The Geography of Health Disparities*

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Abstract

Racial disparities in access to medical care are pervasive in the United States. We combine a simple model of healthcare utilization with empirical methods for estimating causal place effects to study the role of geography in driving these disparities. First, we show that the national Black-white access disparity in a given year can be decomposed into person and place components. We present two such decompositions, one where we assume that place effects are homogeneous and one where we allow for race-specific place effects ('place-by-race' effects). We then estimate these two decompositions using Medicare claims data from 2008-2018 and a mover design that leverages beneficiary migration across areas to estimate causal place effects. When place effects are assumed to be homogeneous, place matters very little for disparities. However, when place effects can vary by race, place matters enormously. Crucially, this 'place-by-race' component is driven almost entirely by the fact that Black and white beneficiaries face very different, largely uncorrelated place effects in a given area, not because of differences in geographic sorting by race. Using a series of empirical exercises, we demonstrate the importance of these different place effects for access to medical care and the potential of different classes of policies to close disparities. We also show that our results are not driven by differential noise in our Black place effect estimates and hold for various levels of geographic granularity. Ultimately, our results suggest that while place-based policies are unlikely to close access disparities, more-targeted *place-by-race-based* policies are a promising path toward improving racial equity in utilization of healthcare services.

Keywords:

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In the United States, racial health inequity is a long-standing challenge. An extensive literature has examined racial health disparities and shows that Black patients fare worse than white patients on myriad outcomes, including access to medical care; provider quality; and health outcomes, among others (Institute of Medicine, 2003; Chandra et al., 2020; Murphy et al., 2013). The roots of these disparities are wide-reaching and encompass a range of structural and interpersonal factors, including *de jure* and *de facto* discrimination; residential segregation; labor market discrimination and wealth inequality; and disparities in exposure to environmental hazards, among others (Bailey et al., 2017; Williams and Jackson, 2005).

In this paper, we focus on one commonly cited driver of these disparities: geography. Geographic variation on a number of healthcare-related measures – such as spending, quality, and outcomes – is a well-known phenomenon of the US healthcare system (Cutler et al., 2019; Finkelstein et al., 2016; Wennberg and Gittelsohn, 1973; Wennberg and Cooper, 1996). Because Black and white Americans live in different places, a fact that is itself a product of a variety of historical factors, this geographic variation may play an important role in explaining Black-white disparities that are observed at a national level (Baicker et al., 2004, 2005). It is critical to assess the role of geographic variation in where Black and white Americans live versus other factors, as policy prescriptions and the interpretation of racial disparities may differ substantially depending on their source.

Despite the interest in the subject, comparatively little *causal* evidence exists quantifying the role of geography in health disparities. Disentangling the role of geography has long been difficult empirically because it is challenging to reliably identify the causal effects of place. Areas differ on myriad observable and unobservable dimensions, making it difficult to attribute differences to places themselves as opposed to underlying differences in the composition of people who live in those places (Chetty and Hendren, 2018a,b). In recent years, however, new methods for credibly identifying the causal effects of place have given rise to a number of studies on how places affect a variety of measures of individual health and healthcare utilization (Finkelstein et al., 2016; Deryugina and Molitor, 2020, 2021; Finkelstein et al., 2021). These empirical advances offer an opportunity to explore the role of geography in racial disparities more rigorously.

We use these empirical tools to estimate causal effects of place on access to healthcare among Medicare beneficiaries. Specifically, we leverage Black and white Medicare beneficiaries who move across regions to estimate "place" effects and "person" effects on geographic variation in healthcare utilization separately by race (Finkelstein et al., 2016). While we do not focus on health *per se*, access to health*care* is a critical input to patient health (Cutler et al., 2006; Bailey and Goodman-Bacon, 2015; Gruber et al., 2022). Further, racial disparities

in access receive a great deal of attention from policymakers and the media, and are the focus of many policy recommendations and reforms (Booker, 2023; Pressley, 2023; Schiff, 2023). Place effects on access to healthcare are likely to appear rapidly when an individual moves between areas, while place effects on health likely take longer to manifest, an important distinction given that our research design will leverage migration to estimate place effects.

We start by showing that national disparities can be decomposed into 'place' and 'person' components using an existing model of healthcare utilization (Finkelstein et al., 2016). In this decomposition, the place component represents the portion of the disparity stemming from Black beneficiaries disproportionately living in places with larger negative place effects on access. This decomposition requires estimates of place effects on access to care and the geographic distribution of Black and white beneficiaries. We use our quasi-experimental estimates of these effects to show that when we assume place effects are homogenous across individuals in a given area, the place component of our decomposition is trivially small and statistically indistinguishable from zero. Places do not appear to be a significant driver of disparities.

Next, we extend our decomposition by relaxing the (implicit) assumption that places have homogeneous effects on access by race and instead allow for "place-by-race" effects. We show that when relaxing this assumption, the place component of the decomposition is made up of two distinct pieces: (1) the correlation between white place effects and the differential geographic distribution of Black and white beneficiaries and (2) the difference between Black and white place effects. Again, these two pieces are straightforward to construct with our quasi-experimental estimates of Black and white place effects and Medicare data on the geographic distribution of Black and white Medicare beneficiaries.

We find that, when allowing for place-by-race effects, place matters greatly for generating disparities in access to healthcare. However, essentially all of the effect of place on disparities stems from stark differences between Black and white place effects, not from Black beneficiaries living in places with negative effects on access for beneficiaries of all races. To make this clearer, our decomposition indicates that moving Black beneficiaries living in regions in the bottom quartile of Black place effects to places in the top quartile of Black place effects would effectively close existing disparities in access to healthcare. In other words, place effects do matter for generating disparities. However, if we move Black beneficiaries living in regions in the bottom quartile of *white* place effects to places in the top quartile of white place effects, disparities would change by very little. This suggests that disparities do not arise because Black beneficiaries live in low-access areas and white beneficiaries live in high-access areas. Instead, the problem is that that Black beneficiaries live in low-access areas *for Black beneficiaries*.

Digging further, we find that, contrary to our priors, these results are driven by the fact that Black and white place effects are not highly correlated. We use a variety of techniques to show that this weak correlation between place effects is not driven by the differential noisiness of the Black place effect estimates. Instead, Black and white beneficiaries living in the same place do indeed experience different effects of place on access to healthcare. We illustrate the implications of this result for access to care using a series of empirical tests that underscore a common point: the causal effect of Black beneficiaries moving to a high-access area for Black beneficiaries is an order of magnitude larger than the causal effect of moving to a high-access area for white beneficiaries (and vice versa for white beneficiaries). By contrast, and consistent with our decomposition results, moving up the distribution of the differential white-Black population distribution has no effect on access.

Our results hold for a variety of definitions of place, including the Hospital Service Area (HSA, our primary unit of geography), Hospital Referral Region (HRR), and HRR-by-ZIP code income quintile. We also show that our findings are robust to varying the omitted place in our place effects estimation and are not driven by noise in our estimates of the Black place effects. In the end, we conclude that Black and white beneficiaries experience quite different place effects on utilization, providing suggestive evidence that Black and white beneficiaries living in similar areas are using different healthcare systems.

On one hand, the policy implications of our results are clear: place-based policies alone will not close disparities in access to healthcare. Instead, place-by-race-based policies are required. On the other hand, our results do not speak to what types of place-by-race-based policies would be most helpful. Future work is required to guide these place-by-race-based policy efforts.

In addition to the literature on disparities, our results also contribute to a large literature on geographic variation in healthcare utilization. A considerable body of work establishes substantial cross-sectional geographic variation in the use of healthcare (Wennberg and Gittelsohn, 1973; Skinner and Fisher, 1997; Fisher et al., 2003a,b). Some of this work points to geography as a potential source of healthcare disparities, though it focuses in large part on the geographic distribution of individuals (Baicker et al., 2004, 2005; Chandra and Skinner, 2003). At the same time, a recent and growing strand of this literature has brought new quasi-experimental methods to separate place and person effects in explaining this geographic variation (Finkelstein et al., 2016). Our work falls at the intersection of these two strands of literature, combining newer conceptual and empirical insights to provide a causally rigorous assessment of the importance of geography in driving disparities. Moreover, while our focus is on the healthcare system, our evidence that place effects can differ substantially across groups has implications for broader research on place effects and place-based policy.

The paper proceeds as follows. Section 1 outlines our conceptual framework and decomposition exercise. Section 2 describes our data and sample construction. Sections 3 and 4 describe our empirical approach and results, respectively. Section 5 concludes.

1 Conceptual Framework

In this section, we outline our conceptual framework for decomposing the role of geography in racial disparities in access to medical care. We begin by outlining our model of health care utilization, which follows that of Finkelstein et al. (2016). Then, we extend the model to study disparities and outline our two decomposition exercises.

1.1 Model of Utilization

Our conceptual framework starts with the model of utilization developed by Finkelstein et al. (2016) and extends it to incorporate racial disparities. An individual i lives in an area j at time t. Each individual has preferences over the use of medical care, denoted η_i, and clinical needs denoted h_{it}. In this paper, we focus primarily on the white-Black disparity in access to medical care, so we denote individuals' race as $r \in \{b, w\}$. We denote the privately optimal level of care for a given individual as:

$$y^*_{ijt} = \arg\max_y u(y_{ijt}|h_{it}, \eta_i) \tag{1}$$

We note that this level of care is optimal only conditional on the wide variety of frictions faced by the patient. These frictions could include behavioral or information frictions, racial discrimination, opportunity costs of time, etc. as well as interactions between these frictions, all of which may generate a wedge between the privately optimal value and the socially optimal value. For the questions we consider in this paper, though, this level of care is merely a statistical object. The conditions under which it is optimal do not really matter, as we merely seek to decompose the differences in this object by race into its various components and provide guidance on the types of policies that would and would not address disparities, not to make normative statements about the existence or size of those disparities.

We start by following Finkelstein et al. (2016) and model y^*_{ijt} as consisting of a place component ψ^r_j and a person component y^*_i (suppressing t for simplicity):

$$y^*_{ij} \equiv \underbrace{\psi^r_j}_{\text{place}} + \underbrace{y^*_i}_{\text{person}} \tag{2}$$

In practice, we compute the place component using causal place effects γ_j, which are

estimated relative to some omitted area. Suppose that the place $j = 1$ is omitted in our place effects estimation. We model the place component of utilization as:

$$\psi_j^r = \bar{y}_{1,t}^r + \gamma_j \tag{3}$$

where γ_j the causal place effect for area j and $\bar{y}_{1,t}^r$ is the average utilization for individuals of race r in the omitted place $j = 1$ at time t.

We are interested in decomposing the national 'disparity' in utilization between Black and white beneficiaries into the pieces due to place and non-place factors. We define the national 'disparity' as the raw difference in average utilization among white beneficiaries and average utilization among Black beneficiaries across the entire country and denote it $\bar{y}_t^w - \bar{y}_t^b$.[1] Using Equation 2, we can write the disparity as:

$$\begin{aligned}
\bar{y}_t^w - \bar{y}_t^b &= \sum_{j=1}^{J} (\sigma_{j,t}^w \bar{y}_{j,t}^w - \sigma_{j,t}^b \bar{y}_{j,t}^b) \\
&= \sum_{j=1}^{J} (\sigma_{j,t}^w (\bar{y}_{1,t}^w + \gamma_j + \bar{y}_{j,t}^{*w}) - \sigma_{j,t}^b (\bar{y}_{1,t}^b + \gamma_j + \bar{y}_{j,t}^{*b})) \\
&= \underbrace{\sum_{j=1}^{J} (\sigma_{j,t}^w (\bar{y}_{1,t}^w + \gamma_j) - \sigma_{j,t}^b (\bar{y}_{1,t}^b + \gamma_j))}_{\text{place component}} + \underbrace{\sum_{j=1}^{J} (\sigma_{j,t}^w \bar{y}_{j,t}^{*w} - \sigma_{j,t}^b \bar{y}_{j,t}^{*b})}_{\text{person component} \equiv \Gamma}
\end{aligned} \tag{4}$$

where $j \in J$ indexes places, σ_{jt}^r is the fraction of the national population of race r in place j at time t, and $\sum_{j=1}^{J} \sigma_{j,t}^r = 1$.[2] Because our primary objective with the decomposition is to separate place factors from all "non-place" factors (which we call the person component) we treat the person component as a residual in our estimation of the decompositions. We denote the person component by Γ in the decompositions that follow.

[1] This differs from the definition of a disparity from the Institute of Medicine (2003), where racial disparities in healthcare quality, for example, are defined as "racial or ethnic differences in the quality of healthcare that are not due to access-related factors or clinical needs, preferences, and appropriateness of intervention" (p. 3-4). We use our alternative definition for a few reasons. First, it does not require us to take a stance on what factors reflect health and preferences. Second, it allows us to sidestep issues stemming from such factors also being products of place. Finally, our eventual goal is to *decompose the place effect* into its various components rather than to *decompose the disparity* into place and person effects (as is made clear in Section 1).

[2] In practice, our focus on relatively small geographies (e.g., HSAs) separately by race limits our ability to estimate place effects for all places because of power. We restrict our place effects estimation to areas for which we have at least 20 white and Black movers, and we define the disparity, population shares, and place effects for these J places (as opposed to all places in the United States).

1.2 Decomposition with Homogenous Place Effects

We begin with a decomposition where we assume that place effects are homogeneous. For each place j, we estimate a place effect that we denote γ_j relative to some omitted place $j = 1$. Beginning from Equation 4, we have:

$$\begin{aligned}\bar{y}_t^w - \bar{y}_t^b &= \sum_{j=1}^{J} \left(\sigma_{j,t}^w(\bar{y}_{1,t}^w + \gamma_j) - \sigma_{j,t}^b(\bar{y}_{1,t}^b + \gamma_j)\right) + \Gamma \\ &= \left(\bar{y}_{1,t}^w \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^w}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^w \gamma_j\right) - \left(\bar{y}_{1,t}^b \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^b}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^b \gamma_j\right) + \Gamma\end{aligned}$$

Rearranging, we have:

$$\bar{y}_t^w - \bar{y}_t^b = \underbrace{(\bar{y}_{1,t}^w - \bar{y}_{1,t}^b)}_{\text{diff. in omitted place}} + \underbrace{\sum_{j=1}^{J} \gamma_j(\sigma_{j,t}^w - \sigma_{j,t}^b)}_{\text{place}} + \underbrace{\Gamma}_{\text{person}} \tag{5}$$

The first component is the disparity in the omitted place. The second component represents the portion of the disparity that is due to beneficiaries living in different places with different overall place effects on utilization of medical care. The third component represents the residual.

The interpretation of this decomposition is not straightforward. Finkelstein et al. (2016) interpret these pieces as reflecting 'supply-side' (place) and 'demand-side' (person) factors, but we note that because this decomposition includes a single homogeneous place effect, seemingly supply-side factors that influence different groups differently (i.e., racial discrimination) will fall into the person component when those groups are not uniformly distributed across areas.

However, when restricting ourselves to more positive questions regarding what sets of policies will or will not close disparities, the decomposition is more informative. Specifically, this decomposition clearly speaks to the question of whether *place-based* policies will or will not help to close disparities in medical care consumption. A large place component would imply an important role for place-based policies. However, this interpretation only applies for place-based policies that uniformly affect the place effect for all groups. The

decomposition does not speak to the value of place-based policies that affect place effects differently for different groups, as those types of policies would influence both the place and person components due the assumption of a homogeneous place effect. Thus, it is possible that this decomposition could suggest that *place-based* policies will not be useful even when *place-by-race*-based policies indeed could be useful in closing disparities.

