly median.[16] Suggestively, Zips that are further inland appear to have more negative place effects; although there are "good" and "bad" locations in most areas of the state. To contextualize the role of place in infant health, we now conduct two sets of analyses that describe the absolute and relative impact of location quality on infant birth weight.

5.2.1 Impacts of moving to more advantaged areas

First, we use our estimated Zip effects to estimate the absolute impact of moving to a higher quality area. At baseline, we define this as the expected gain in birth weight associated with a move from a below- to an above-median birth weight Zip.[17]. We also consider a range of alternative definitions of "higher quality" areas, including comparisons of the top and bottom 25, 10, 5 and 1 percent of Zips.

The first row of Table 2 shows that moving to an above-median Zip increases birth weight by 19 grams ($s.e. = 2.690$). This represents an 8 percent effect improvement relative to the

[16]We convert the estimates to standard deviations for easier interpretability.

[17]We estimate this as the difference between the average place effect for above and below median Zips (i.e., $\hat{\gamma}_R - \hat{\gamma}_{R'}$).

average within-mother change in weight across births. It also compares favorably with the effects of policies that target maternal health. For example, it is larger than the impact of access to Food Stamps and Medicaid during pregnancy, which has a 1 to 5 gram effect (Almond, Hoynes and Schanzenbach, 2011; East et al., 2021); similar to the impact of access to WIC during pregnancy (Hoynes, Page and Stevens, 2011; Rossin-Slater, 2013), which has a 2 to 27 gram effect; and comparable to reducing smoking during pregnancy by one cigarette per day, which has a 15-gram effect (Permutt and Hebel, 1989).

The remaining columns of Table 2 show the effects of moving when we consider more stark changes in the quality of a mother's location. The estimated effects in Columns 2-5 indicate that the effect of moving scales up with larger changes in Zip quality. For example, moving from a bottom 1 percent to a top 1 percent location increases birth weight by 65 grams, which is three times as large as the effect of moving from a bottom 50 percent to a top 50 percent location.

5.2.2 Decomposition analysis

Second, we conduct two types of decomposition analyses of the overall gaps in birth weight between areas. As previewed in Section 2, our main decomposition computes the share of the total difference in birth weight attributable to place- or family- (mother) specific factors (i.e., $S_{place}(R, R') = \frac{\gamma_R - \gamma_{R'}}{\overline{y}_R - \overline{y}_{R'}}$ for groups R and R'). Rows 2-4 of Table 2 report results using the various definitions of relatively advantaged and disadvantaged areas.

Column 1 decomposes the difference in birth weight between above- and below-median Zips. Overall, the gap is 117-grams, which is equivalent to roughly 4 percent of the average birth weight. The 19-gram causal increase in birth weight due to place effects represents 16.2 percent of the total difference. This implies that the remaining 83.8 percent is 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 other 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 overall difference in average birth weight increases substantially, from 193 to 725 grams. Nevertheless, the estimated share of the gap explained by place is relatively stable, ranging from 13.9 to 9 percent. Hence, the majority of geographic differences in birth weight appears to reflect *sorting* of mothers.

As an alternative to the additive decomposition, Table 3 decomposes 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 variance decomposition shows that 89 percent of the variance in birth weight would be eliminated if maternal characteristics were equalized, while 15 percent of the variance would be eliminated if place effects were equalized. This is consistent with the results from the additive decomposition, which similarly suggested that place effects account for around one-sixth of the disparity across locations. We also find that there is 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.

How should we think about these decomposition results? Relative to past estimates of the share of health-related outcomes explained by place, our estimate is at the lower end of the spectrum. At the higher end, place effects have been shown to account for at least 54 percent of the gap in seniors' health care utilization across Hospital Referral Regions (Finkelstein, Gentzkow and Williams, 2016), and 70 percent of the gap in alcohol consumption across states (Hinnosaar and Liu, 2022). 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 less than one-third as large as the shares for health care utilization and alcohol purchases, 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.

5.3 Heterogeneity

Next, we study whether the influence of place on infant health varies with the socioeconomic background or race of mothers. This analysis is broadly motivated by previous research suggesting that contextual factors may have stronger impacts on disadvantaged populations (Currie and Walker, 2011; Almond, Currie and Duque, 2018). The existing empirical findings for such heterogeneous place effects (e.g., of pollution) are mixed, however, which makes it useful to revisit this question with our new approach.[18] For simplicity, all of our heterogeneity analyses focuses on estimating the impact of moving from a below- to above- and below-median area.

Table 4 presents the results. Column 1 reproduces our baseline estimate from Table 2, while Columns 2–5 report estimates for mothers who are non-college-educated, college-educated, white non-Hispanic, or Hispanic, respectively. We focus on Hispanic mothers because they constitute the predominant minority group in our sample.

The most notable pattern across these subgroups is that the relative importance of place is significantly larger for mothers with less than a college education. For mothers with a college education, we find that moving to an above-median Zip leads to an 8.5 gram improvement in birth weight, such that place explains roughly 7 percent of the birth weight gap (Column 2). In contrast, moving to an above-median Zip increases birth weight by 24 grams for non-

[18]For example, Alexander and Schwandt (2019) find that reductions in vehicle emissions lead to a similar increase in birth weight for college- and non-college-educated mothers.

college-educated mothers, and place effects account for nearly 21 percent of the variation across place (Column 3).[19,20]

Moreover, this pattern by education does not appear to be driven by differences in the ethnic make-up of less-educated mothers. In Columns 4–5, we find a similar role of place across White and Hispanic mothers. Together, these results indicate that less-advantaged mothers, regardless of race, are more sensitive to the local environment during pregnancy. We provide further support for this finding when we explore specific mechanisms in Section 6.

6 Mechanisms: Correlates of Place Effects

To examine potential channels through which place could influence infant health, we conduct a descriptive analysis of the correlates of our causal place effects. Specifically, we estimate the correlation of the estimates $\hat{\gamma}_j$ from Equation 1 and proxies for four types of contextual factors: (i) demographic and economic measures, such as racial composition and household income; (ii) crime rates, to capture community-stress, the potential for exposure to in-utero violence, and social capital; (iii) 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 (iv) environmental measures such as temperature and pollution, including the level of 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 B provides details on each measure and the underlying data sources.

[19] Appendix Figure A3 presents event studies estimated separately for college- and non-college-educated mothers. We do not find evidence of pre-trends for either group. Consistent with the decomposition, we find significantly larger benefits of moving to a better location for non-college-educated mothers.

[20] Given that non-college-educated mothers are slightly over-represented among movers (see Table 1), this suggests that our main effects may be higher than the role of place in the population of California mothers. Consistent with this, Appendix Table A2 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 32 percent.

Figure 5 plots the bivariate correlation for each of these factors, along with 95-percent confidence intervals.[21] The most striking result from this figure 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. These pollution results are consistent with findings from experimental studies in animal models showing that exposure to ozone during pregnancy raises maternal pulmonary inflammation and reduces offspring weight (Salam et al., 2005). It also aligns with evidence that broad reductions in pollutants, including ozone and $PM_{2.5}$, improve infant weight (Alexander and Schwandt, 2019).

We find smaller but still meaningful associations with other area characteristics. 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.[22] 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).

Figure 6 expands on these results by examining whether these correlations vary between college- and non-college-educated mothers. For both groups, we find the largest correlations between place effects and the level of pollutants (ozone and $PM_{2.5}$). However, the correlation with ozone is three times larger for non-college-educated mothers relative to

[21] 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 A10 shows that family (mother) effects on birth weight are moderately correlated with the share of non-White mothers (-0.30 correlation). Correlations are smaller in magnitude for the remaining characteristics. Appendix Table A7 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.

[22] 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).

college-educated mothers. We can statistically reject that the correlation is the same across the groups (p-value < 0.01). This could suggest that less-educated mothers are either more exposed to airborne pollutants, or are more susceptible to harmful effects from exposure. For the remaining characteristics, we find largely overlapping confidence intervals between the correlations for higher- and lower-educated mothers.

Finally, to better understand the biological pathways behind the increase in birth weight, we examine other measures of infant health. Appendix Table A3 shows the estimated effect of moving to a destination with a 100-gram higher average weight on a child's birth weight; the likelihood of being born low birth weight (< 2500 grams); the likelihood of being born premature (< 37 weeks); and gestational age at birth (in days), using a difference-in-difference version of our event study specification.[23] We find an improvement in each of the outcomes: gestational age increases by 0.55 days, and the likelihoods of being low birth weight and premature each decline by 1.5 percent relative to the mean.[24] This suggests that higher quality locations improve birth weight in part by increasing gestation, and that at least some of the rise in birth weight is attributable to a reduction in more rare and costly birth outcomes, such as being low birth weight.

7 Robustness Exercises

In this section, we report results from five exercises that provide evidence in support our key identifying assumption and assess the robustness of our results.

Post-move maternal shocks:

One potential concern is that post-move shocks to maternal factors could generate improvements infant health and be correlated with location quality. To assess this possibility,

[23]Specifically, we substitute the interaction between $\hat{\hat{\delta}}_m$ and indicators for relative birth order with an interaction between $\hat{\hat{\delta}}_m$ and an indicator for being a birth that occurred post-move.

[24]Thus, moving from a below- to above-median location (an 116-gram improvement in location birth weight) would lead to a 1.7 percent decrease in the probabilities of being low birth weight and of being premature and a 0.64 day increase in gestational age.

we construct a maternal index for each infant as the fitted value from a regression of birth weight on a number of proxies for partner quality, financial resources, or delivery complications.[25] This approach allows us to aggregate many different maternal characteristics into a single index (which can provide more power to detect an effect); to assign proportionally greater weight to outcomes that have a stronger correlation with birth weight; and to easily compare magnitudes with our main effects. Panel (a) of Appendix Figure A4 shows that there is little change in the maternal index after a move. The magnitude of the post-birth increase is around 1 gram, which implies that these factors could at most explain 10 percent of our estimated impact of moving. This provides suggestive evidence that the observed change in birth weight after a move is unlikely due to time-varying individual covariates.[26]

To validate that the small effect on the maternal index is not due to lack of statistical power or poor model fit, we also examine the impact of moving on a second index that is based on place-based covariates. In particular, we generate a place-based index as the fitted value from a regression of birth weight on the 11 place-based characteristics in our correlational analysis. Panel (b) of Appendix Figure A4 shows that the place-based index increases substantially after a move. The increase in the index is an order of magnitude larger than the effect that we predicted using maternal covariates, consistent with the strong correlations of our Zip fixed effects with place-based factors. Importantly, this is not due to greater predictive power of place-based factors for infant health generally, as the R^2 of the prediction regression is in fact larger when we use maternal covariates.

[25] 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. Based on the R^2 of the prediction regression, these covariates are one-third as predictive of birth weight as indicators for maternal race and education categories.

[26] We find similarly small effects when we expand the index to include indicators for whether the mother worked in the last year, her expected income based on her reported occupation and the average income for women by occupation calculated from the 2007–2017 ACS, and whether she received any WIC for the pregnancy. These measures are only available after 2007, and we limit this robustness analysis to 2007 and onward. See Appendix Figure A5.

Instrumental variable estimates:

As a second robustness test, we use an IV approach to address the potential concern that the quality of a mother's destination may be correlated with unobserved, time-varying determinants of child health. In particular, we instrument for the difference in average birth weight between a mother's origin and destination (i.e., $\hat{\delta}_m$) using the average difference for all *other* mover mothers from her same origin.[27] This reduces the scope for selection bias by eliminating variation in the change in location quality due to individual choice. Appendix Figure A6 shows that point estimates from the IV version of our event study are essentially the same as those from our main results.[28]

County-level results:

As an alternative measure of location, we conduct an analysis of place effects at the county-level. This addresses potential concerns that average birth weight may be noisily measured at the Zip code level, or that within-county moves may underestimate the effect of place because many administrative rules are held constant within counties. Appendix Figure A7 shows that we find slightly larger impacts of moving when we focus on across-county moves: a 30-gram increase associated with an 100 gram improvement in location quality. These effects imply that place accounts for 30 percent of the across-county variation in birth weight. Thus, our Zip effects may be a lower bound on the effect of moving to a more advantaged location. We examine possible sources for the larger effects of across-county moves and find the greatest support for a distance-based explanation: across-county moves cover longer-distances, and thus only identify impacts based on larger shifts in the local

[27]Broadly similar approaches appear in other recent papers. For example, Chetty and Hendren (2018) study long-run earnings for children whose families move to new locations. As a robustness check, they reproduce their main exposure effect estimates by predicting the change in location quality using other movers from a child's origin. Relative to their approach, we innovate by combining an IV approach with an event study framework. This uniquely allows us to examine the validity of the instrument by testing whether predicted changes in location quality affect birth weight for children born before a mother moves.

[28]Notably, the IV estimate for the coefficient for the birth that occurs in relative period $\theta_{r(m,k)} = -2$ is not statistically significant. This favors the plausibility of the exclusion restriction in our setting.

environment.[29] In contrast, we find little evidence for measurement error in the results (e.g., our Zip effects are unchanged when we restrict to larger Zips). We also do not find systematic improvements in means-tested program participation, such as WIC, suggesting that changes in administrative burden are unlikely to drive the difference.[30]

Functional form:

We also examine whether our results are sensitive to changes in the functional form of our model (logs or levels) or changes in our sample criteria. 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 A9 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. In terms of changes in the sample definition, Appendix Table A5 demonstrates that our decomposition results are not meaningfully changed when we expand our sample to include mothers that move multiple times.

Place effects and fertility:

Finally, we conduct an analysis to 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

[29] In support of this, we find that longer-distance *Zip-level moves*, relative to shorter-distance moves, have larger impacts on birth weight (see Appendix Table A4) that are comparable to our estimated effects of moving across counties.

[30] In particular, Appendix Figure A8 shows that moving to a higher-birth-weight county does not statistically increase WIC participation.

a mother's destination, $\hat{\delta}_m$, is a significant predictor of a total completed fertility, controlling for fixed maternal characteristics.[31] Appendix Table A6 shows that an 100-gram increase in $\hat{\delta}_m$ is associated with a substantively small and statistically insignificant decline in completed fertility.[32] This provides strong evidence that selective fertility is not a factor in our estimates.

8 Discussion

One final question is to what extent being born in a better location is likely to improve *long-run* outcomes. Understanding the size of any lasting effects is relevant for gauging whether improved birth outcomes could be a mechanism for previously-documented impacts of childhood neighborhoods on intergenerational mobility, as well as inferring the size of the potential fiscal externality from these moves.

Because we are unable to observe long-run outcomes directly, we project our place impacts on birth weight to achievement and earnings using estimates of the effect of birth weight from previous studies based on twin comparisons (Black, Devereux and Salvanes, 2007; Figlio et al., 2014). This is likely to be a conservative estimate of the total effect on outcomes, since improved location can affect fetal development in ways not captured by birth weight (see, e.g., Persico, Figlio and Roth, 2020). Nevertheless, based on these effects of birth weight, the estimated 38-gram (1.2 percent) gain from moving between top and bottom 10-percent locations would be expected to lead to a 0.6 percent of a standard deviation improvement in test scores and a 0.12 percent increase in earnings.

Taking the long-run projections at face value, these results suggest that in-utero exposure to better neighborhoods likely explains a small share of how childhood neighborhoods shape adult outcomes. This is consistent with evidence that the majority of prior place-based

[31] 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.

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

benefits appears to accrue during adolescence, with smaller impacts during early-childhood (Deutscher, 2020; Chetty et al., 2020*b*). Collectively, this indicates that childhood place effects on long-run outcomes operate primarily through post-birth mechanisms, such as schools or neighborhood peer effects.

9 Conclusion

This paper uses birth records and a movers-based research design to estimate the absolute and relative importance of place-effects for early-life health. We find that the gain in birth weight from moving to a higher-quality location (as proxied by higher average birth weight) compares favorably with policies directly targeting maternal health, including core safety net programs. In terms of their relative importance, place effects can explain up to 16 percent of the variation in birth weight across locations. A descriptive analysis suggests that causal place effects are most related to the presence of airborne pollutants, particularly the level of ozone.

Overall, our analysis provides the first estimates of the total role of place-based factors on infant health. These effects capture the effects of more-difficult-to-measure characteristics of neighborhoods, such as the degree of social capital, and more salient features studied in prior work, such as pollution or climate. Our work provides new evidence about the importance of neighborhoods for infant development, complementing recent research that has found large impacts of childhood location on long-run outcomes (Chetty, Hendren and Katz, 2016; Chetty et al., 2020*a*). Based on our estimates, a back-of-the-envelope calculation suggests that a small portion of the lasting effects of neighborhoods may be due to improvements in early life health.