1.3 Place-by-Race Decomposition

Motivated by the interpretation challenges of the simple homogeneous place effect decomposition, we next consider a decomposition that allows place effects to differ by race. Denote the place effect for individuals of race r as γ_j^r. As in the homogeneous place effects case, we can express average utilization for individuals of race r in place j as:

$$\bar{y}_{j,t}^r = \underbrace{\bar{y}_{1,t}^r + \gamma_j^r}_{\text{place comp. } \psi_j^r} + \underbrace{\bar{y}_{j,t}^{*r}}_{\text{person}} \tag{6}$$

Plugging into Equation 4, we have:

$$\begin{aligned}
\bar{y}_t^w - \bar{y}_t^b &= \sum_{j=1}^{J} \left(\sigma_{j,t}^w(\bar{y}_{1,t}^w + \gamma_j^w) - \sigma_{j,t}^b(\bar{y}_{1,t}^b + \gamma_j^b)\right) + \Gamma \\
&= \left(\bar{y}_{1,t}^w \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^w}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^w \gamma_j^w \right) - \left(\bar{y}_{1,t}^b \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^b}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^b \gamma_j^b \right) + \Gamma \\
&= \underbrace{(\bar{y}_{1,t}^w - \bar{y}_{1,t}^b)}_{\text{diff. in omitted place}} + \underbrace{\left(\sum_{j=1}^{J} \sigma_{j,t}^w \gamma_j^w - \sigma_{j,t}^b \gamma_j^b \right)}_{\text{place-by-race}} + \underbrace{\Gamma}_{\text{person}}
\end{aligned} \tag{7}$$

This decomposition may lead to very different conclusions about the portion of the disparity that is due to place. This is because when we assumed that place effects were homogeneous by race, any differences in place effects by race would have ended up in the person component. But now, with place-by-race effects, differences in place effects by race are captured as part of the place component rather than the residual person component. Importantly, the comparison of the relative importance of the place component from Equation 5 versus the place-by-race component from Equation 7 tells us about the extent to which place-based policies versus place-by-race-based policies will be successful at closing disparities.

This also motivates an additional decomposition of the place component into two further pieces. Adding and subtracting the distribution of Black beneficiaries multiplied by the white place effect ($\sigma^b_{j,t}\gamma^w_j$) and then rearranging allows us to write:

$$\bar{y}^w_t - \bar{y}^b_t = \underbrace{(\bar{y}^w_{1,t} - \bar{y}^b_{1,t})}_{\text{diff. in omitted place}} + \underbrace{\underbrace{\sum_{j=1}^{J} \gamma^w_j(\sigma^w_{j,t} - \sigma^b_{j,t})}_{\text{diff. geo. dist.}} + \underbrace{\sum_{j=1}^{J} \sigma^b_{j,t}(\gamma^w_j - \gamma^b_j)}_{\text{diff. place effects}}}_{\text{place-by-race}} + \underbrace{\Gamma}_{\text{person}} \tag{8}$$

This formulation of the decomposition provides additional insight: it allows us to disentangle how much of the place component is due to the differential geographic distribution of individuals by race (the second term) and how much is due to differential place effects (the third term). This matters considerably because these explanations imply different policy remedies for closing disparities. If the place-by-race component of disparities arises because of individuals living in different places, then policies to reduce geographic variation may have promise for closing disparities. If, however, the place-by-race component arises because of differential place effects, then policies to address specific sources of those places effects may be necessary.

The decompositions in Equations 5, 7, and 8 all contain a series of empirical objects that we can estimate in the data. The remainder of the paper is devoted to estimating these objects with the two goals of (1) comparing the relative importance of the place component and the place-by-race component from Equations 5 and 7 and (2) comparing the relative importance of the differential geographic distribution of Black and white beneficiaries versus the importance of differential Black and white place effects in determining the place-by-race component of the disparity (Equation 8). We estimate the homogeneous causal place effects and race-specific causal place effects (γ^r_j) using a movers design outlined in Section 3. We recover the population shares (σ^r_{jt}) using the Medicare administrative data detailed in Section 2. In all cases, the person component is the residual term.

2 Data and Sample Construction

To estimate the decomposition, we combine several sources of Medicare administrative data. Using the data, we construct a panel dataset at the individual level comprised of individuals enrolled in Traditional Medicare (Parts A and B) from 2008-2018. We start with the Master Beneficiary Summary File (MBSF), a 100% sample of Medicare beneficiaries. We then link this to several claims datasets capturing utilization, including inpatient claims (100% sample), outpatient claims (100% sample), and Carrier claims (20% sample).

2.1 Medicare Enrollment and Claims Data

We use the MBSF to identify individuals enrolled in Traditional Medicare (TM) from 2008-2018. The MBSF contains a number of important demographic and geographic characteristics that facilitate our empirical design and decomposition. First, we observe a host of demographic characteristics about individuals enrolled in TM during our sample period, including their age, race and ethnicity, and ZIP code of residence in a given year. Previous work suggests that race and ethnicity classifications in Medicare administrative data may misclassify some individuals, particularly those who are Hispanic or Asian or Pacific Islander (Eicheldinger and Bonito, 2008). Thus, instead of using the original variable in the Medicare data that classifies individuals' race based on data from the Social Security Administration (SSA), we use a measure developed by researchers that substantially improves upon the SSA classifications and has been validated in other work (Eicheldinger and Bonito, 2008; Jarrín et al., 2020). Data on beneficiaries' ZIP code of residence in each year allows us to trace out individuals' mobility over time, capturing beneficiary moves and classifying them accordingly (e.g., as cross-county moves, cross-state moves, etc.). We make use of this granular geographic data in our empirical approach.

We combine enrollment data with detailed claims describing beneficiaries' healthcare utilization. We use the claims files to construct various measures of access to healthcare based on utilization. These files allow us to measure the use of medical care in facilities such as hospitals and physicians' offices. In the claims, we observe detailed Healthcare Common Prodecure Coding System (HCPCS) codes that allow us to classify a given claim according to the services rendered. We make use of this for identifying preventive care services that we use to measure access, as described in more detail in Section 2.2.

2.2 Measures of Healthcare Access

We use a series of claims-based measures of healthcare utilization to assess access to care across different places. First, we follow Finkelstein et al. (2016) and construct a measure of resource-based utilization that is stripped of geographic variation in prices. The resulting measure allows us to compare the amount of utilization across areas absent concerns that the level of spending reflects differences in prices rather than differences in quantities.[3] We take the log of this measures and refer to it as Log(Utilization) throughout the remainder of the paper.

Next, we construct a variety of measures of access to healthcare based on other types

[3]For a complete description of the procedure for constructing this measure from the claims, please see Finkelstein et al. (2016), Online Appendix.

of utilization in the claims. In building these measures, we follow the existing literature that has measured access using claims data by focusing on the use of recommended primary care services (Carey et al., 2020). We start by using the HCPCS codes in the claims to identify outpatient evaluation and management (E&M) services (codes 99201-99205 and 99241-99245) (Zheng et al., 2017). We construct both extensive margin (any E&M visit in a year) and intensive margin (number of E&M visits) measures of E&M use using the claims.

In addition to measures of E&M use, we use the claims to estimate the receipt of recommended preventive screenings and immunizations. For these outcomes, we draw on the United States Preventive Services Task Force (USPSTF) recommendations for elderly adults. We review all preventive services that receive an A or B grade from the USPSTF for individuals aged 65 and over, and we identify the receipt of these in the claims using the HCPCS and Current Procedural Terminology (CPT) codes available from USPSTF.[4] These include recommendations for preventive services such as colorectal cancer screening, depression screening, diabetes screening, influenza vaccination, and others. For each recommendation, we construct an indicator for whether a beneficiary received the service in a given year.

2.3 Sample Construction

We again follow Finkelstein et al. (2016) in applying sample restrictions. First, we restrict the sample to individuals who appear in the 20% sample of the Carrier claims file so that our analytic sample only contains individuals for whom we have inpatient, outpatient, and Carrier utilization. Next, we drop patient-year observations where individuals are younger than 65 or older than 99 years of age. In order to ensure homogeneity in coverage type, we restrict to those only in Traditional Medicare (i.e., we drop any patient-year observations where an individual is enrolled in a Medicare Advantage plan for at least one month). To simplify the analysis below, we restrict our attention to individuals in the sample who either move once or not at all. Finally, we restrict to individuals enrolled in Medicare Parts A and B for all 12 months of the year.

After applying these restrictions, we are left with a beneficiary-year panel that spans 2008-2018. The panel is comprised of both individuals who move exactly once and individuals who do not move. This serves as the main sample for our analyses. Table 1 shows summary statistics for four groups in our analytic sample: non-movers, those who move across Hospital Service Areas (HSAs), those who move across Hospital Referral Regions (HRRs), and those who move across HRR-by-ZIP code income quintiles. Reassuringly, we find that HSA, HRR, and HRR-by-ZIP income quintile movers are similar to non-movers on a variety of demographic and health-related characteristics. Movers are slightly older and

[4]The full set of recommendations can be found here.

slightly sicker, and they have slightly higher utilization as a result, but the differences are small.

3 Empirical Strategy

Our goal is to establish the contribution of place and place-by-race effects to national disparities in access to care. In Section 1, we provide decompositions of national disparities into place and person components and place-by-race and person components. In this section, we outline our empirical strategy for estimating the different pieces of the decomposition.

First, we need estimates of the national Black-white disparity in access to care ($\bar{y}_t^w - \bar{y}_t^b$). Second, we need estimates of the share of the national population of Black Medicare beneficiaries and the share of the national population of white beneficiaries in a given 'place' (σ_j^r). Both of these parameters are straightforward to estimate using the Medicare administrative data. In practice, we compute the 'national' disparity and 'national' population using only areas (e.g., HSAs) for which we have 20 or more Black and white movers. While this restricts the scope of our assessment of disparities, it allows us to focus on HSAs for which we can estimate place effects precisely for both groups.

Third, we need estimates of the causal effects of place, first for all movers and then for white and Black movers, respectively. While average levels of utilization, both overall and stratified by race, are observed in the Medicare data, these averages consist of both *causal* effects of places on healthcare utilization (γ_j) and differences across places in the composition of types of Medicare beneficiaries with different optimal levels of healthcare consumption (y_i^*). Because the decomposition relies on the causal effects of place, we require a method for separating these causal effects from differences in composition.

3.1 Movers Design

To estimate causal place effects, we leverage beneficiary migration across areas. This 'movers design' has become increasingly common in the literature on the causal effects of place in recent years (Finkelstein et al., 2016, 2021). The key identifying assumption underlying the approach is that changes over time in movers' potential 'untreated' (non-moving) outcomes are orthogonal to the difference in the average level of the outcome between the source and destination places across all beneficiaries in those places. In other words, those moving from low access to high access areas cannot be on different trends in utilization than those moving from high access areas to low access areas. If this assumption holds, then changes in access to care upon moving can be interpreted as the difference in the causal effects of the source and destination places.

There are a few natural concerns with this identifying assumption. First, there may be concerns that the *level* of access to care differs between movers and non-movers in a systematic way. However, because we include individual fixed effects in our estimation, time-invariant level differences between movers and non-movers are less of a concern than systematically differential trends in access. Nonetheless, we show in Table 1 that movers and non-movers are quite similar on a variety of beneficiary characteristics, including measures such as utilization and the number of chronic conditions. A second concern is that the timing of moves is non-random, and so changes in access upon moving may in fact reflect changes in patient demand for care (e.g., if a beneficiary moves to a new area specifically in search of a specific type of care) rather than the causal effect of a place. To address this concern, our empirical approach flexibly controls for such trends by including fixed effects for the year relative to moving.

One additional, more subtle threat remains. In order to decompose disparities into place and person components, we must extrapolate the place effects estimated from movers to the place effects for non-movers. In other words, we must assume that treatment effects are consistent across movers and non-movers. This assumption is clearly untestable. However, the similarity of movers and non-movers on observable characteristics is again reassuring here.

We again highlight that this design will only pick up short-term place effects. Longer run place effects will end up in the person component. For this reason, we avoid estimating place effects on health (which are likely to take a long time to appear) and instead focus on access, where short-run effects are highly relevant and unlikely to differ much from longer-run effects.

3.2 Estimation

We implement our movers design using the sample outlined in Section 2.3. We begin by establishing the importance of place for the measures of access we consider. To do so, we follow the procedure outlined in Finkelstein et al. (2016) and estimate event-study-style regressions of the following form:

$$y_{it} = \alpha_i + \theta_{r(i,t)}\hat{\delta}_i + \tau_t + x'_{it}\beta + \varepsilon_{it} \tag{9}$$

where α_i is an individual fixed effect meant to account for fixed differences across individuals (e.g., clinical needs, preferences for medical care); τ_t is a calendar year fixed effect; x'_{it} is a set of five-year age bins for ages 65-99; and ε_{it} is an error term. The key component of the estimation is $\hat{\delta}_i$, the destination-origin difference in the average of the outcome variable.

We estimate this quantity in the data using our mover sample and a random 25% sample of non-movers. Using the combined mover and non-mover sample, we compute average access in each area (e.g., HSA) in each year, and then take an average over all years to construct the origin-destination difference in average utilization. We upweight non-movers by a factor of four to account for the random 25% sample used to estimate this quantity.

The coefficients of interest are the $\theta_{r(i,t)}$ terms, which reflect the extent to which an individual's access to care converges to the destination average in each year, normalizing the year before the move to 0. If places matter for access, then we should see convergence towards the destination average in the years following the move (i.e., $r(i,t) \geq 0$), whereas if places are unimportant we should see relatively little shift. The magnitude of the jump (if any) in the $\theta_{r(i,t)}$ coefficients is indicative of the extent to which places matter for access to care.

Equation 9 allows us to assess whether places matter for access, but our decomposition requires that we estimate the causal effect of each place in our data on access to care. To do so, we modify Equation 9 and estimate the following:

$$y_{it} = \alpha_i + \gamma_j + \theta_{r(i,t)} + x'_{it}\beta + \tau_t + \varepsilon_{it} \tag{10}$$

All of the components of Equation 10 are as above, with two exceptions. We include a set of year-relative-to-move indicators $\theta_{r(i,t)}$ that allow access to care to vary systematically by the time relative to moving in order to allow for the possibility that there are trends in utilization before and after moving (e.g., because of changes in health status). Second, we include a vector of area fixed effects γ_j. This vector of coefficients is the key object of interest. Under the identification assumption outlined above, the change in access upon moving identifies the causal effect of beneficiaries' areas on the outcomes of interest, and those causal effects are captured by the coefficients on the area fixed effects. We shrink these estimates using an empirical Bayes (EB) procedure to address concerns about noise in our estimation.[5]

For the decomposition, we need a set of race-specific place effects for each area. To recover these, we estimate Equation 10 separately for white and Black movers. For our primary results throughout the paper, we use Hospital Service Areas (HSAs) as the relevant geography. HSAs are a unit of geography that reflect patient flows for hospitalization, and there are 3,436 in the United States (Wennberg and Cooper, 1996). However, we measure the sensitivity of our results to using both broader (Hospital Referral Region) and narrower (Hospital Referral Region by ZIP code income quintile) levels of geography.

[5]We follow the empirical Bayes procedure outlined in Chandra et al. (2016) and thank Adam Sacarny for his Stata package 'ebayes', which we use to conduct the shrinkage.

There are two natural concerns with this estimation approach. First, because we have far fewer Black movers than white movers, HSA place effects for Black movers will be estimated with more noise. The EB procedure described above helps to address this concern. In addition, however, we test the robustness of our results to using a more restrictive sample of white beneficiaries where we select a random set of white beneficiaries in each origin-destination dyad that is equal in size to the number of Black beneficiaries in the dyad. A second concern is that the estimates are sensitive to the omitted HSA in our place effects estimation. We therefore test the robustness of our main findings to using different HSAs as the omitted place in our estimation of Equation 10. We discuss these robustness checks in more detail in Section 4.5.

4 Results

4.1 Descriptive Patterns of Access to Medical Care

Before moving to our causal evidence and decomposition, we explore simple cross-sectional differences in access to medical care across places. Figure 1 first shows cross-sectional "place effects" on Log(Utilization) for Black and white beneficiaries by HSA. To recover these, we estimate the following:

$$y_{it} = \kappa_j + \tau_t + x'_{it}\beta + \varepsilon_{it} \tag{11}$$

where all objects are as defined in Equation 10, except that $x'_{it}\beta$ now contains an indicator for beneficiary sex and the count of chronic conditions. We plot the $\hat{\kappa}_j$ coefficients, which are not causally identified but rather reflect cross-sectional differences in utilization across HSAs controlling for age, the number of chronic conditions, sex, and year. In some cases, the number of Black movers is small, so we use our empirical Bayes procedure to shrink these "place effects" for both white and Black movers.

We emphasize two points about this figure. First, there is considerable geographic variation in utilization across HSAs. Indeed, the estimated $\hat{\kappa}_j$ coefficients vary widely for both races. Second, while some areas are located near the 45-degree line, many stray from it. There are many places with greater utilization for white beneficiaries than Black beneficiaries (and vice versa), and the correlation between Black and white cross-sectional utilization is modest at best. We explore these cross-sectional differences for our remaining outcomes and find similar results (Appendix Figure A1).

These plots providence useful graphical motivation for our study. The scatter plots make clear that there is not only geographic variation in access to medical care, but also that this

variation is differs across different racial and ethnic groups. Nonetheless, these are simple cross-sectional differences, and we are therefore limited in what we can infer about the causal role of these different places in access to care versus the role of geographic sorting. With this in mind, we turn to our results drawing on causal place effects estimates.

4.2 The Importance of Place in Access to Care

We begin by assessing the importance of place in access to medical care for white and Black beneficiaries. To do so, we estimate the event-study-style regressions described in Equation 9 separately for white and Black movers. The coefficients of interest are the $\theta_{r(i,t)}$ terms, which capture changes in utilization upon moving as a fraction of the origin-destination difference in average utilization. Appendix Figure A2 plots the event study coefficients separately by mover race for our different measures of access.

Consistent with prior estimates, we find that when an individual moves from a place with a given level of utilization to a place with a different level of utilization, their utilization changes by about half of the difference in access between the source and destination areas. The event studies show relatively flat pre-trends, indicating that beneficiaries moving to high access areas are on similar trends to beneficiaries moving to low access areas, and providing evidence that our identifying assumptions for the TWFE regression described by Equation 10 are satisfied. This estimate is largely consistent for both white and Black movers and for the different measures of access that we derive from the claims, though our estimates for Black movers are noisier.

These event study estimates confirm that places play an important role in access to medical care for white and Black movers alike. To further characterize the importance of places and estimate our decomposition, we next estimate place effects for HSAs. To do so, we restrict our sample to HSAs that have 20 or more Black and white movers, then estimate place effects for those HSAs as specified in Equation 10.

Figure 2 shows the distribution of the estimated place effects for Log(Utilization). Panel A shows estimated HSA place effects using all movers (the 'overall' HSA place effect), while Panels B and C show the estimated HSA place effects for white and Black movers, respectively. All three distributions underscore that there is wide variation in the causal effects of place on utilization. While each distribution is centered slightly to the left of zero, there are many places that causally increase utilization and many that causally reduce it. Notably, our estimated HSA place effects for Black movers are more negative than those for white movers. The average HSA effect on utilization causes greater reductions for Black beneficiaries than white beneficiaries.

4.3 Decompositions

With these place effects in hand, we next turn to our decompositions. We have two primary goals: (1) comparing the relative importance of the place component and the place-by-race component from Equations 5 and 7 and (2) disentangling the relative importance of the geographic distribution of individuals and differential causal place effects for the place-by-race component, as formalized in Equation 8. We focus our interpretation of the decomposition results on these two pieces.

We begin with a decomposition that assumes place effects are constant across individuals. The results of this decomposition are shown in Table 2. Column (1) shows the national disparity. Black beneficiaries have higher overall utilization than white beneficiaries, but receive fewer evaluation and management (E&M) visits and colorectal cancer screenings than white beneficiaries. Higher overall utilization may be attributable to Black beneficiaries being sicker, on average, than white beneficiaries, as is the case for movers (Appendix Table A1). Column (2) of the table shows the disparity in the HSA that is omitted in our place effects estimation. Columns (3) and (4) show our estimates of the person and place components, respectively. Our estimates of the place component are small and not statistically distinguishable from zero across all outcomes. When we assume place effects are homogeneous across individuals in a given area we find little role for place in driving disparities. This suggests that disparities do not arise because of Black beneficiaries living in places that have lower access for everyone.

Next, we relax the assumption that place effects are homogeneous across groups in a given HSA and estimate the decomposition outlined in Equation 8. The results are shown in Table 3. As before, columns (1) and (2) show the national disparity and disparity in the omitted HSA; these are unchanged. Columns (3) and (4) show the person and place-by-race components, respectively. Across all outcomes, the person component is negative. We interpret this as evidence that "optimal" utilization is higher for Black beneficiaries than white beneficiaries, which is again consistent with the evidence in Appendix Table A1 that Black movers are sicker than white movers, on average.

This decomposition returns strikingly different results on the importance of place. When place effects are allowed to vary by race, places play a large role in driving disparities, sometimes accounting for more than 100% of the disparity. The exact value of the place component is complicated to interpret, but for our purposes the primary result of interest is how the place component in column (4) of Table 3 compares to the place component in column (4) of Table 2. On this point, our results are clear. When we assume homogeneous place effects, the place component is small and statistically indistinguishable from zero. When we allow for heterogeneous place effects by race, the place component is large and

significant.

In order to dig into this result further, we use Equation 8 to decompose the place component into two parts: the fraction driven by the differential geographic distribution of individuals and the fraction driven by differential place effects. Columns (6) and (8) of Table 3 show the key result. We find that virtually all of the place component is driven by differential place effects between white and Black beneficiaries in a given HSA, not differential geographic sorting by race. Across all outcomes, the role of the geographic distribution of individuals is small and statistically indistinguishable from zero, while the role of differential place effects is large – sometimes exceeding 100% of the overall place component – and significant.

To underscore the importance of place further, we conduct a simple reallocation exercise, asking: how would disparities change if we made the places with the lowest place effects on access for Black beneficiaries look like the places with the highest place effects for the same group? To do so, we simply replace bottom quartile Black place effects in the decomposition with the average Black place effect of top quartile places, holding fixed the person component, and then recompute the disparity. Comparing the estimates in column (1) of Tables 3 and 4 shows the results. Improving the Black place effects for bottom quartile HSAs completely eliminates existing disparities. In fact, in all cases, the white-Black disparity is *negative* after this reallocation, suggesting that Black beneficiaries' access would be higher than white beneficiaries' access (all else equal).

Ultimately, it appears that while the place component of disparities is unimportant when assuming place effects do not vary by race, the place-by-race component of disparities is extremely important, often explaining more than 100% of the disparity. Further, this critical place-by-race component stems not from Black and white beneficiaries living in different places but from Black beneficiaries facing very different place effects from white beneficiaries. This final result rationalizes the discrepancy between the unimportance of the place component in the homogeneous decomposition and the extreme importance of the place-by-race component in the heterogeneous decomposition: differential place effects by race explain the entire place component of disparities in access to healthcare. Disparities in access are not driven by Black beneficiaries disproportionately living in places where access is poor for all. Instead, disparities are driven by Black beneficiaries living in places where access is uniquely poor for Black beneficiaries. These results suggests that while place-based policies are unlikely to close disparities, more-targeted place-by-race-based policies can clearly be effective and are likely to be necessary.

4.4 Importance of Place-by-Race Effects

In the previous section, we established that place-by-race effects are hugely important for explaining disparities in access to healthcare. We showed that this is driven by Black and white beneficiaries facing very different place effects. In this section, we dig deeper into this result. First, we establish that race-specific place effects are indeed important by showing that when Black beneficiaries move from areas with low Black place effects to areas with high Black place effects, access sharply increases. By contrast, similar moves based on white place effects generate little systematic change. Next, we show that this is due to a lack of correlation between the Black and white place effects for a given area, a result robust to varying our estimation samples and level of geography. Finally, we use our two-way fixed effects framework to compare the causal effect of moving up different place effects distributions for different groups.

Utilization for Different Types of Moves. We begin by examining how access to medical care changes for different types of movers in the raw data in the spirit of Card et al. (2013). We classify movers into sixteen groups based on the place effects quartile of their origin and destination. In Figure 3, we plot average Log(Utilization) by year relative to move for four of these groups: those moving from the bottom place effects quartile to the top quartile (red); those moving from the top place effects quartile to the bottom (blue); those moving from the bottom quartile to the bottom quartile (purple); and those moving from the top quartile to the top quartile (green). In each panel, we vary the race of the movers and vary the race of the place effects used to classify the moves. Panel A shows how Black movers' utilization changes when their moves are classified according to Black place effects, and panel B shows how Black movers' utilization changes when their moves are classified according to *white* place effects. Panel C shows how white movers' utilization changes when their moves are classified according to white place effects, and panel D shows how white movers' utilization changes when their moves are classified according to *Black* place effects.

The results in the figures are striking. Panel A shows that when Black beneficiaries move from places with low Black place effects to places with high Black place effects, their utilization increases substantially. Similarly, when Black beneficiaries move from places with high Black place effects to places with low Black place effects, their utilization *decreases* substantially. Within-quartile moves, on the other hand, have little effect on utilization, suggesting any effects are not driven by 'disruptions' associated with the move. By contrast, when we classify moves based on the white place effects, we find little systematic pattern in Black movers' utilization (panel B). There are small increases in utilization for movers

from bottom to top quartile HSAs, but these changes are trivial compared to the changes in utilization we observe when we classify moves based on the Black place effects. Panel B also provides further evidence that our results are not driven simply by noise in the Black place effect estimates, because it relies only on the more precisely estimated white place effects. Even when using these more precise place effect estimates, we find little systematic change in utilization across move types.

In panels C and D, we show similar patterns for white movers: moves up and down the white place effects quartiles are accompanied by concomitant changes in utilization, while moves up and down the Black place effects quartiles show little systematic pattern. Appendix Figures A5 and A6 show that this pattern holds across all of our measures of access.

These results are consistent with the results of the decomposition suggesting that differential place effects are an important contributor to observed disparities in access to medical care. Moreover, the lack of a systematic pattern in the race-discordant figures (e.g., white movers classified by Black place effects) suggests that these place effects are largely uncorrelated.

Correlations between Place Effects. Motivated by the plots of raw utilization above, we now explore the correlations between Black and white place effects in more detail. In Figure 4, we show that the estimated correlation between the Black and white place effects is weak across a number of outcomes, ranging from 0.18 to 0.297. In Appendix Table A2, we show that this result is remarkably robust to varying the level of geography. When we zoom out to broader areas (HRRs), we find that place effects are slightly more correlated, but the relationship is still modest at best. When we zoom in to more granular areas (HRRxZIP code income quintile), we find that the correlation between Black and white place effects is similarly weak.

A natural concern is that the lack of relationship between the place effects is due to noise in the estimation of the Black place effects. To address, we construct a sample of white HSA movers where we randomly drop movers in order to equalize the number of white and Black movers in a given origin-destination HSA dyad. We then use this sample to estimate a set of white place effects that is similarly noisy to our estimated Black place effects. Column (4) of Appendix Table A2 shows that little changes: the correlation between the Black and white HSA place effects with similar levels of noise still ranges from just 0.079 to 0.178. We also test the robustness of this result to varying the omitted category in our place effects regressions. To do so, we randomly select 100 HSAs, re-estimate the Black and white place effects using each HSA as the omitted category, shrink those place effects, and then compute the correlation between the shrunken Black and white place effects for that omitted place.

Appendix Figure A10 shows the distribution of these correlations. For all outcomes, the average correlation is low and there is little dispersion around the mean.

Moves Up the Place Effects Distribution. Finally, we move beyond raw means and correlations and use our two-way fixed effects framework to estimate regressions that allow us to determine statistical precision and compare how Black and white movers' access changes when moving to areas with high access for white beneficiaries versus areas with high access for Black beneficiaries. Here, instead of pooling across places in each quartile of place effects, we pool at the level of the ventile of place effects. Specifically, we run the following regression:

$$y_{it} = \alpha_i + \delta^{vent}_{h(i,t)} + x'_{it}\beta + \tau_t + \theta_{r(i,t)} + \varepsilon_{it} \tag{12}$$

where α_i is a person fixed effect; $\delta^{vent}_{h(i,t)}$ is a full set of indicators for the place effects ventile of HSA h for individual i at time relative to moving t; x'_{it} is a set of 5-year age-sex cells; and τ_t and $\theta_{r(i,t)}$ calendar year and year relative to move fixed effects, respectively. We normalize the bottom ventile to zero so that the coefficient $\delta^{vent}_{h(i,t)}$ reflects the causal effect of moving from the bottom ventile of the race-specific place effects distribution to a higher ventile in that same distribution. Estimating this regression separately for white and Black movers and varying the race of the place effects distribution allows us to compare the causal effect of moving up different place effects distributions for a given group of movers (e.g., the causal effect of Black movers moving up the white and Black place effects distributions).

Figure 5 plots the $\hat{\delta}^{vent}_{h(i,t)}$ estimates for Log(Utilization). The patterns are strikingly similar to what we observed in the raw data above. Panel A shows the estimates for Black movers, with the causal effect of moving up the Black place effects distribution shown in blue and the causal effect of moving up the white place effects distribution shown in green. Moving up the Black place effects distribution increases access considerably, as moving from the bottom to top ventile of Black place effects increases utilization by nearly 1.5 log points. The line of best fit for the estimated coefficients is strikingly linear and indicates that each successive move up the Black place effects ventiles increases utilization by 0.05 log points. The green line shows that moves up the white place effects distribution also increase utilization by a small amount, but the change is an order of magnitude smaller than the effect of moving up the Black place effects distribution. At every ventile of utilization, we find a larger effect of moving to that ventile in the Black place effects distribution than moving to that same ventile in the white place effects distribution for Black movers.

The same pattern emerges when we look at white movers in panel B. Moves up the white place effects distribution increase utilization by approximately 0.02 log points per ventile.

By contrast, moves up the Black place effects distribution have little effect of on utilization for white movers, increasing utilization by just 0.003 log points, again nearly an order of magnitude smaller than the effect of moving up the (race-concordant) white place effects distribution. In Appendix Figure A7, we show that these results are consistent for all of our measures of access. Similarly, in Appendix Figure A8 we show that the story is qualitatively similar when we examine moves up the cross-sectional distribution of utilization. These ventile regressions further substantiate the results of our decomposition exercise, showing not only that place effects are uncorrelated and have different implications for access in the cross-section, but also that moves up race-concordant versus race-discordant place effects distributions have strikingly different causal effects on access. Again, the green line in panel A of Figure 5 also helps to assuage concerns that noise in the Black effects estimates is an important driver of our results, showing that moves up the more precisely estimated white place effects distribution have little effect on Black beneficiaries' access to care.

Our two-way fixed effects framework also allows us to formally test the role of the differential geographic distribution in driving disparities. For each HSA, we compute the differential white-Black population share, and then estimate the causal effect of moving up ventiles of the differential population distribution using Equation 12. Figure 6 shows the results. Consistent with the results of our decomposition in Table 3, moves up the differential geographic distribution have little effect on utilization. For both white and Black movers, almost all of the coefficients are statistically indistinguishable from zero, and the lines of best fit are flat. In other words, moves to HSAs with a larger fraction of the white population relative to the Black population have little impact on individuals' utilization. This holds true for all of our measures of access, as shown in Appendix Figure A9. This is further evidence that disparities do not arise from Black beneficiaries disproportionately living in access-poor HSAs relative to white beneficiaries.

Taken together, these results lead us to conclude that Black and white beneficiaries face very different place effects, and that these place effects appear to be largely uncorrelated with each other. This lack of a correlation does not appear to be due to statistical noise but instead due to real differences in the experiences of Black and white beneficiaries living in the same areas. These differences matter considerably for the design of policies designed to close disparities. Simply replicating the success of areas that have delivered better access for white beneficiaries would have far less success in closing disparities than replicating the success of areas that deliver better access *specifically for Black beneficiaries.* The reason is simple and underscored by the foregoing results in this section: the areas that deliver higher access for white beneficiaries are not the same areas that deliver higher access for Black beneficiaries.

4.5 Robustness

We conduct a series of exercises to assess the robustness of our main results. There are a few natural concerns with our approach. The first is that the HSA is not the relevant level of geography for us to study. The second is that our estimates are partly due to noise in our estimates of the Black place effects. The third is that our results are sensitive to the choice of omitted HSA in our place effects regressions. We address each of these in turn here.