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10 Figures and Tables

Table 1: Summary Statistics

	All:	Estimation sample:		
	All	All	Non-movers	Movers
Infant birth weight (g)	3,333.372	3,334.395	3,317.200	3,352.434
	(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)
Number of births	2.205	2.446	2.379	2.516
	(1.141)	(0.646)	(0.612)	(0.673)
Observations	15,318,719	8,457,806	4,330,108	4,127,698

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 2: Estimated Impacts of Moving and Decomposition Results

	(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%
Panel A. Effects of Moving					
Estimated impact (grams)	18.944	26.982	37.832	40.676	64.949
	(2.690)	(4.648)	(8.117)	(12.279)	(27.581)
Panel B. Decomposition:					
Overall difference (grams)	116.899	193.469	295.752	387.577	725.233
Share due to place effects	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 estimates of (i) the impact of moving to more advantaged areas on birth weight (Panel A) and (ii) additive decomposition results of the role of place- and family-based factors in explaining the gap in birth weight across locations (Panel B). All results are based on estimates of Equation 1, where the dependent variable is birth weight (in grams). Each column defines a set of areas R and R', such as the top-50% and bottom-50% of Zip codes (Column 1). The first row in Panel A reports the estimated difference due to place effects (i.e., $\gamma_R - \gamma_{R'}$). The first row of Panel B presents the overall difference in average birth weight between two areas (i.e., $\overline{y}_R - \overline{y}_{R'}$). The second and third rows of Panel B report the shares of the overall difference attributable to place and family (mother) characteristics. Standard errors (in parentheses) are calculated using a mother-level bootstrap approach that has 50 repetitions.

Table 3: Variance Decomposition of Geographic Differences in Birth Weight

	(1) Estimates
Variances of birth weight (grams):	
Birth weight	8,981.612
Place effects	963.706
Family (mother) effects	7,660.681
Corr. of average place and family effects	0.066
	(0.070)
Share of variance reduced if:	
Family (mother) effects were made equal	0.893
	(0.080)
Place effects were made equal	0.147
	(0.132)

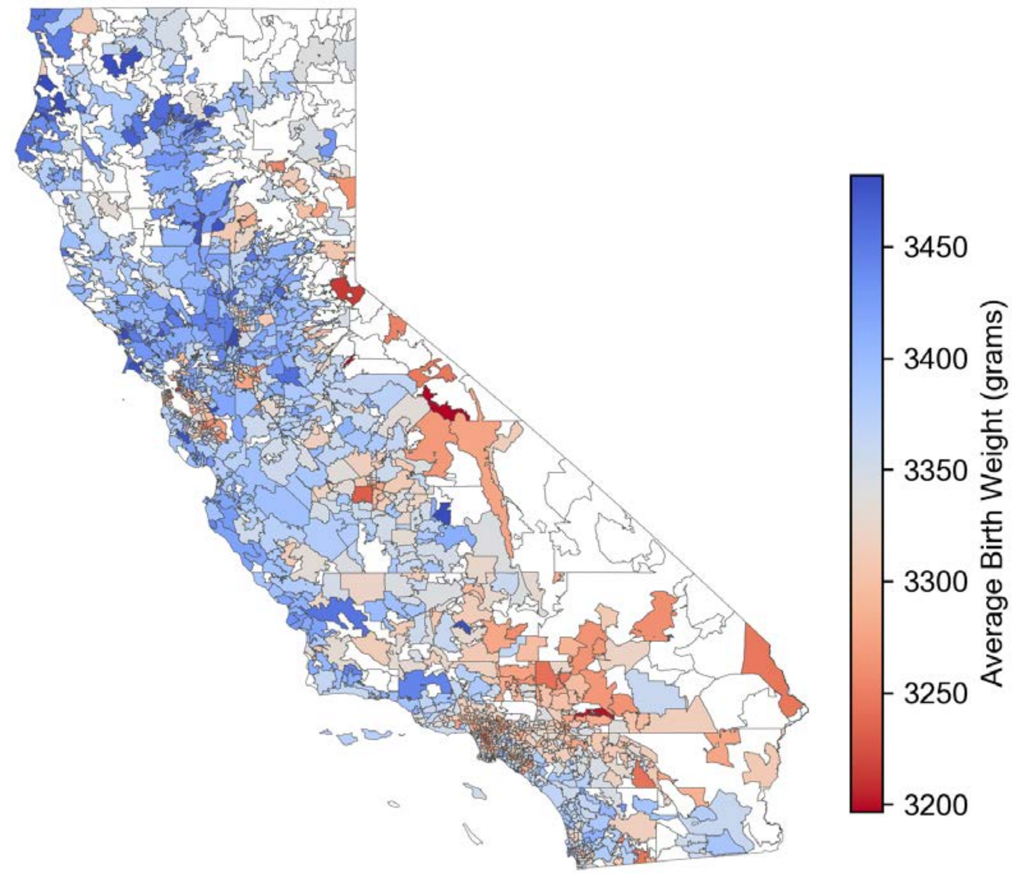
Notes: This table presents variance decomposition results. All results are based estimates of Equation 1, where the dependent variable is birth weight (in grams). We use a split-sample approach to estimate variances and covariances as detailed in Section 3. The first row reports the variance of zip-code 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.

Table 4: Estimated Impacts of Moving and Decomposition Results, By Group

	(1) All	(2) College Educated	(3) Non-college Educated	(4) White	(5) Hispanic
Panel A. Effects of Moving					
Estimated impact (grams)	18.944	8.494	24.171	23.330	23.939
	(2.690)	(4.513)	(2.868)	(3.603)	(3.867)
Panel B. Decomposition:					
Overall difference (grams)	116.899	123.744	113.267	106.827	91.603
Share due to place effects	0.162	0.069	0.213	0.218	0.261
	(0.023)	(0.036)	(0.025)	(0.034)	(0.042)
Share due to family (mother)	0.838	0.931	0.787	0.782	0.739

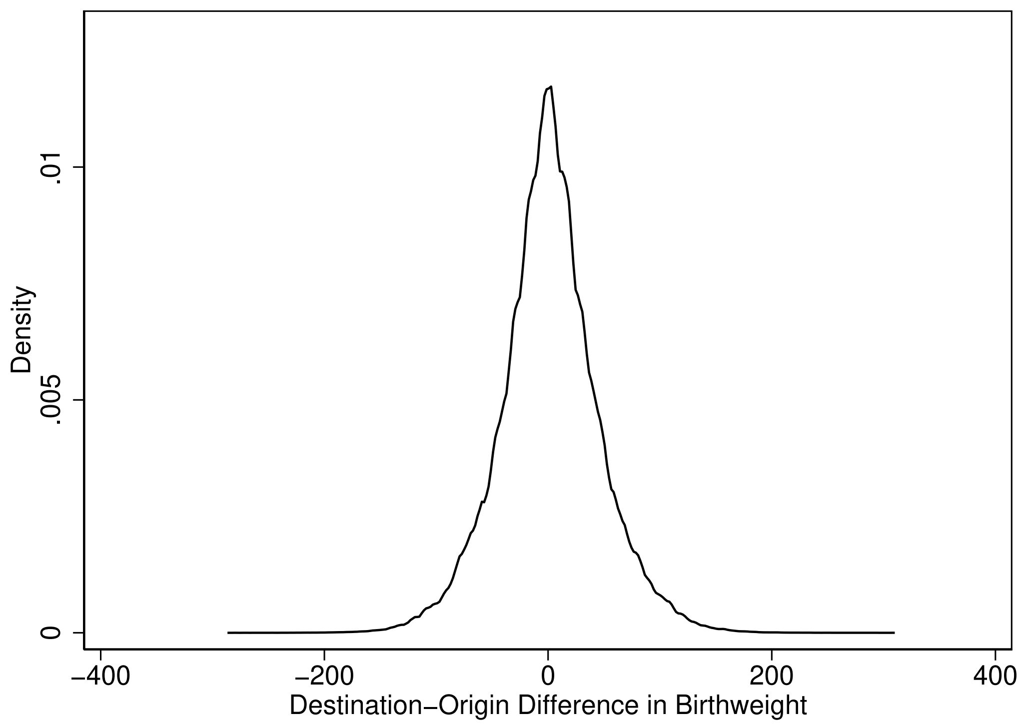
Notes: This table presents estimates of (i) the impact of moving from a below- to an above-median birth weight Zip on a child's own birth weight (Panel A) and (ii) additive decomposition results of the role of place- and family-based factors in explaining the gap in birth weight between below- and above-median birth weight locations (Panel B) for selected groups. Columns 2-5 report results for college educated, non-college, white, and Hispanic mothers, respectively. All results are based on estimates of Equation 1, where the dependent variable is birth weight (in grams). The first row in Panel A reports the estimated impact of moving from a below- to an above-median birth weight Zip. The first row of Panel B presents the overall difference in average birth weight between two areas. The second and third rows of Panel B report the shares of the overall difference attributable to place and family (mother) characteristics. Standard errors (in parentheses) are calculated using a mother-level bootstrap approach that has 50 repetitions.