We first test the robustness of our results to varying the level of geography. We consider both broader geographies (HRRs) and narrower geographies (HRR-by-ZIP code income quintile) relative to our main estimates using HSAs. As noted above, Appendix Table A2 shows that across all levels of geography, the white and Black place effects that we estimate are largely uncorrelated. Our decomposition results are consistent across levels of geography as well. When we estimate the decomposition at the HRR level (Appendix Tables A3 and A4), we again find that places are largely unimportant when we assume place effects are homogeneous. When we allow for heterogeneity in the place effects across HRRs, however, places matter enormously, and, consistent with our HSA results, the importance of place is driven entirely by differential place effects. When we conduct the decomposition at the HRR-by-ZIP code income quintile level, our results on the role of place are similar, with the place component mattering much more in our heterogeneous decomposition and virtually all of that place component being driven by differential place effects (Appendix Tables A5 and A6). Our broader conclusions about the importance of place in disparities remain unchanged: place-by-race effects are quantitatively important for disparities, and places matter because of differential place effects.

We also test the robustness of our results to using noisier estimates of the white place effects. As noted in Section 4.4, we show in Appendix Table A2 that using a randomly selected set of white beneficiaries to estimate a similarly noisy set of white place effects does little to change the lack of correlation between the Black and white place effects. The same is true for our broader decomposition, shown in Appendix Table A7. When we re-estimate the place-by-race decomposition with these noisier white place effects, we again find that place play an important role in driving disparities. Differential place effects account for more than 100% of the place component across all of our outcomes.

Finally, we test the robustness of our results to varying the omitted place in our place effects regression. As noted above, we do so by randomly choosing 100 HSAs in our sample and re-estimating the place effects using each HSA as the omitted place. Appendix Figure A10 shows that correlation between the place effects is quite robust to varying the omitted place. In addition to testing the robustness of the correlation to varying the omitted place, we also test the robustness of our main decomposition result that differential place effects, not

differential geographic sorting, drive the place-by-race component of disparities. To do so, we recompute the pieces of the decomposition for each omitted place, compute the fraction of the place-by-race component accounted for by differential place effects and differential geographic sorting, and plot the distributions of each of those fractions. Appendix Figure A11 shows the results. Panels A, C, and E show histograms of the fraction of the place component accounted for by differential place effects, while Panels B, D, and F do the same for the differential geographic distribution. Across all outcomes, the distributions for the differential place effects are centered near 1 with little dispersion, while the distributions for the differential geographic distribution are centered at or near zero with little dispersion. Varying the omitted place has little impact on our main conclusion that differential place effects, not differential geographic sorting by race, are the primary driver of the place-by-race component in our decomposition.

5 Conclusion

Addressing persistent racial disparities in access to medical care is an important policy priority. These disparities are well-documented in the literature, as are various specific strategies to address them, such as expanding access to insurance (Wallace et al., 2021). In this paper, we step back from specific policies and take a broader view of policy approaches to disparities in order to offer evidence on the *types* of policies with potential for closing racial disparities. More specifically, we consider the role of geography in driving disparities and assess the potential of place-based policies for addressing these gaps.

We outline a conceptual framework for understanding the role of geography in driving racial health disparities and conduct a decomposition that splits the national Black-white disparity for a given access measure into "place" and "person" effects. Our framework allows us to consider both the impact of place-based policies on disparities and the importance of *place-by-race* based policies where we allow place effects to vary by race.

Using a mover design that leverages beneficiary migration across areas to infer causal effects, we estimate the decompositions. We first show that place effect heterogeneity is critical in designing policies to close disparities. When we require place effects to be constant across individuals in an area, places have very little influence on disparities, leading us to conclude that place-based policies would do little to close these gaps. However, when we allow place effects to vary by beneficiary race, places matter enormously, accounting for more than 100% of the disparity in some cases. We use the conceptual framework to decompose this "place-by-race" component into two pieces: differential causal effects by race and differential geographic sorting by race.

We ultimately find that the place-by-race component of our decomposition is driven almost entirely by differential causal effects of place by race. Differential geographic sorting by race has little influence on national disparities. Put another way, simply reallocating Black beneficiaries to the places where white beneficiaries tend to live would not reduce disparities, because disparities do not stem simply from Black beneficiaries disproportionately living in places with low access. Instead, places matter because they have differential effects on access for Black and white beneficiaries, and those effects are largely uncorrelated. To illustrate this, we conduct a series of empirical exercises showing that when Black beneficiaries move to HSAs with the best access for Black beneficiaries, their access improves substantially, while similar moves to HSAs with the best access for white beneficiaries have considerably less impact on their access to care.

Our results speak to classes of policies that are likely to help close disparities in access to healthcare. While our decomposition assuming constant causal effects of place suggests that place-based policies would do very little to affect disparities in access to healthcare, our results makes clear that place-*by-race* policies have considerable scope to close these gaps. Identifying precisely which policies allow certain places to deliver better access to Black beneficiaries is an important avenue for future work and will be critical for informing policy efforts to reduce racial disparities in access to medical care moving forward.

References

Baicker, Katherine, Amitabh Chandra, and Jonathan S. Skinner, "Geographic variation in health care and the problem of measuring racial disparities," *Perspectives in Biology and Medicine*, 2005, *48* (1 Suppl), S42–53.

_ , _ , _ , and John E. Wennberg, "Who You Are And Where You Live: How Race And Geography Affect The Treatment Of Medicare Beneficiaries: There is no simple story that explains the regional patterns of racial disparities in health care.," *Health Affairs*, January 2004, *23* (Suppl2), VAR–33–VAR–44.

Bailey, Martha J. and Andrew Goodman-Bacon, "The War on Poverty's Experiment in Public Medicine: Community Health Centers and the Mortality of Older Americans," *American Economic Review*, March 2015, *105* (3), 1067–1104.

Bailey, Zinzi D, Nancy Krieger, Madina Agénor, Jasmine Graves, Natalia Linos, and Mary T Bassett, "Structural racism and health inequities in the USA: evidence and interventions," *The Lancet*, April 2017, *389* (10077), 1453–1463.

Booker, Cory, "Black Maternal Health Momnibus Act," May 2023.

Card, David, Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality*," *The Quarterly Journal of Economics*, August 2013, *128* (3), 967–1015.

Carey, Colleen M., Sarah Miller, and Laura R. Wherry, "The Impact of Insurance Expansions on the Already Insured: The Affordable Care Act and Medicare," *American Economic Journal: Applied Economics*, October 2020, *12* (4), 288–318.

Chandra, Amitabh, Amy Finkelstein, Adam Sacarny, and Chad Syverson, "Health Care Exceptionalism? Performance and Allocation in the US Health Care Sector," *American Economic Review*, August 2016, *106* (8), 2110–2144.

_ and Jonathan Skinner, "Geography and Racial Health Disparities," Technical Report w9513, National Bureau of Economic Research, Cambridge, MA February 2003.

_ , Pragya Kakani, and Adam Sacarny, "Hospital Allocation and Racial Disparities in Health Care," Technical Report w28018, National Bureau of Economic Research, Cambridge, MA October 2020.

Chetty, Raj and Nathaniel Hendren, "The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects*," *The Quarterly Journal of Economics*, August 2018, *133* (3), 1107–1162.

_ and _ , "The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates*," *The Quarterly Journal of Economics*, August 2018, *133* (3), 1163–1228.

Cutler, David, Angus Deaton, and Adriana Lleras-Muney, "The Determinants of Mortality," *Journal of Economic Perspectives*, May 2006, *20* (3), 97–120.

_ , **Jonathan S. Skinner, Ariel Dora Stern, and David Wennberg**, "Physician Beliefs and Patient Preferences: A New Look at Regional Variation in Health Care Spending," *American Economic Journal: Economic Policy*, February 2019, *11* (1), 192–221.

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

_ **and** _ , "The Causal Effects of Place on Health and Longevity," *Journal of Economic Perspectives*, November 2021, *35* (4), 147–170.

Eicheldinger, Celia and Arthur Bonito, "More accurate racial and ethnic codes for Medicare administrative data," *Health Care Financing Review*, 2008, *29* (3), 27–42.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "SOURCES OF GEOGRAPHIC VARIATION IN HEALTH CARE: EVIDENCE FROM PATIENT MIGRATION," *The Quarterly Journal of Economics*, November 2016, *131* (4), 1681–1726.

_ **,** _ **, and** _ , "Place-Based Drivers of Mortality: Evidence from Migration," *The American Economic Review*, August 2021, *111* (8), 2697–2735.

Fisher, Elliott S., David E. Wennberg, Thérèse A. Stukel, Daniel J. Gottlieb, F. L. Lucas, and Etoile L. Pinder, "The implications of regional variations in Medicare spending. Part 1: the content, quality, and accessibility of care," *Annals of Internal Medicine*, February 2003, *138* (4), 273–287.

_ **,** _ **,** _ **,** _ **,** _ **, and** _ , "The implications of regional variations in Medicare spending. Part 2: health outcomes and satisfaction with care," *Annals of Internal Medicine*, February 2003, *138* (4), 288–298.

Gruber, Jonathan, Adrienne Sabety, Rishi Sood, and Jin Yung Bae, "Reducing Frictions in Healthcare Access: The ActionHealth NYC Experiment for Undocumented Immigrants," Technical Report w29838, National Bureau of Economic Research, Cambridge, MA March 2022.

Institute of Medicine, *Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care*, Washington, DC: The National Academies Press, 2003.

Jarrín, Olga F., Abner N. Nyandege, Irina B. Grafova, XinQi Dong, and Haiqun Lin, "Validity of Race and Ethnicity Codes in Medicare Administrative Data Compared With Gold-standard Self-reported Race Collected During Routine Home Health Care Visits," *Medical Care*, January 2020, *58* (1), e1–e8.

Murphy, Sherry L, Jiaquan Xu, and Kenneth D Kochanek, "Deaths: Final Data for 2010," Technical Report 61(4), National Center for Health Statistics, Hyattsville, MD 2013.

Pressley, Ayanna, "Anti-Racism in Public Health Act of 2023," April 2023.

Schiff, Adam, "Equal Health Care for All Act," May 2023.

Skinner, Jonathan and Elliott Fisher, "REGIONAL DISPARITIES IN MEDICARE EXPENDITURES: AN OPPORTUNITY FOR REFORM," *National Tax Journal*, September 1997, *50* (3), 413–425.

Wallace, Jacob, Karen Jiang, Paul Goldsmith-Pinkham, and Zirui Song, "Changes in Racial and Ethnic Disparities in Access to Care and Health Among US Adults at Age 65 Years," *JAMA internal medicine*, September 2021, *181* (9), 1207–1215.

Wennberg, J. and null Gittelsohn, "Small area variations in health care delivery," *Science (New York, N.Y.)*, December 1973, *182* (4117), 1102–1108.

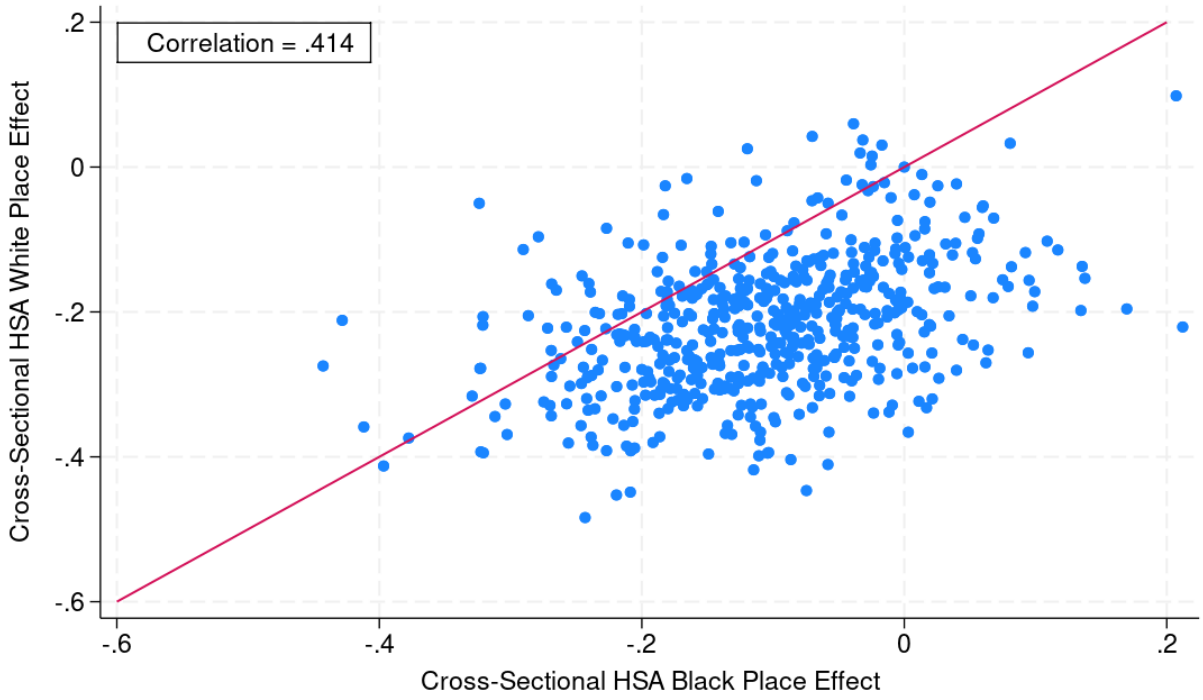
Wennberg, John E. and Megan McAndrew Cooper, *The Dartmouth Atlas of Health Care in the United States: The Center for the Evaluative Clinical Sciences* The Dartmouth Atlas of Health Care, Chicago (IL): American Hospital Publishing, Inc., 1996.

Williams, David R. and Pamela Braboy Jackson, "Social Sources Of Racial Disparities In Health," *Health Affairs*, March 2005, *24* (2), 325–334.

Zheng, Nan Tracy, Susan Haber, Sonja Hoover, and Zhanlian Feng, "Access to Care for Medicare-Medicaid Dually Eligible Beneficiaries: The Role of State Medicaid Payment Policies," *Health Services Research*, December 2017, *52* (6), 2219–2236.

Figures and Tables

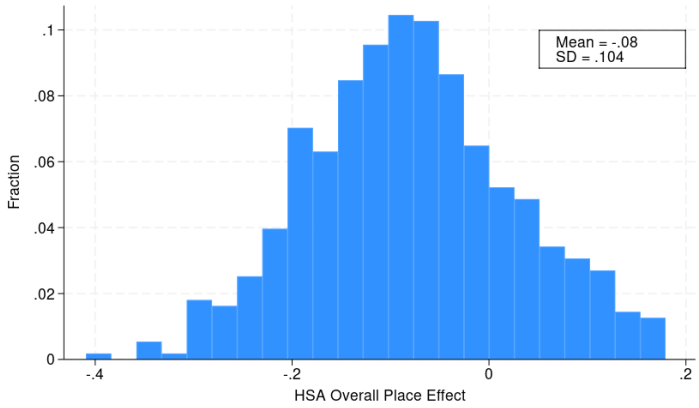
Figure 1. Cross-Sectional HSA "Place Effects" by Race



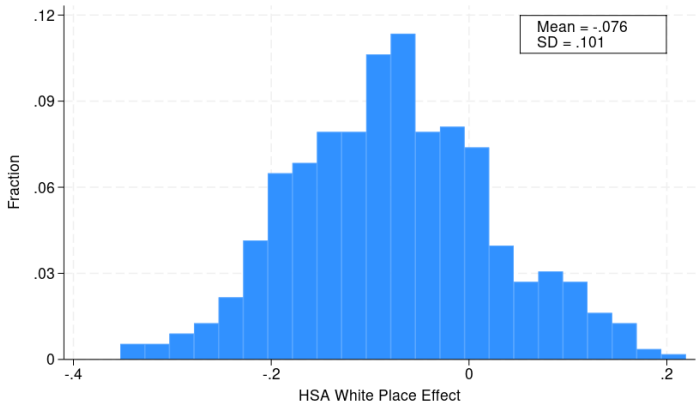
Notes: Figure shows estimates of cross-sectional HSA "place effects" by race. We construct these by estimating Equation 11 on a sample of non-movers.

Figure 2. Distribution of HSA Place Effects, Log(Utilization)

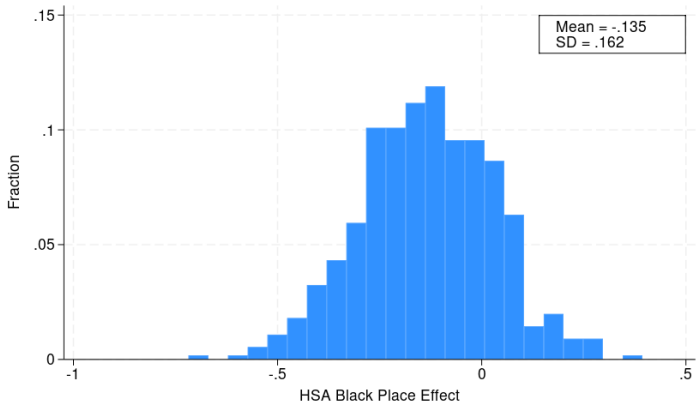
(A) Overall Place Effects



(B) White Place Effects



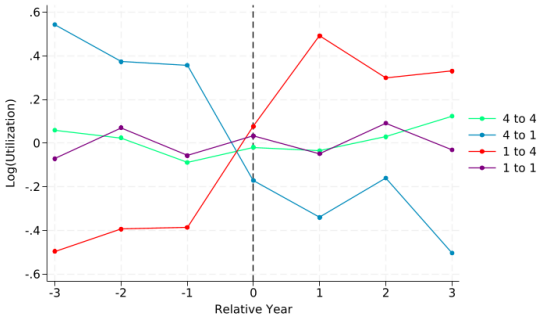
(C) Black Place Effects



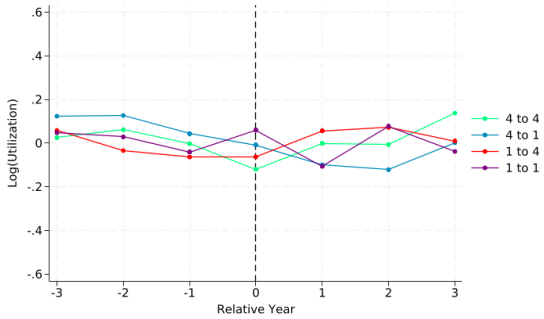
Notes: Figure depicts the distribution of HSA place effects for Log(Utilization), estimated using the specification in Equation 10. Panel A shows the distribution of overall HSA place effects $\hat{\gamma}_j$. Panel B shows the distribution of white HSA place effects $\hat{\gamma}_j^w$. Panel C shows the distribution of Black HSA place effects $\hat{\gamma}_j^b$.

Figure 3. Changes in Log(Utilization) for Different Types of Moves

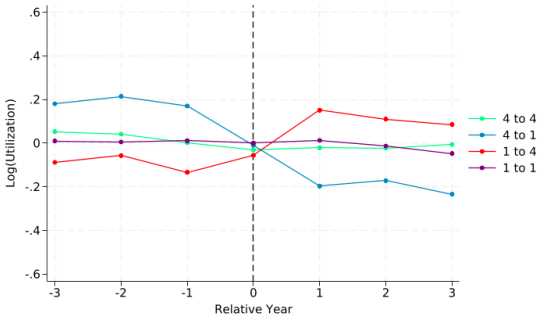
(A) Black Movers, Black Place Effects



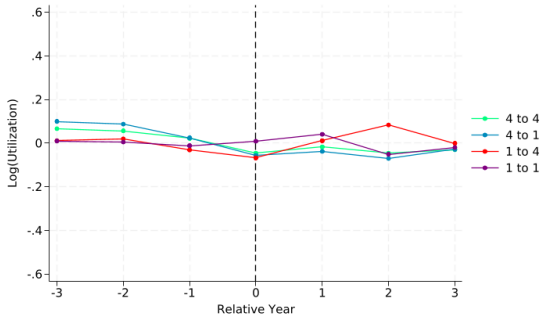
(B) Black Movers, White Place Effects



(C) White Movers, White Place Effects



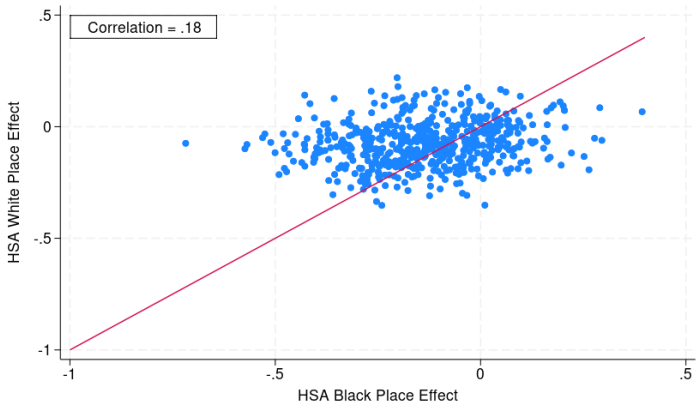
(D) White Movers, Black Place Effects



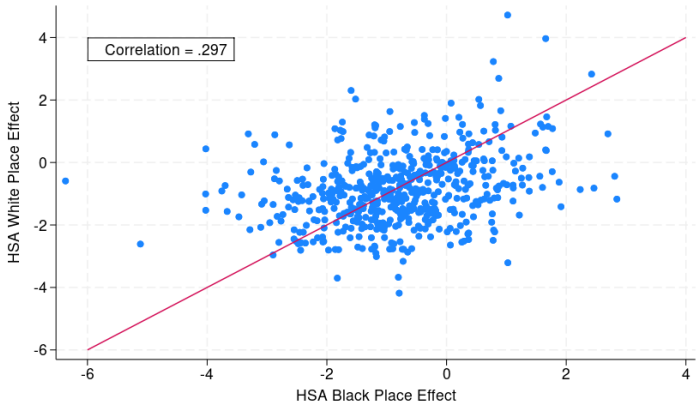
Notes: Figures show average Log(Utilization) by year relative to moving for different types of moves. Panel A shows averages for Black HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Panel B shows averages for Black HSA movers whose moves are classified by the origin-destination white place effects quartiles. Panel C shows averages for white HSA movers whose moves are classified by the origin-destination white place effects quartiles. Panel D shows averages for white HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Averages show Log(Utilization) residualized on calendar year and time relative to moving fixed effects as well as 5-year age cells.

Figure 4. Correlation between Black and White HSA Place Effects

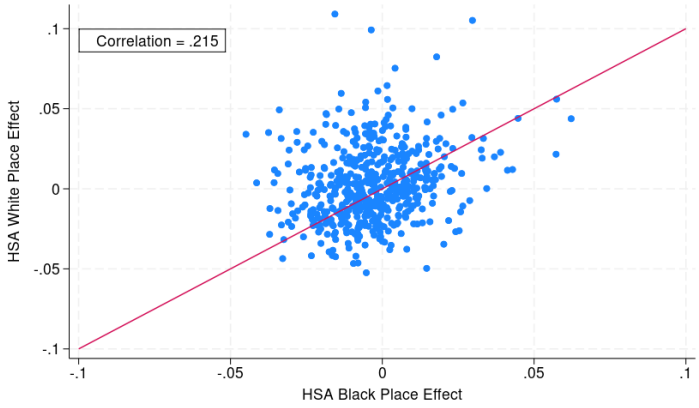
(A) Log(Utilization)



(B) Number of E&M Visits



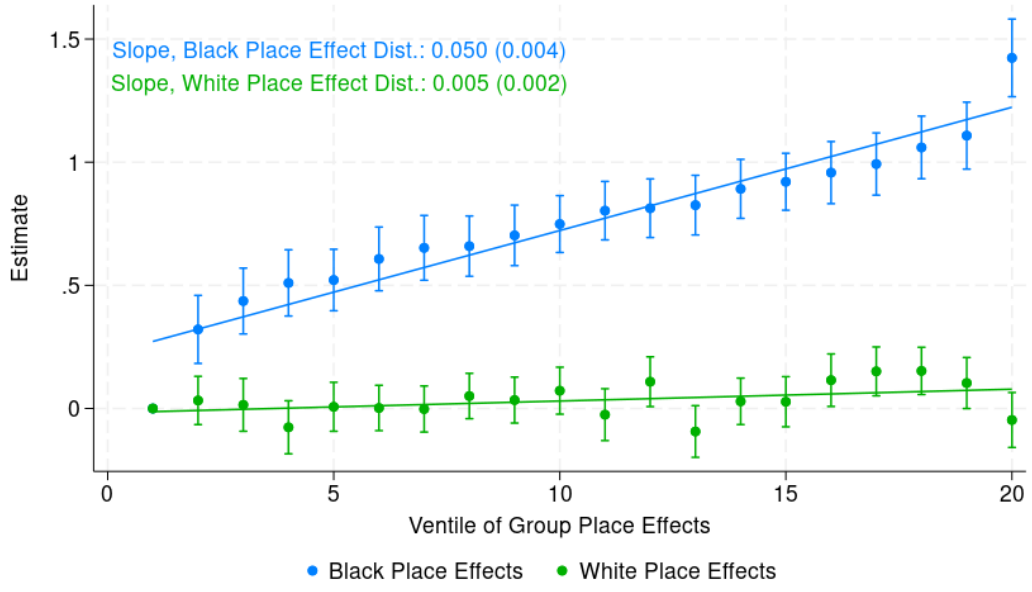
(C) Colorectal Cancer Screening



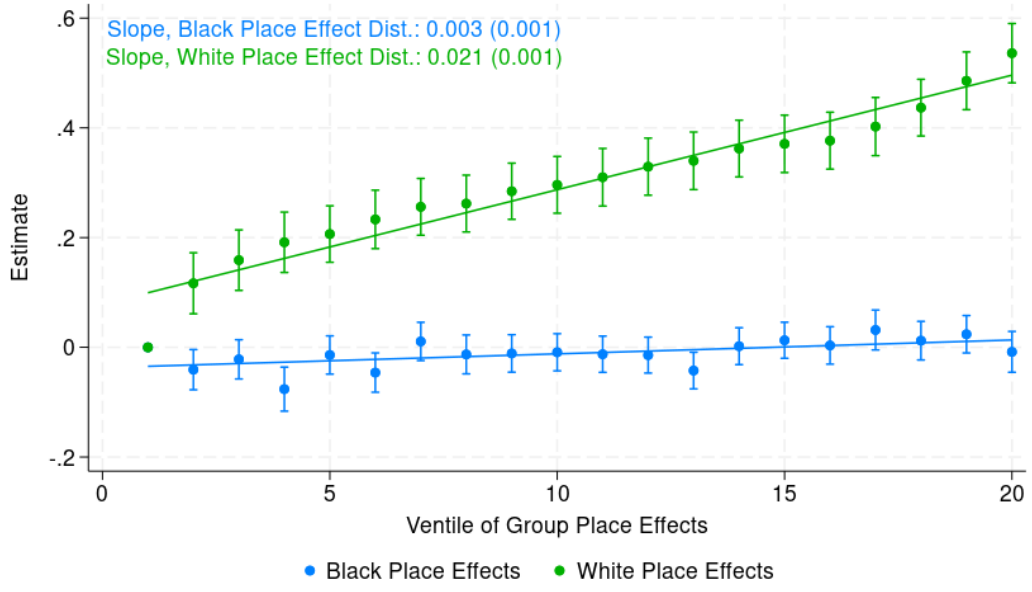
Notes: Scatter plots show the relationship between estimated HSA white place effects ($\hat{\gamma}_j^w$) and estimated HSA Black place effects ($\hat{\gamma}_j^b$). Panel A shows place effects on Log(Utilization), Panel B on number of evaluation and management visits, and Panel C on receipt of colorectal cancer screening.

Figure 5. Effect of Moving Up the Place Effects Distribution, Log(Utilization)

(A) Black HSA Movers

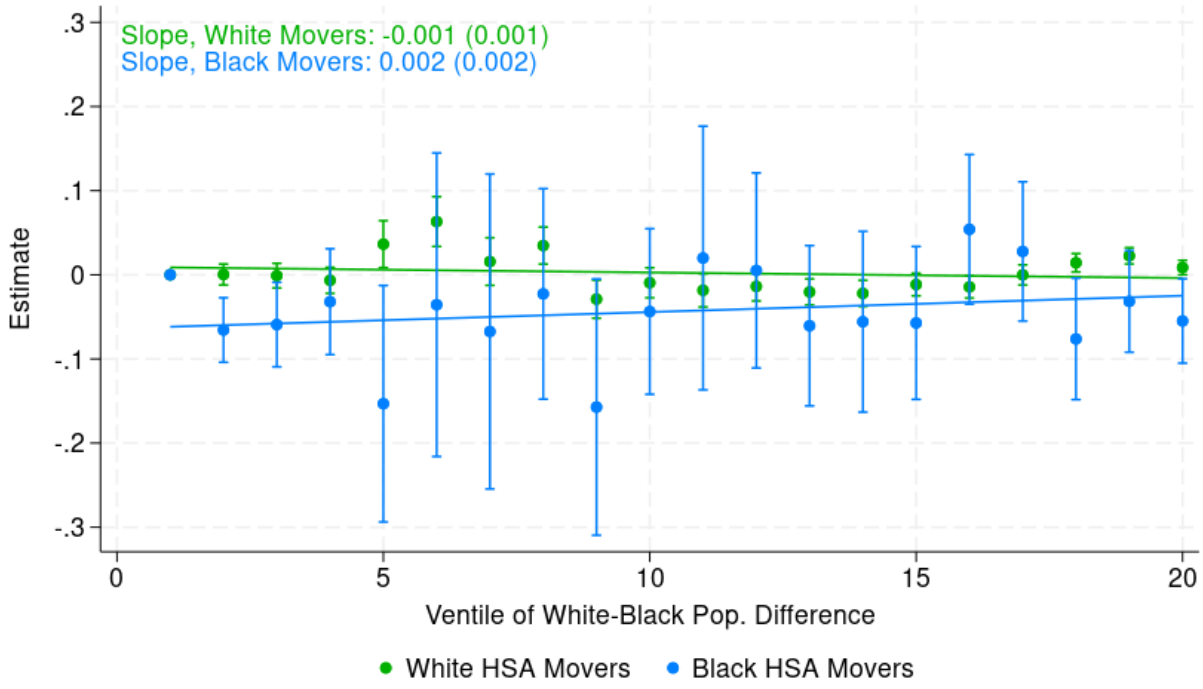


(B) White HSA Movers



Notes: Figures show estimates of Equation 12 using ventiles of the white and Black place effects and Log(Utilization) as the outcome. In Panel A, we plot the effect of Black HSA movers moving up the distribution of Black place effects (blue) and white place effects (green). In Panel B, we do the same for white HSA movers.

Figure 6. Effect of Moving Up the Differential Population Distribution



Notes: Figures shows estimates of Equation 12 using ventiles of the white-Black population share difference and Log(Utilization) as the outcome. Each point estimate reflects the causal effect of moving up the distribution of differential white-Black population share.

Table 1. Descriptive Statistics, Movers and Non-Movers

			Movers					
	Non-Movers		HRRxInc. Quint.		HSA		HRR	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Demographics								
Female	0.56	(0.50)	0.60	(0.49)	0.58	(0.49)	0.58	(0.49)
White	0.83	(0.37)	0.85	(0.36)	0.86	(0.34)	0.87	(0.34)
Black	0.07	(0.26)	0.06	(0.25)	0.05	(0.22)	0.05	(0.22)
Hispanic	0.05	(0.22)	0.05	(0.22)	0.04	(0.21)	0.04	(0.20)
API	0.02	(0.15)	0.03	(0.16)	0.02	(0.15)	0.02	(0.15)
AIAN	0.00	(0.07)	0.00	(0.06)	0.00	(0.05)	0.00	(0.05)
Other	0.01	(0.09)	0.01	(0.08)	0.01	(0.08)	0.01	(0.08)
Age at First Obs.	72.01	(6.83)	73.16	(7.29)	72.78	(7.12)	72.67	(7.06)
Geography								
Northeast	0.19	(0.39)	0.18	(0.38)	0.19	(0.39)	0.18	(0.39)
South	0.40	(0.49)	0.39	(0.49)	0.39	(0.49)	0.40	(0.49)
Midwest	0.24	(0.43)	0.22	(0.41)	0.20	(0.40)	0.19	(0.40)
West	0.17	(0.38)	0.21	(0.41)	0.22	(0.42)	0.22	(0.42)
Health and Health Care Use								
Log(Utilization)	7.81	(1.47)	7.92	(1.47)	7.87	(1.46)	7.88	(1.45)
Num. Chronic Conditions	3.74	(2.74)	3.97	(2.88)	3.78	(2.82)	3.78	(2.79)
Years Obs.	7.99	(3.08)	8.17	(2.90)	8.13	(2.93)	8.17	(2.90)
Died in Sample	0.24	(0.43)	0.26	(0.44)	0.24	(0.43)	0.23	(0.42)
Observations	10,381,978		5,792,613		3,567,532		3,038,220	

Notes: Abbreviations: HSA - Hospital Service Area; HRR - Hospital Referral Region; API - Asian-American or Pacific Islander; AIAN - American Indian or Alaska Native. This table presents characteristics of non-movers and different types of movers in our analytic sample. We restrict to individuals who only move once in the data.