Figure 1: Average Birth Weight by Zip Code



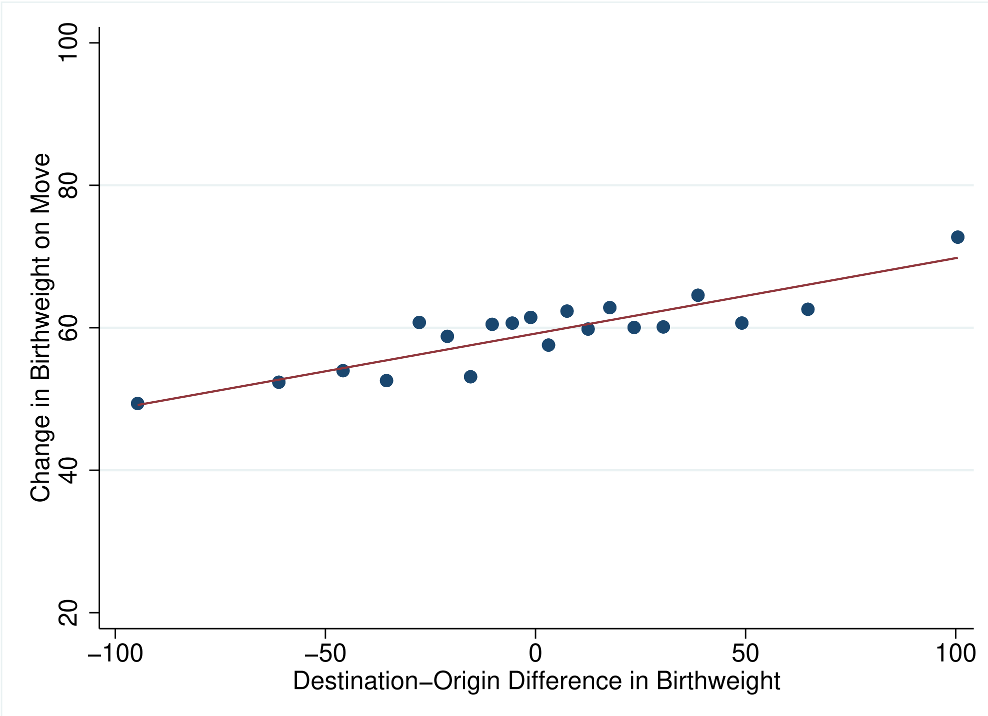
Notes: This figure provides a map of average birth weight (in grams) at the zip code level. The legend indicates the level of birth weight with dark blue and dark red colors indicating places with the highest and lowest birth weight, respectively. White areas are Zip codes where there are no mothers 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 2: Distribution of Destination-Origin Difference in Average Child Birth Weight



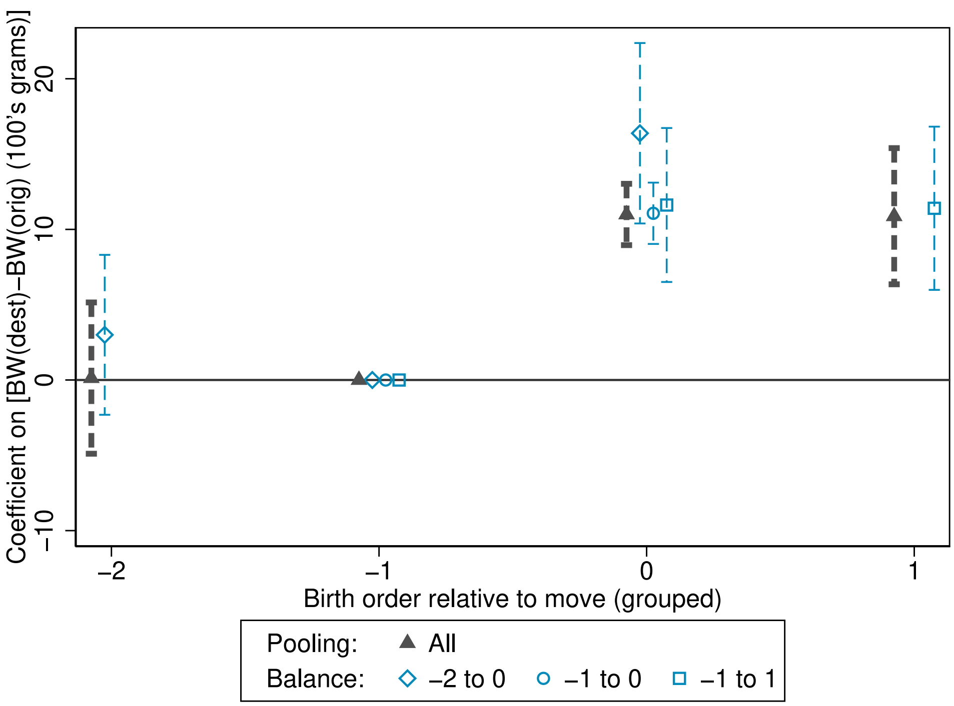
Notes: This figure shows the kernel density of the destination-origin difference in average child birth weight ($\hat{\delta}_m$) for mothers who move across zip codes.

Figure 3: Destination-Origin Differences in Average Child Birth Weight



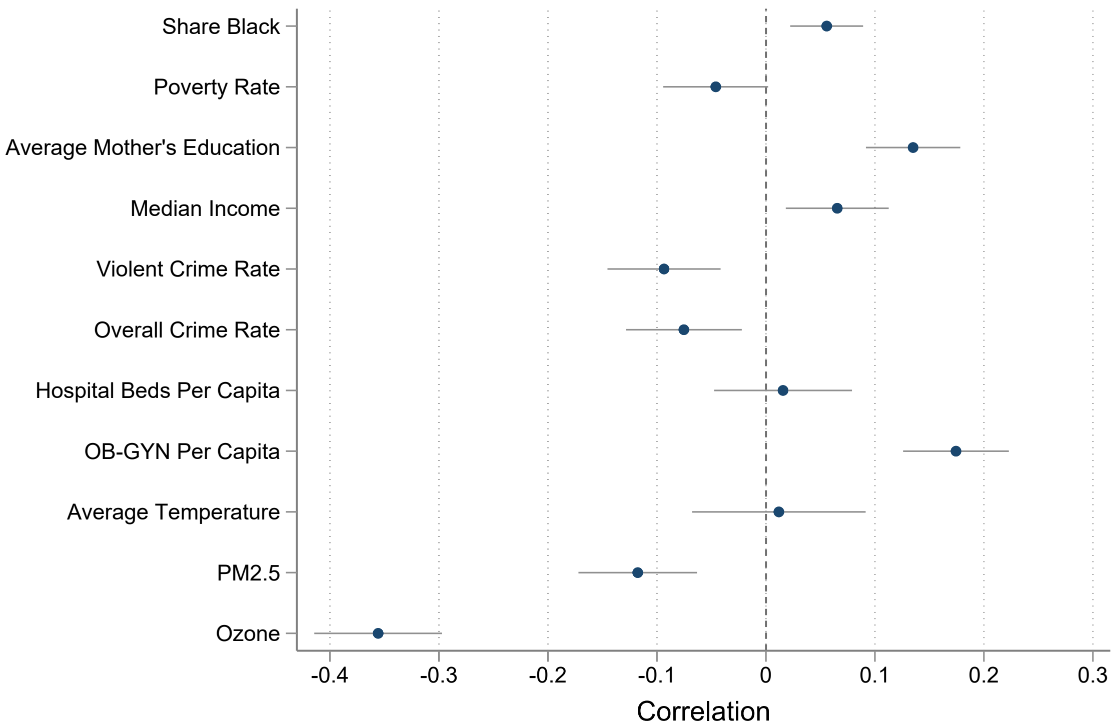
Notes: This figure shows the relationship between changes in birth weight before and after a move and the type of move that a mother experiences. For each mover, we calculate the difference $\hat{\delta}_m$ in average birth weight between their destination and origin zip codes and group the data into 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.