Table 2. HSA Decomposition, Homogenous Place Effects, 2018

	National Disparity (1)	Omitted Disparity (2)	Person Component (3)	Place Component (4)
Log(Utilization)	-0.147	-0.070	-0.076	-0.001
SE			(0.007)	(0.007)
Num. E&M Visits	0.212	0.525	-0.368	0.056
SE			(0.089)	(0.089)
Colorectal Cancer Screen	0.002	0.004	-0.004	0.002
SE			(0.001)	(0.001)

Notes: Table shows estimates of the decomposition outlined in Equation 5. Column (1) shows the national white-Black disparity in the outcome, and column (2) is the disparity in the omitted HSA. Column (3) shows the person component of the decomposition. Column (4) shows the place component. Estimates are restricted to HSAs with 20 or more Black and white movers, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.

Table 3. HSA Decomposition, Heterogenous Place Effects, 2018

					Decompose Place Component			
	National Disparity	Omitted Disparity	Person Component	Place Component	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Utilization)	-0.147	-0.070	-0.113	0.036	0.033	91.70	0.003	8.30
SE			(0.012)	(0.012)	(0.010)		(0.008)	
Num. E&M Visits	0.212	0.525	-0.157	-0.156	-0.227	145.41	0.071	-45.41
SE			(0.082)	(0.082)	(0.080)		(0.090)	
Colorectal Cancer Screen	0.002	0.004	-0.008	0.006	0.005	82.22	0.001	17.78
SE			(0.002)	(0.002)	(0.002)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 8. Column (1) shows the national white-Black disparity in the outcome, and column (2) is the disparity in the omitted HSA. Column (3) shows the person component of the decomposition. Column (4) shows the place component, and columns (5)-(8) show the portion of place component coming from different place effects by race (columns (5) and (6)) and the portion coming from differential geographic distribution by race (columns (7) and (8)). Estimates are restricted to HSAs with 20 or more Black and white movers, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.

Table 4. HSA Decomposition, Reallocation Exercise, 2018

					Decompose Place Component			
	National Disparity	Omitted Disparity	Person Component	Place Component	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Utilization)	-0.222	-0.070	-0.113	-0.039	-0.042	107.61	0.003	-7.61
SE	(0.011)			(0.011)	(0.010)		(0.008)	
Num. E&M Visits	-0.387	0.525	-0.157	-0.755	-0.825	109.37	0.071	-9.37
SE	(0.109)			(0.109)	(0.099)		(0.093)	
Colorectal Cancer Screen	-0.009	0.004	-0.008	-0.005	-0.006	121.36	0.001	-21.36
SE	(0.002)			(0.002)	(0.002)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 8. For all HSAs in the bottom quartile of the Black place effects distribution, we replace the place effect with the average top quartile Black place effect. Column (1) shows the national white-Black disparity in the outcome, and column (2) is the disparity in the omitted HSA. Column (3) shows the person component of the decomposition. Column (4) shows the place component, and columns (5)-(8) show the portion of place component coming from different place effects by race (columns (5) and (6)) and the portion coming from differential geographic distribution by race (columns (7) and (8)). Estimates are restricted to HSAs with 20 or more Black and white movers, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.

Online Appendix For: The Geography of Health Disparities

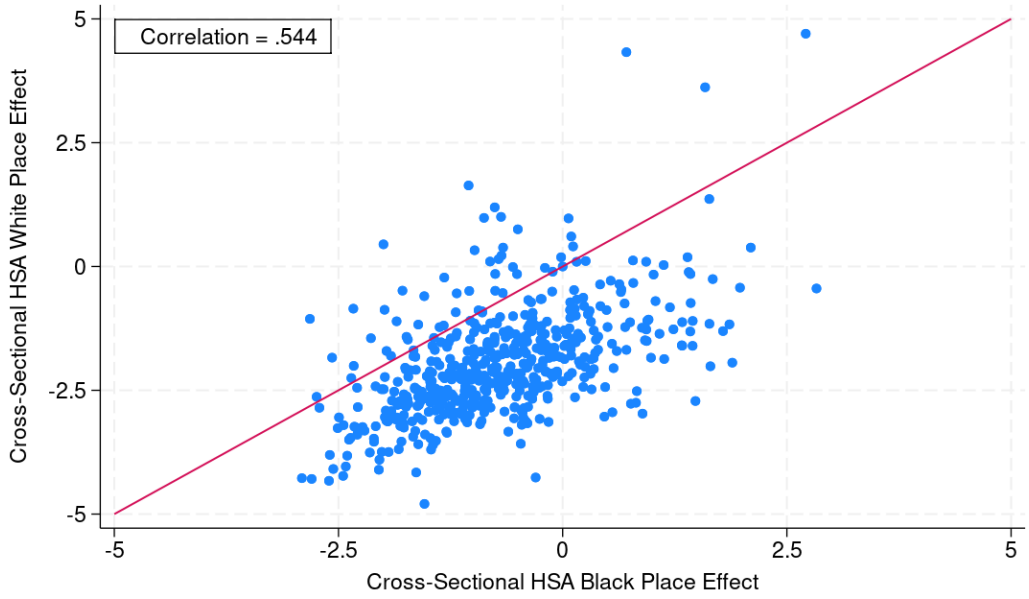
Layton and Peterson

February 13, 2025

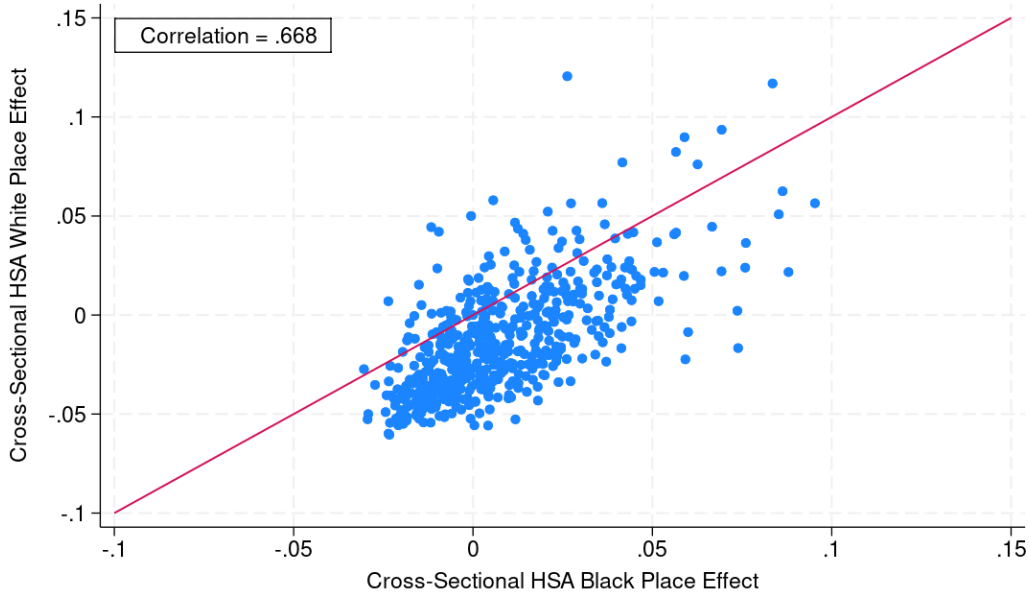
A Appendix Figures and Tables

Appendix Figure A1. Cross-Sectional HSA "Place Effects" Estimates by Race

(A) Number of E&M Visits



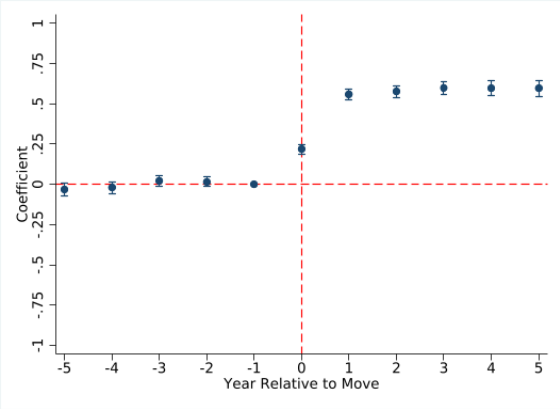
(B) Colorectal Cancer Screening



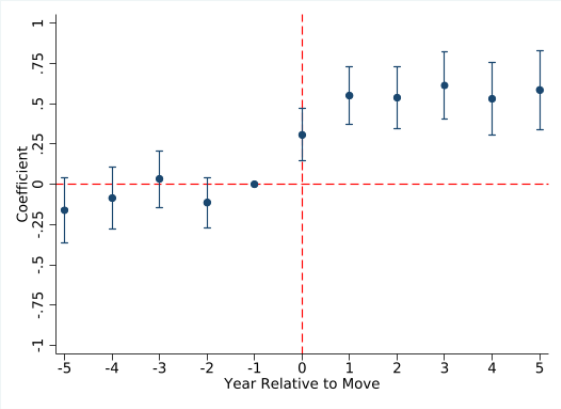
Notes: Figures show estimates of Equation 11 using a sample of non-movers and the number of evaluation and management visits (Panel A) and receipt of any colorectal cancer screening (Panel B) as the outcomes.

Appendix Figure A2. Changes in Access to Care Upon HSA Move by Race

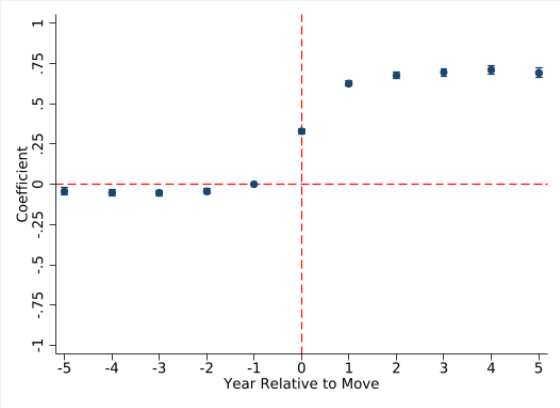
(A) Log(Utilization), White Movers



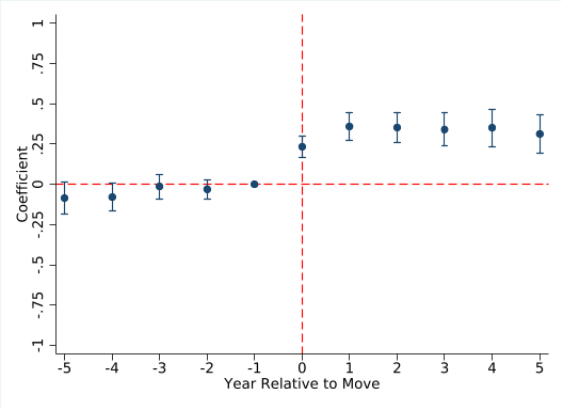
(B) Log(Utilization), Black Movers



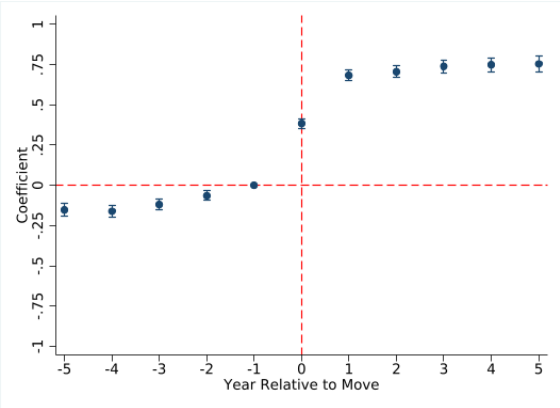
(C) Num. E&M Visits, White Movers



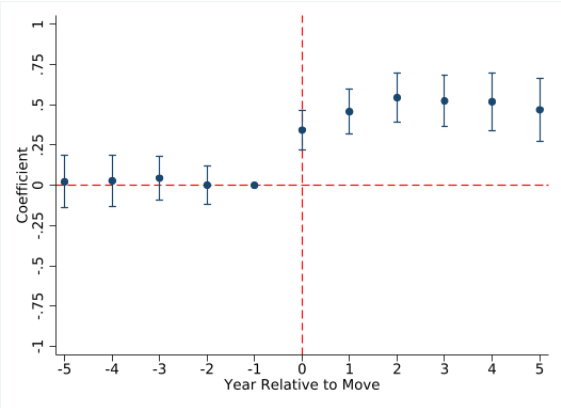
(D) Num. E&M Visits, Black Movers



(E) Colorectal Cancer Screening, White Movers



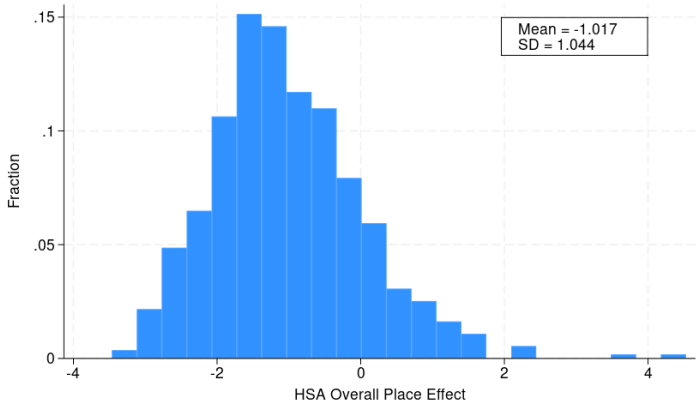
(F) Colorectal Cancer Screening, Black Movers



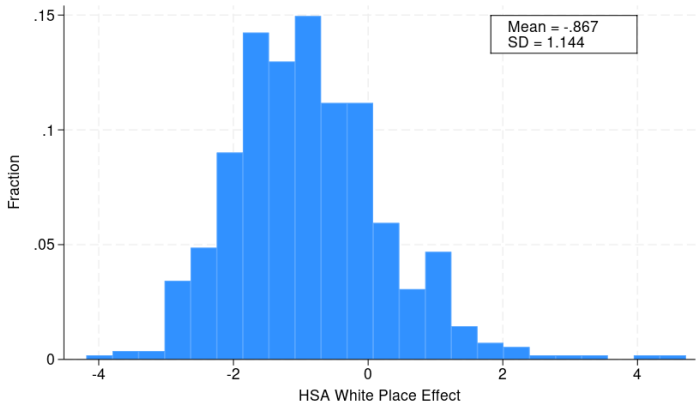
Notes: Figures plot the $\hat{\theta}_{r(i,t)}$ coefficients from Equation 9, estimated separately for white and Black HSA movers. Panels (A) and (B) use Log(Utilization) as the outcome. Panels (C) and (D) use number of evaluation and management visits as the outcome. Panels (E) and (F) use receipt of colorectal cancer screening as the outcome.

Appendix Figure A3. Distribution of HSA Place Effects, Num. E&M Visits

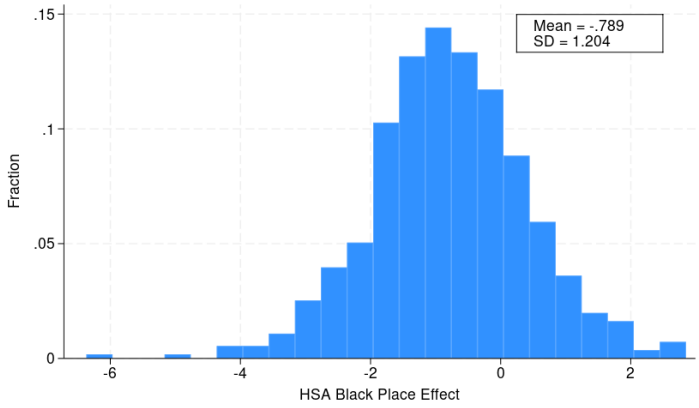
(A) Overall Place Effects



(B) White Place Effects



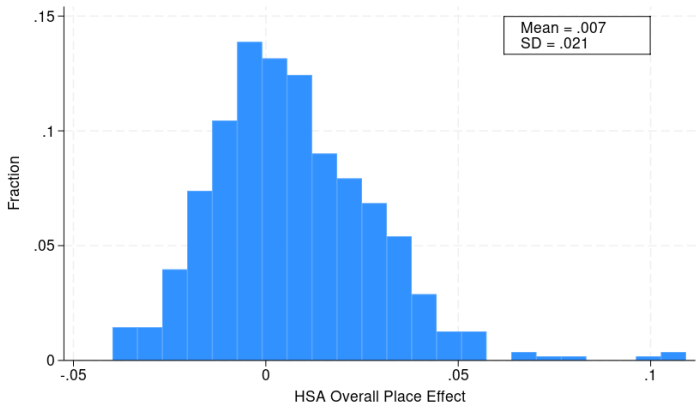
(C) Black Place Effects



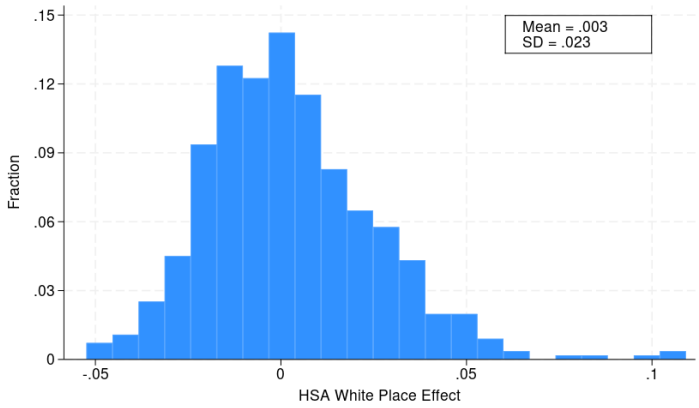
Notes: Figure depicts the distribution of HSA place effects for number of E&M visits, estimated using the specification in Equation 10. Panel A shows the distribution of overall HSA place effects $\hat{\gamma}_j$. Panel B shows the distribution of white HSA place effects $\hat{\gamma}_j^w$. Panel C shows the distribution of Black HSA place effects $\hat{\gamma}_j^b$.

Appendix Figure A4. Distribution of HSA Place Effects, Colorectal Cancer Screening

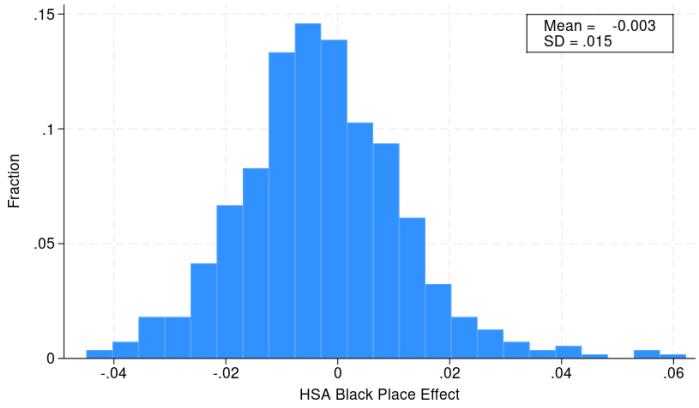
(A) Overall Place Effects



(B) White Place Effects



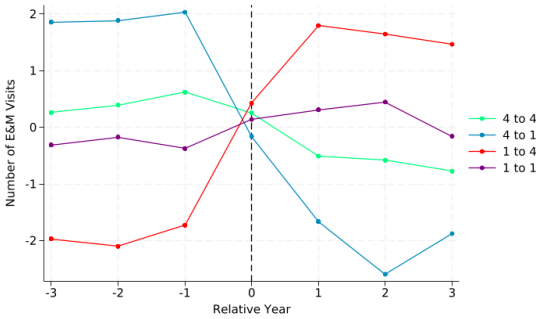
(C) Black Place Effects



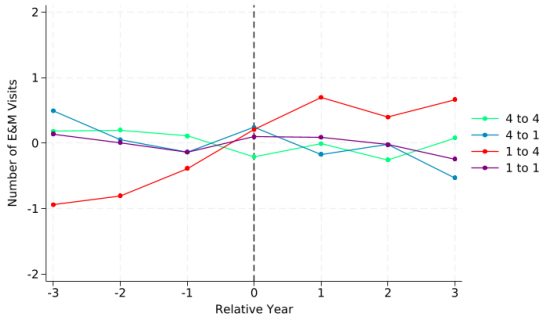
Notes: Figure depicts the distribution of HSA place effects for receipt of a colorectal cancer screening, estimated using the specification in Equation 10. Panel A shows the distribution of overall HSA place effects $\hat{\gamma}_j$. Panel B shows the distribution of white HSA place effects $\hat{\gamma}_j^w$. Panel C shows the distribution of Black HSA place effects $\hat{\gamma}_j^b$.

Appendix Figure A5. Changes in Number of E&M Visits for Different Types of Moves

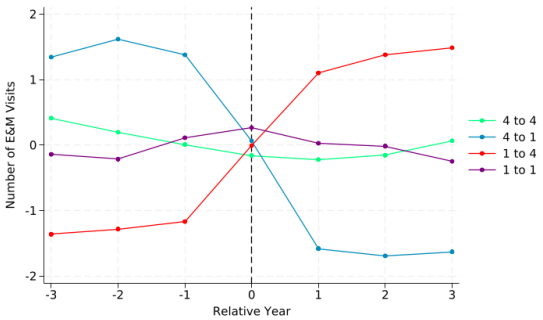
(A) Black Movers, Black Place Effects



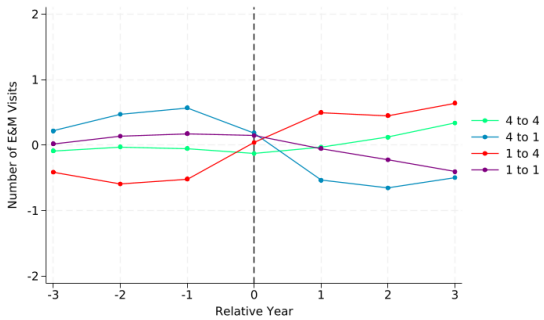
(B) Black Movers, White Place Effects



(C) White Movers, White Place Effects



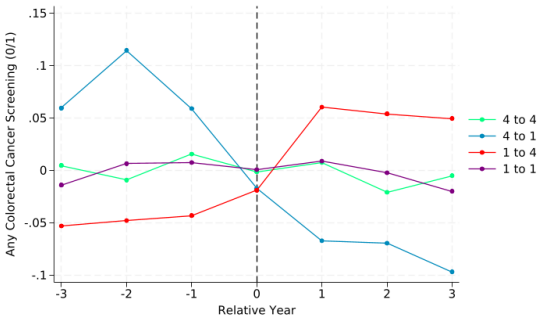
(D) White Movers, Black Place Effects



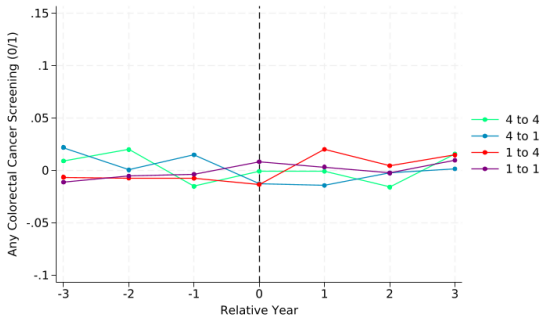
Notes: Figures show average number of E&M vists by year relative to moving for different types of moves. Panel A shows averages for Black HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Panel B shows averages for Black HSA movers whose moves are classified by the origin-destination white place effects quartiles. Panel C shows averages for white HSA movers whose moves are classified by the origin-destination white place effects quartiles. Panel D shows averages for white HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Averages show the outcome residualized on calendar year and time relative to moving fixed effects as well as 5-year age cells.

Appendix Figure A6. Changes in Receipt of Colorectal Cancer Screening for Different Types of Moves

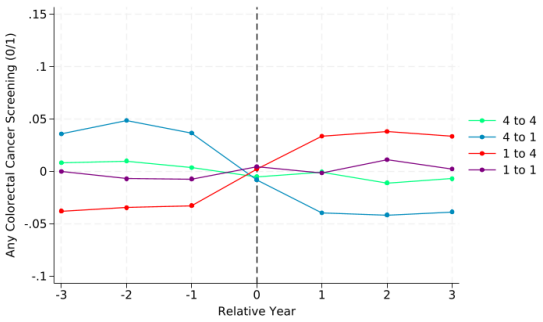
(A) Black Movers, Black Place Effects



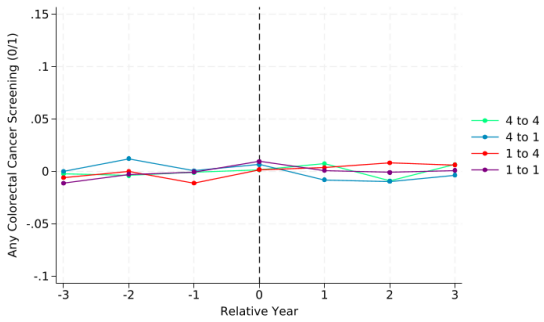
(B) Black Movers, White Place Effects



(C) White Movers, White Place Effects



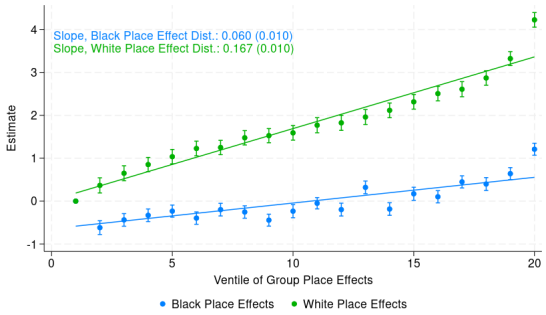
(D) White Movers, Black Place Effects



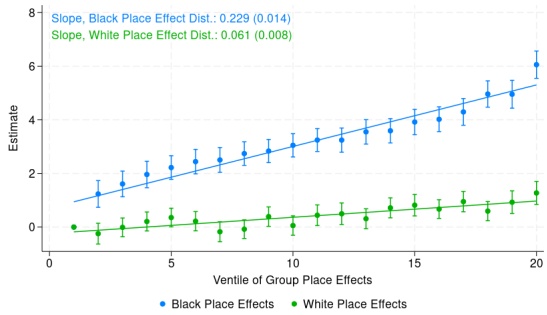
Notes: Figures show probability of receiving a colorectal cancer screening by year relative to moving for different types of moves. Panel A shows averages for Black HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Panel B shows averages for Black HSA movers whose moves are classified by the origin-destination white place effects quartiles. Panel C shows averages for white HSA movers whose moves are classified by the origin-destination white place effects quartiles. Panel D shows averages for white HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Averages show the outcome residualized on calendar year and time relative to moving fixed effects as well as 5-year age cells.

Appendix Figure A7. Effect of Moving Up the Place Effects Distribution

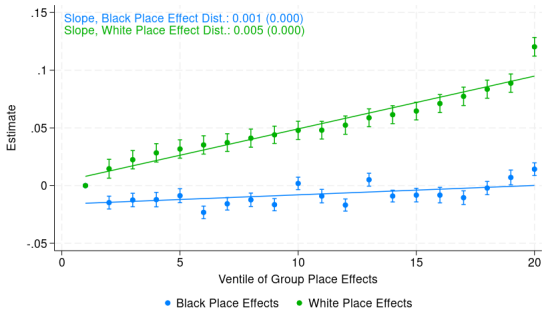
(A) Num. E&M Visits, White Movers



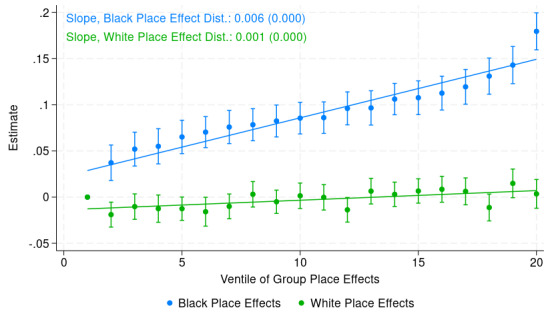
(B) Num. E&M Visits, Black Movers



(C) Colorectal Cancer Screening, White Movers



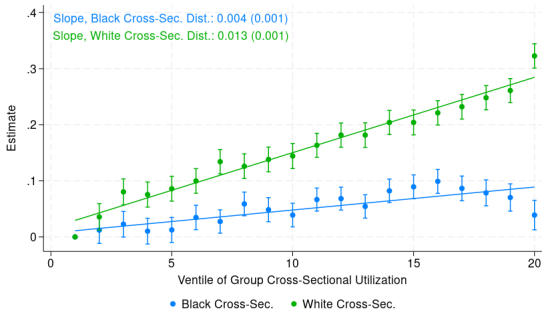
(D) Colorectal Cancer Screening, Black Movers



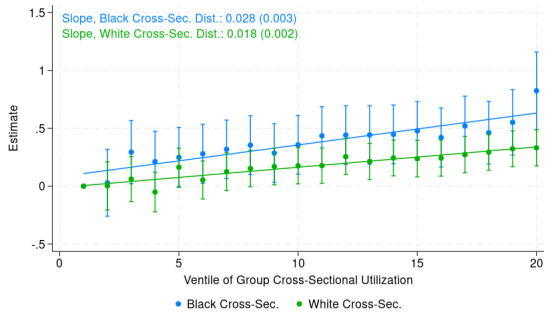
Notes: Figures plot the $\hat{\delta}^{vent}_{h(i,t)}$ coefficients from Equation 12, estimated separately for white and Black HSA movers. Panels (A) and (B) use number of evaluation and management visits as the outcome. Panels (C) and (D) use receipt of colorectal cancer screening as the outcome.