Figure 4: Event Study Analysis of Child Birth Weight



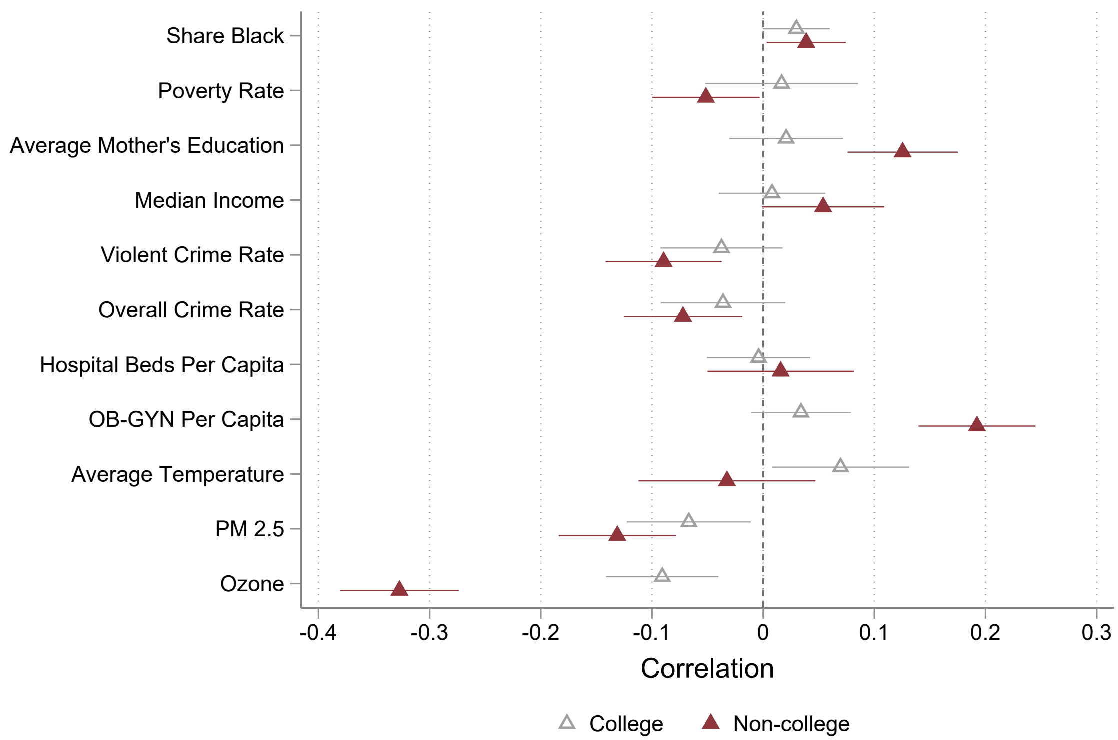
Notes: This figure reports the coefficient estimates of $\hat{\theta}_{r(m,k)}$ from Equation 5. The coefficient for the birth that occurs immediately before the move is normalized to 0. The x-axis indicates the birth order relative to the mother's move, $r(m, k)$. Each dot is a point estimate and represents the impact on birth weight measured in grams. The dashed vertical lines surrounding each dot are estimates of the 95-percent confidence interval. We report results for a sample that includes all mothers, as well as for three subsamples of mothers that are balanced in event time to estimate subsets of the event study coefficients. The filled grey triangles report "pooled" estimates based on all mothers; the blue hollow dots report estimates based on the sample of mothers that have two births and one occurs after a move; the blue hollow squares report estimates based on the sample of mothers that have three births and one occurs prior to a move while two occur after a move; and the blue hollow diamonds report estimates based on the sample of mothers that have three births where two occur prior to a move and one occurs after a move. To reduce noise in the figure, the "pooled" coefficient shown at "-2" and "-1" 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 "pooled" 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 5: 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 B.

Figure 6: Correlates of Spatial Variation in Place Effects on Birth Weight, by Maternal Education



Notes: This figure shows the correlation of estimates of place effects based on Equation 1, estimated separately for college-educated and non-college-educated mothers, and place characteristics. For each characteristic listed on the y-axis, the grey unfilled triangle markers and the red filled triangle markers report the point estimates of the correlations for non-college-educated and college-educated mothers, respectively, 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 B.

Online Appendix

A Appendix Tables and Figures

Table A1: Distribution of Distance Between Origin and Destination

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	8,457,806

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 A2: 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	10.934***	8.010***
	(1.032)	(2.603)
Mean Y	3334.416	3328.036
Observations	8,457,481	8,117,145

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 the term $\hat{\delta}_m \times post_{mk}$. 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.

Table A3: Impact of Moving to a Higher Quality Location on Other Infant Outcomes

	(1) Birthweight	(2) LBW	(3) Gestation	(4) Premature
Dest-Origin Diff. in BW (100's of grams) x Post	10.934***	-0.001**	0.545***	-0.002***
	(1.032)	(0.000)	(0.115)	(0.001)
Mean Y	3334.416	0.067	267.571	0.130
Observations	8,457,481	8,457,481	8,450,228	8,450,228

Notes: This table presents estimates of the within-mother change in infant outcomes 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 $\hat{\delta}_m \times post_{mk}$. Column (1) presents effects on birth weight; Column (2) presents effects on the likelihood of being low birth weight ($\mathbb{1}(<2500$ grams$)$); Column (3) presents effects on gestational age at birth (in days); Column (4) presents effects on the likelihood of being premature ($\mathbb{1}(<37$ weeks$)$). Standard errors are clustered at the mother-identifier level.

Table A4: Impacts of Place on Birth Weight by Distance of Move

	(1)
Dest-Origin Diff. in BW (100's of grams) x Post x Move 0-5 mi	6.006**
	(2.525)
Dest-Origin Diff. in BW (100's of grams) x Post x Move 5-10 mi	1.794
	(2.345)
Dest-Origin Diff. in BW (100's of grams) x Post x Move 10-25 mi	6.928***
	(2.101)
Dest-Origin Diff. in BW (100's of grams) x Post x Move at least 25 mi	22.435***
	(1.788)
Mean Y	3333.630
Individuals	8,357,113

Notes: This table presents estimates of the within-mother change in birth weight around a move, scaled by the destination-origin change in quality, $\hat{\delta}_j$, from a model that allows 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 A5: Estimated Impacts of Moving and Decomposition Results, 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%
Panel A. Effects of Moving				
Estimated impact (grams)	18.944	26.982	22.286	33.651
Panel B. Decomposition:				
Overall difference (grams)	116.899	193.469	116.899	193.469
Share due to place effects	0.162	0.139	0.191	0.174
Share due to family (mother)	0.838	0.861	0.809	0.826

Notes: This table presents estimates of (i) the impact of moving to more advantaged areas on birth weight (Panel A) and (ii) additive decomposition results of the role of place- and family-based factors in explaining the gap in birth weight across locations (Panel B). Columns 1 and 2 reproduces our estimate for all mothers from Table 2. Columns 3 and 4 report results from a sample that includes multiple-move mothers. All results are based on estimates of Equation 1, where the dependent variable is birth weight (in grams). The first row in Panel A reports the estimated impact of moving from a below- to an above-median birth weight Zip code (i.e., $\gamma_R - \gamma_{R'}$). The first row of Panel B presents the overall difference in average birth weight between below- and above-median birth weight Zip codes (i.e., $\overline{y}_R - \overline{y}_{R'}$). The second and third rows of Panel B report the shares of the overall difference attributable to place and family (mother) characteristics.

Table A6: Tests 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

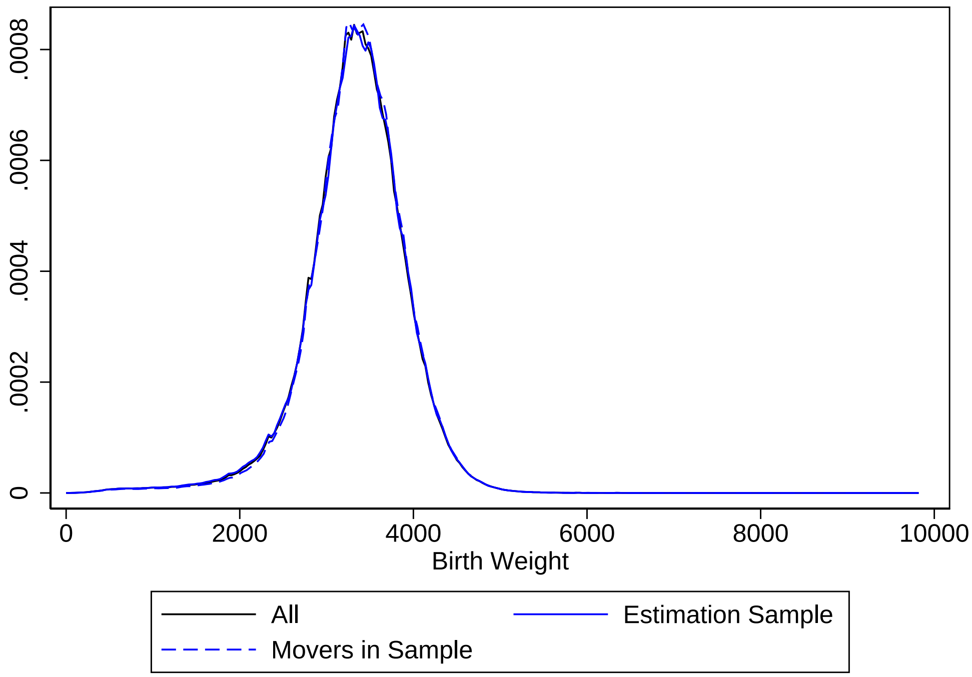
Notes: This table presents results from mother-level regressions where the outcome is the total completed fertility of each mother, and the key regressor of interest is the destination-origin difference in average child birth weight ($\hat{\delta}_m$) for each mother. Column 1 includes no additional 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.

Table A7: 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.	-31.172	-3.880	-103.453	-11.138
Diff. in Mom Characteristic	-0.033	-0.312	-0.156	-0.015
Share	0.009	0.010	0.138	0.001

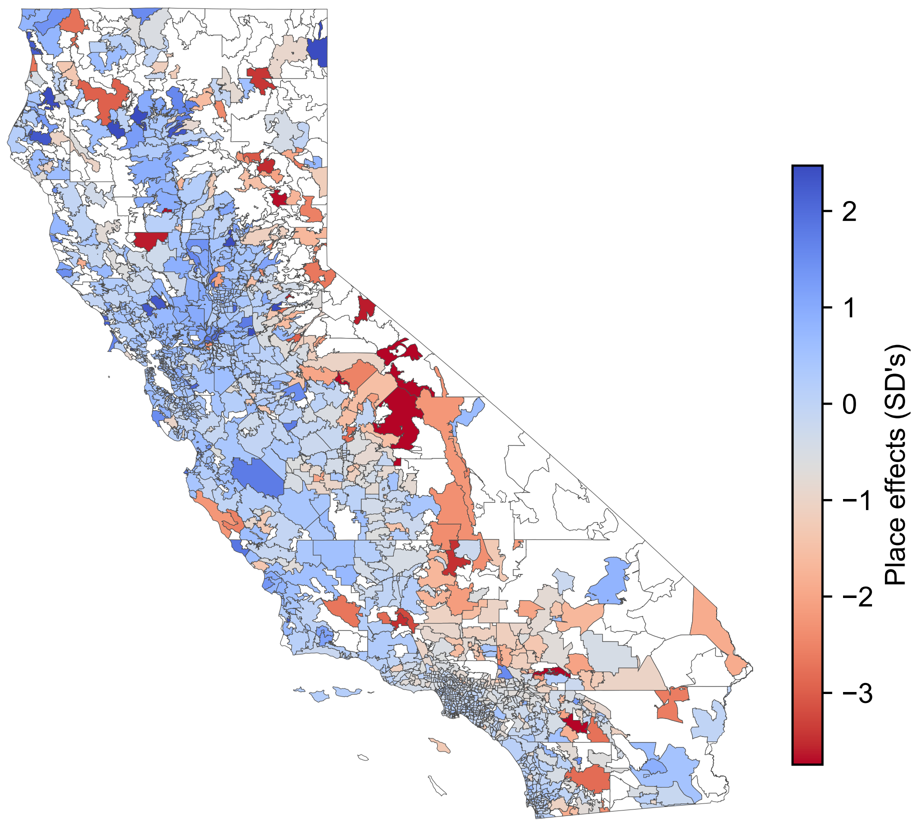
Notes: This table presents results for the difference in birth weight between areas that can be explained by differences in specific maternal characteristics. All results are based on dividing areas based on those that have above- and below-median birth weight. Each column provides results where the 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



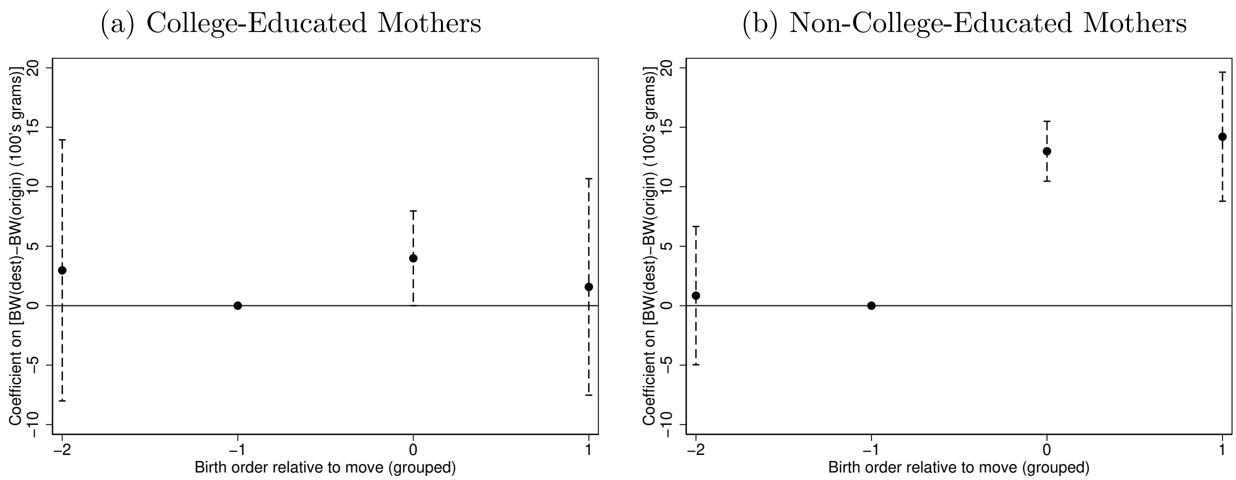
Notes: This figure shows the kernel densities for the birth weight of children born to all mothers in California (from 1989 to 2017), all mothers in our estimation sample, and mover mothers in our estimation sample.

Figure A2: 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.

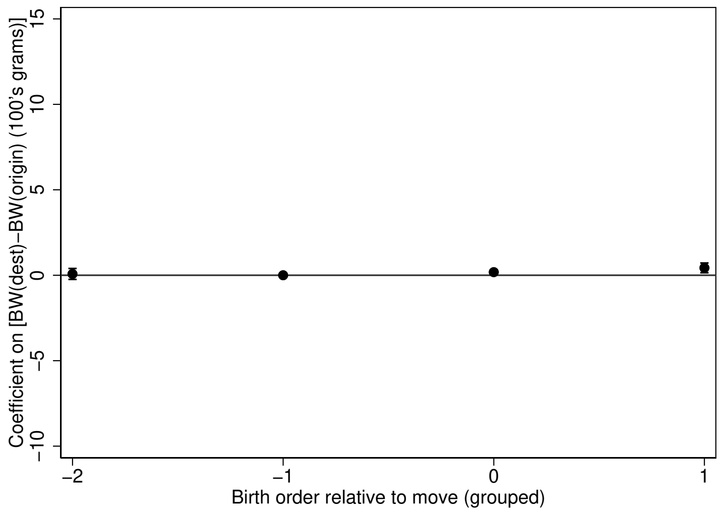
Figure A3: Event Study Analysis of Birth Weight for College- and Non-College-Educated Mothers



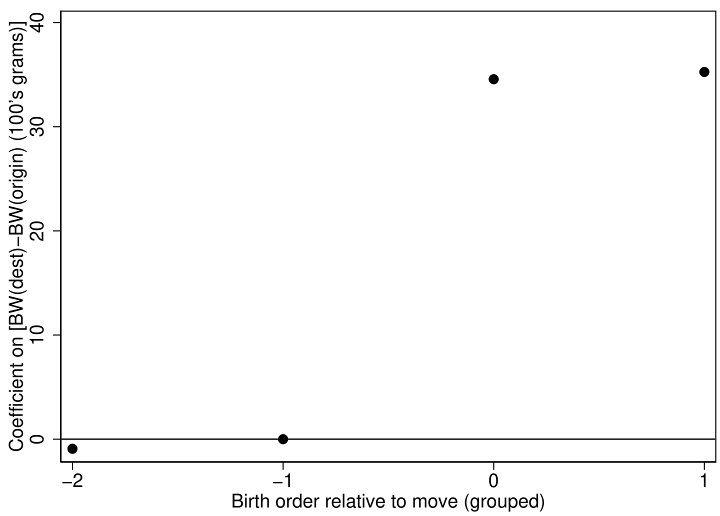
Notes: This figure reports the coefficient estimates of $\hat{\theta}_{r(m,k)}$ from Equation 5 where the sample is either college-educated mothers (Panel a) or non-college-educated mothers (Panel b). See the notes for Figure 4 for additional details about the interpretation of the estimates.

Figure A4: Predicted Infant Birth Weight Around a Move

(a) Maternal Index

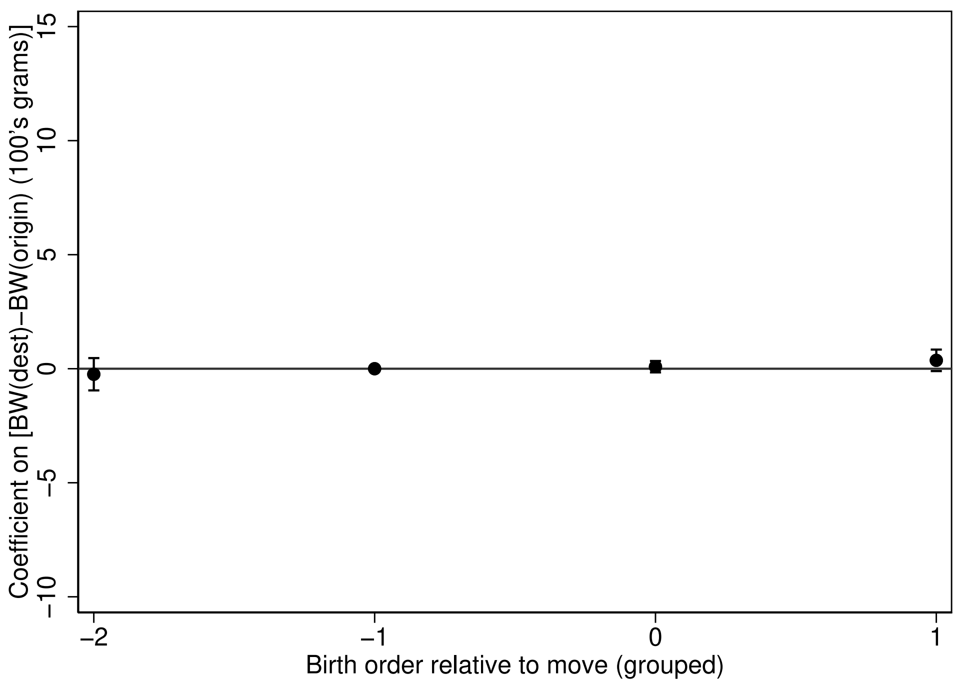


(b) Place-based Index



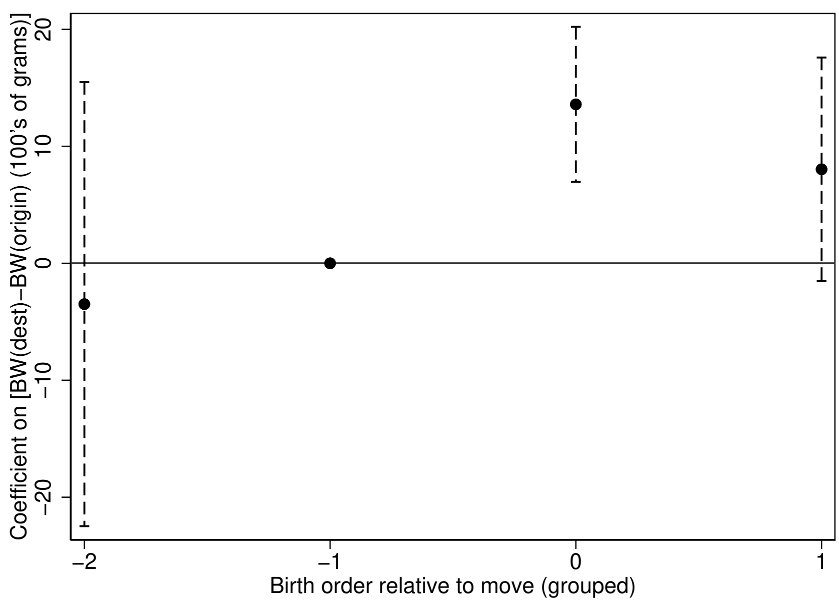
Notes: This figure shows coefficients from our event study model (Equation 5) in which the dependent variable is *predicted* infant birth weight using either maternal and household covariates (Panel a) or place-based characteristics (Panel b). We generate the predicted "maternal index" in Panel (a) as 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. We generate the predicted "place-based index" in Panel (b) as the fitted value from a regression of birth weight on Zip-level median income, poverty share, share black, share of mothers with a college degree; county-level hospital beds per-capita and OB/GYNs per capita; county-level arrests per capita and violent arrests per capita; Zip-level $PM_{2.5}$, ozone, and average temperature. Details on each place-based measure and the underlying data sources are provided in Appendix B. See the notes for Figure 4 for additional details about the interpretation of the estimates.

Figure A5: Maternal Index Around a Move Using Additional Covariates (2007 onward)



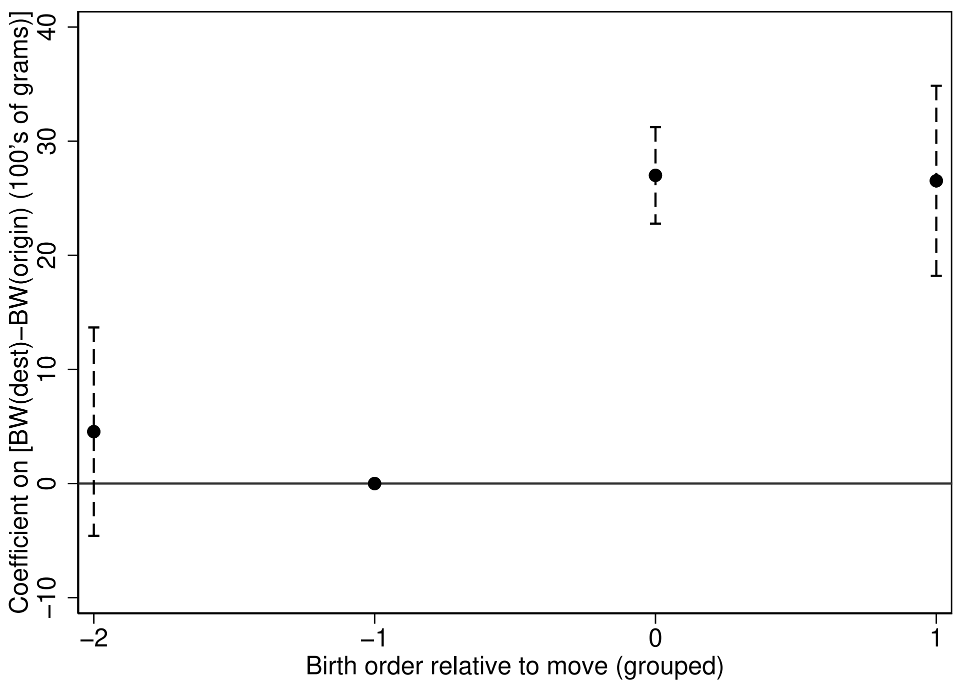
Notes: This figure shows coefficients from our event study model (Equation 5) when we use *predicted* infant birth weight as an outcome. We generate predicted birth weight using the baseline prediction model for the maternal index (described in the notes of Appendix Figure A4), augmented with additional covariates that include indicators for whether the mother worked in the last year, her expected income based on her reported occupation and the average income for women by occupation calculated from the 2007–2017 ACS, and whether she received any WIC for the pregnancy. See the notes for Figure 4 for additional details about the interpretation of the estimates.

Figure A6: Event Study Analysis of Birth Weight Using an Instrument for Changes in Location Quality



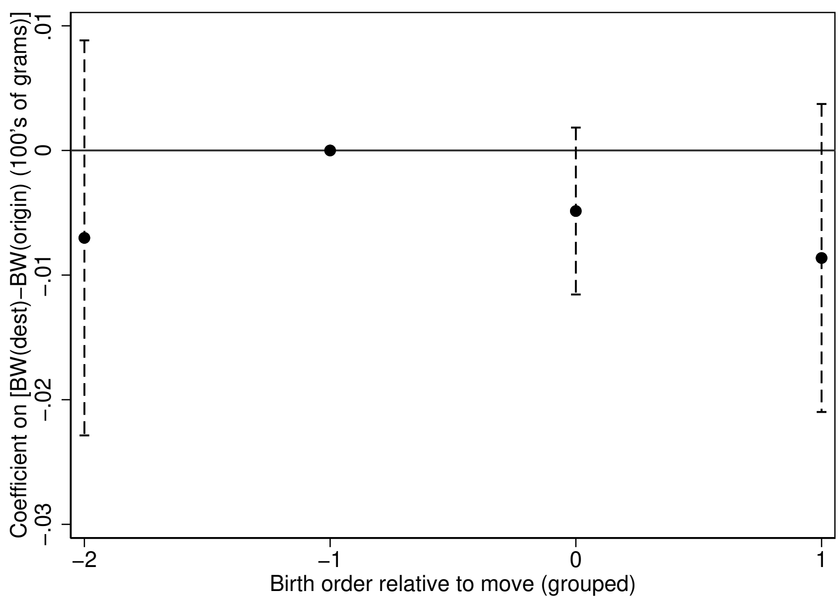
Notes: This figure shows coefficients from our event study model (Equation 5) in which we instrument for the change in mother m's location quality $\hat{\delta}_m$. The instrument is based on computing the leave-out average of $\hat{\delta}_m$ using all mover mothers from a given origin zip while excluding the focal mother. Standard errors are clustered at the origin zip code level. The first stage coefficients and standard errors are 0.988 (s.e. = 0.004), 1.00 (s.e. = 0.0007), and 1.00 (s.e. = 0.003) for the estimates two periods before a move, one period after a move, and two periods after a move, respectively. See the notes for Figure 4 for additional details about the interpretation of the estimates.

Figure A7: Event Study of Birth Weight using Moves Across Counties



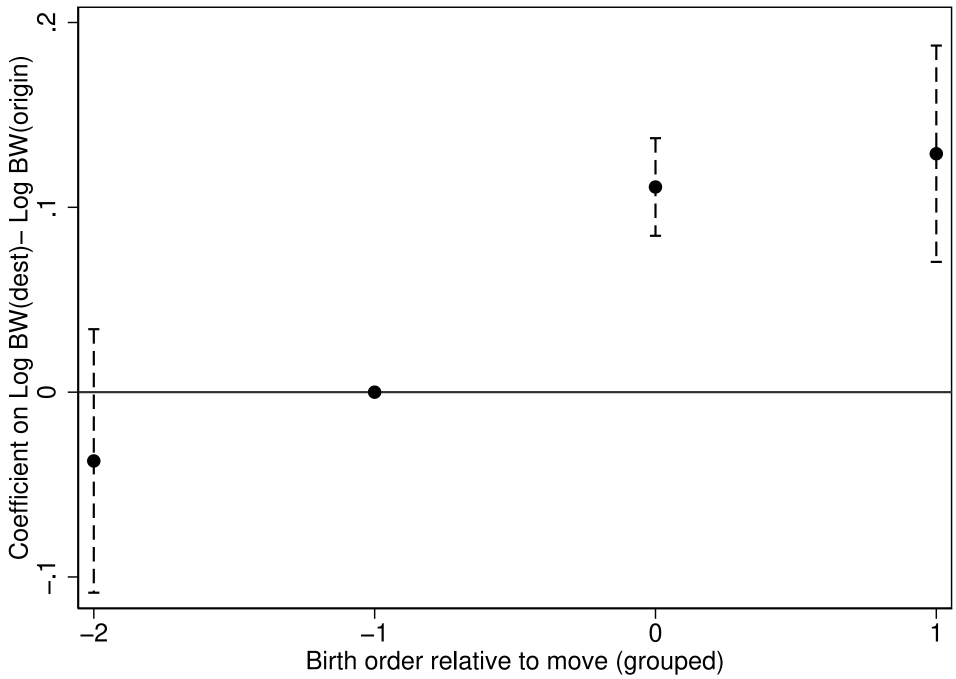
Notes: This figure reports the coefficient estimates of $\hat{\theta}_{r(m,k)}$ from Equation 5 where the dependent variable is child birth weight and we define moves as a change in a mother's county of residence. See the notes for Figure 4 for additional details about the interpretation of the estimates.

Figure A8: Event Study of WIC Participation using Moves Across Counties



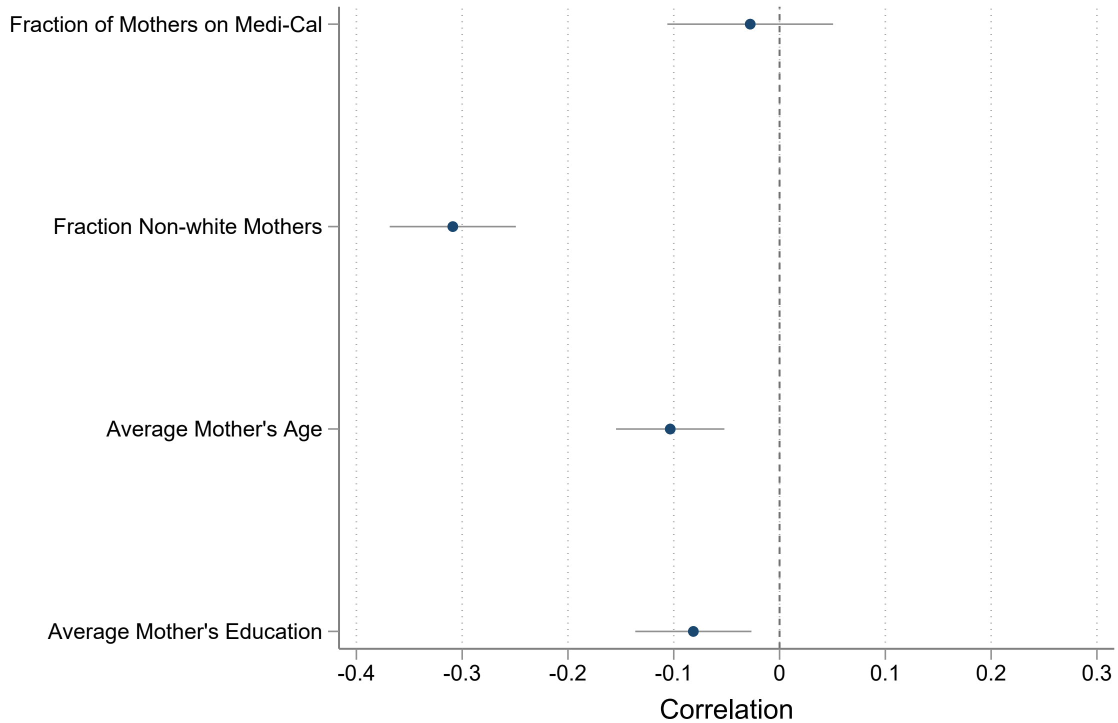
Notes: This figure reports the coefficient estimates of $\hat{\theta}_{r(m,k)}$ from Equation 5 where the dependent variable is an indicator for whether a mother received WIC during her pregnancy and we define moves as a change in a mother's county of residence. The sample includes births from 2007-2017, for which information about maternal WIC participation is available. See the notes for Figure 4 for additional details about the interpretation of the estimates.

Figure A9: 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 Figure 4 for additional details about the interpretation of the estimates.

Figure A10: Correlates of Spatial Variation in Family (Mother) Effects



Notes: This figure shows the correlation of estimates of family (mother) effects (i.e., $\overline{y}_j^m$) 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 B.

B 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).

5. **Temperature:** We rely on Zip-level temperature data for California used in Heutel, Miller and Molitor (2021) (Heutel, Miller and Molitor, 2020).