Appendix Figure A8. Effect of Moving Up the Cross-Sectional Utilization Distribution

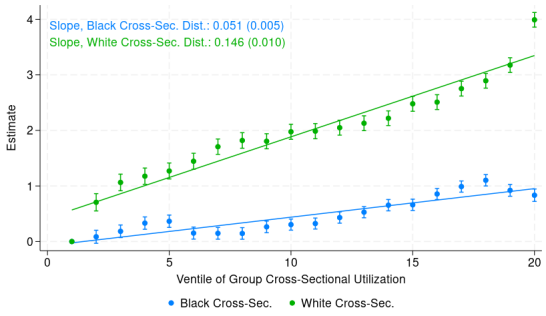
(A) Log(Utilization), White Movers



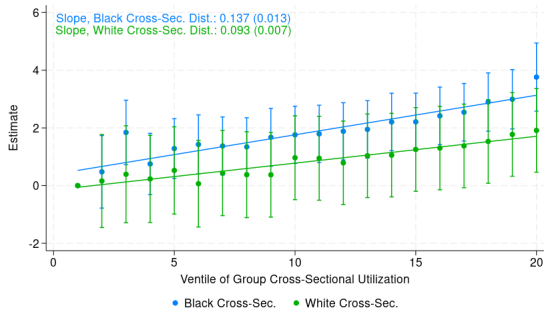
(B) Log(Utilization), Black Movers



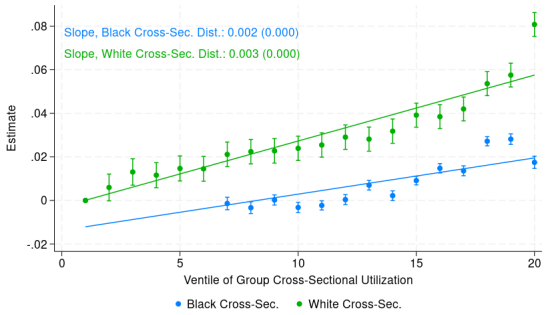
(C) Num. E&M Visits, White Movers



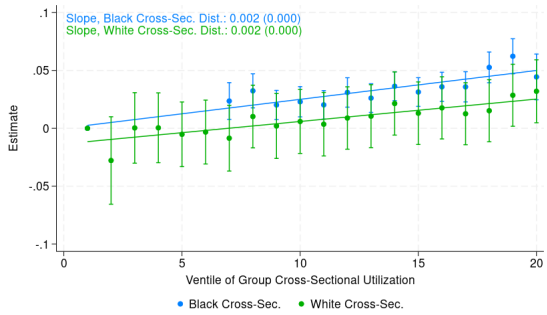
(D) Num. E&M Visits, Black Movers



(E) Colorectal Cancer Screening, White Movers



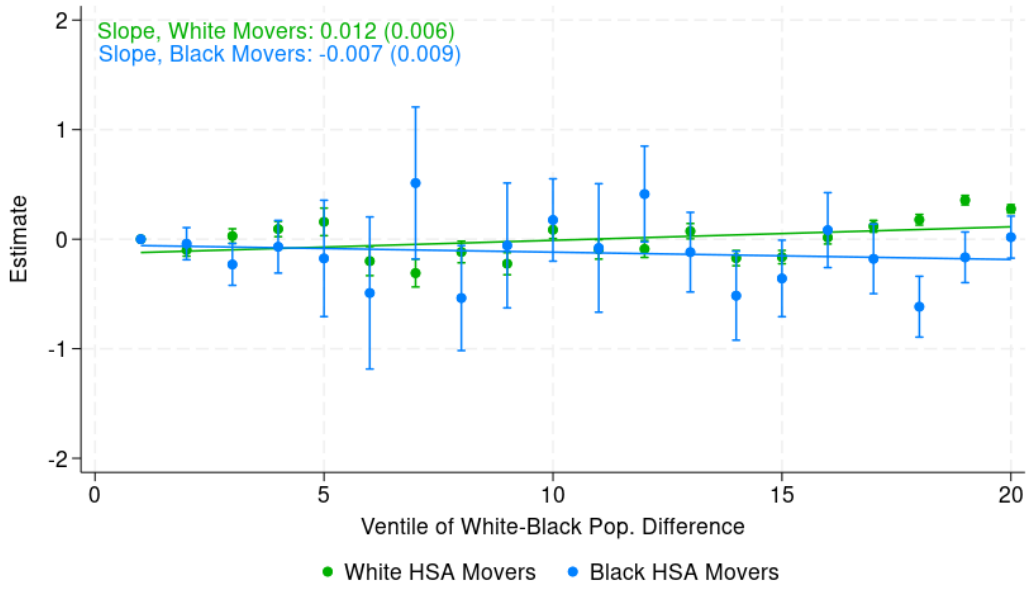
(F) Colorectal Cancer Screening, Black Movers



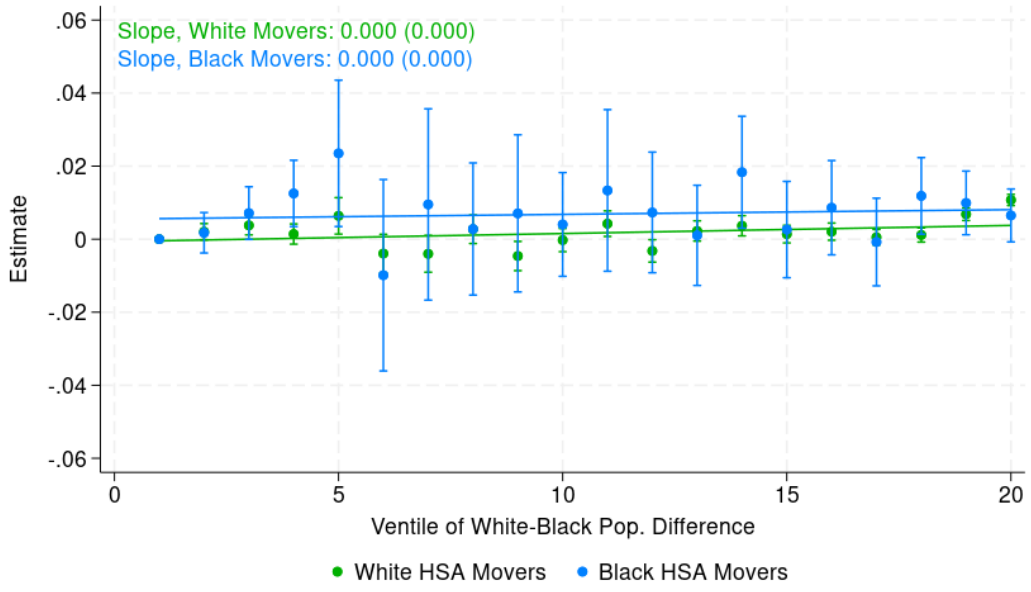
Notes: Figures plot the $\hat{\delta}^{vent}_{h(i,t)}$ coefficients from Equation 12, estimated separately for white and Black HSA movers and using ventiles based on the cross-sectional distribution of utilization. Panels (A) and (B) use Log(Utilization) as the outcome. Panels (C) and (D) use number of evaluation and management visits as the outcome. Panels (E) and (F) use receipt of colorectal cancer screening as the outcome.

Appendix Figure A9. Effect of Moving up the Differential Population Distribution

(A) Number of E&M Visits



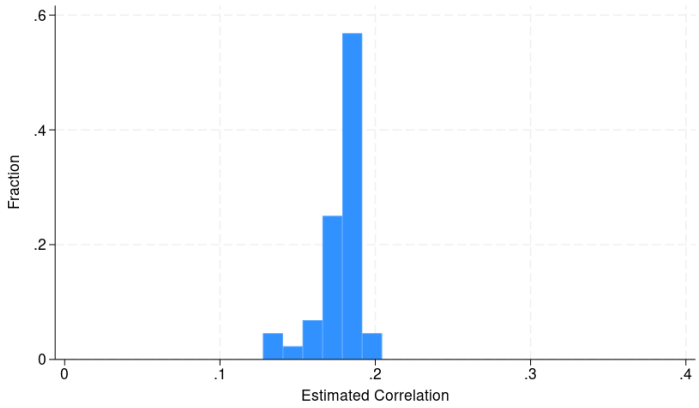
(B) Colorectal Cancer Screening



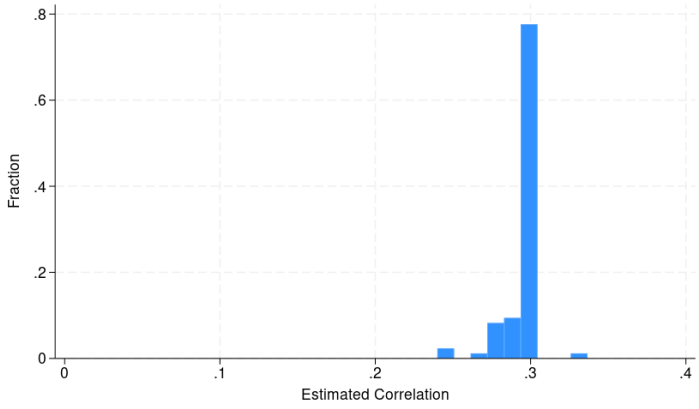
Notes: Notes: Figures plots the $\hat{\delta}^{vent}_{h(i,t)}$ coefficients from Equation 12 and using ventiles based on the cross-sectional distribution of utilization. Each point estimate reflects the causal effect of moving up the distribution of differential white-Black population share.

Appendix Figure A10. Distribution of Black-White Place Effects Correlations Varying Omitted Place

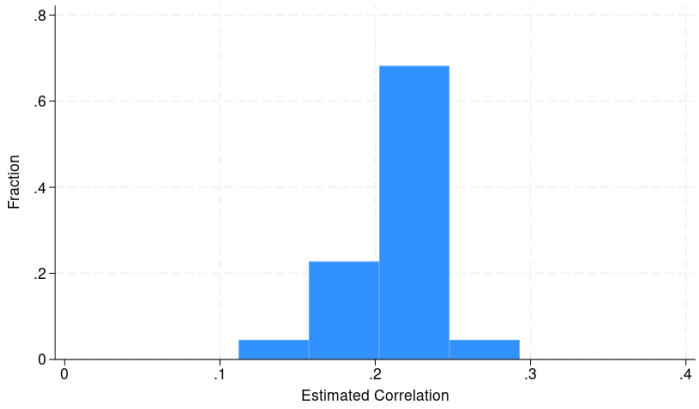
(A) Log(Utilization)



(B) Num. E&M Visits



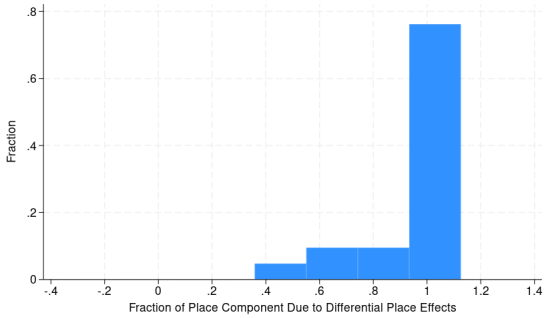
(C) Colorectal Cancer Screening



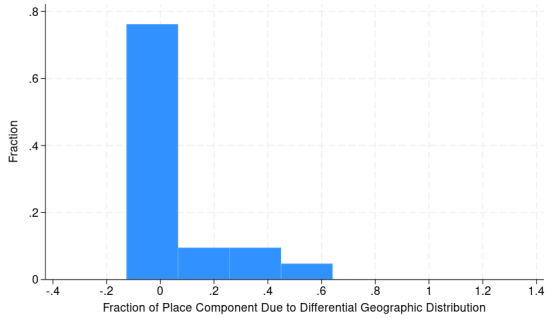
Notes: Figures show the distribution of Black-white place effects correlations varying the omitted category in our place effects regressions. To construct these distributions, we randomly sample 100 HSAs from our data, re-estimate the Black and white place effects with each HSA as the omitted category, shrink them, and then save the correlation between the shrunken Black and white place effects for that HSA.

Appendix Figure A11. Distribution of Place Decomposition Components Varying Omitted Place

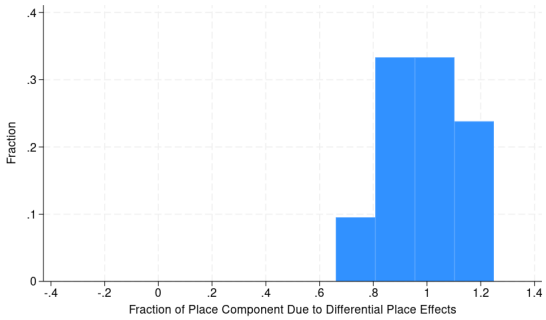
(A) Log(Utilization), Frac. Due to PEs



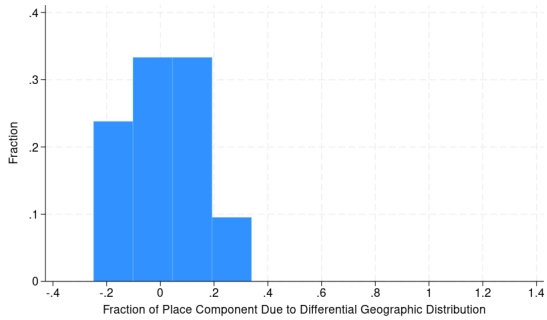
(B) Log(Utilization), Frac. Due to Geo.



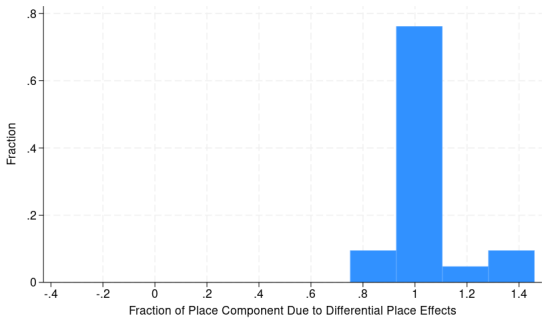
(C) Num. E&M Visits, Frac. Due to PEs



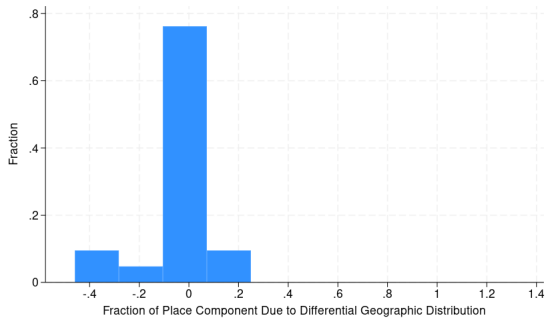
(D) Num. E&M Visits, Frac. Due to Geo.



(E) Colorectal Cancer Scrn., Frac. Due to PEs



(F) Colorectal Cancer Scrn., Frac. Due to Geo.



Notes: Each figure shows the distribution of one of the place component pieces varying the omitted category in the place effects estimation. Panels A, C, and E show the distribution of the fraction of the place component accounted for by differential place effects across our outcomes. Panels B, D, and F show the distributions of the fraction of the place component accounted for by differential geographic distribution across our outcomes.

Appendix Table A1. Summary Statistics by Mover Race

	HRRxInc. Quint. Movers				HSA Movers				HRR Movers			
	White		Black		White		Black		White		Black	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Demographics and Geography												
Female	0.60	(0.49)	0.61	(0.49)	0.59	(0.49)	0.60	(0.49)	0.58	(0.49)	0.61	(0.49)
Age at First. Obs.	73.38	(7.35)	72.26	(7.16)	72.94	(7.18)	72.23	(7.02)	72.81	(7.11)	72.26	(6.99)
Northeast	0.18	(0.39)	0.16	(0.36)	0.19	(0.39)	0.21	(0.40)	0.18	(0.38)	0.21	(0.40)
South	0.39	(0.49)	0.55	(0.50)	0.39	(0.49)	0.50	(0.50)	0.40	(0.49)	0.50	(0.50)
Midwest	0.23	(0.42)	0.20	(0.40)	0.21	(0.40)	0.19	(0.39)	0.20	(0.40)	0.20	(0.40)
West	0.20	(0.40)	0.09	(0.28)	0.21	(0.41)	0.11	(0.31)	0.22	(0.41)	0.10	(0.30)
Health and Healthcare Use												
Log(Utilization)	7.94	(1.45)	7.99	(1.61)	7.89	(1.45)	7.89	(1.59)	7.89	(1.44)	7.90	(1.58)
Num. Chronic Conditions	3.99	(2.85)	4.23	(3.09)	3.81	(2.80)	3.96	(3.02)	3.81	(2.77)	4.01	(2.99)
Years Obs.	8.31	(2.85)	7.42	(3.02)	8.25	(2.88)	7.45	(3.05)	8.30	(2.86)	7.54	(3.03)
Died in Sample	0.27	(0.44)	0.29	(0.46)	0.24	(0.43)	0.27	(0.44)	0.24	(0.42)	0.26	(0.44)
Observations	4,895,132		376,127		3,083,095		181,204		2,633,996		154,858	

Notes: Table shows summary statistics by type of mover and mover race. The sample is the analytic sample described in Section 2.3. Across a number of measures, we find that Black and white movers are observably similar, both for those who move across HRRs and those who move only across ZIP codes.

Appendix Table A2. Black-White Place Effects Correlation by Place Effects Sample

	Place Effects Sample			
	Hospital Service Area (HSA)	Hospital Referral Region (HRR)	HRRxZIP Inc. Quintile	HSA White Noise Sample
	(1)	(2)	(3)	(4)
Log(Utilization)	0.18	0.47	0.243	0.115
Num. E&M Visits	0.297	0.447	0.339	0.178
Colorectal Cancer Screen	0.215	0.335	0.175	0.079

Notes: Table shows the correlation between the estimated Black ($\hat{\gamma}_j^b$) and white ($\hat{\gamma}_j^w$) place effects, varying the level of geography of the place effects. Column (1) shows the correlation for our primary set of estimates using Hospital Service Areas (HSAs). Column (2) shows the correlation for Hospital Referral Regions (HRRs). Column (3) shows the correlation for HRR-by-ZIP Code Income Quintile. Column (4) shows the correlation for HSAs using a sample of white movers that has been randomly chosen to match the number of Black movers in a given origin-destination dyad.

Appendix Table A3. HRR Decomposition, Homogenous Place Effects, 2018

	National Disparity (1)	Omitted Disparity (2)	Person Component (3)	Place Component (4)
Log(Utilization)	-0.150	-0.226	0.087	-0.012
SE			(0.012)	(0.012)
Num. E&M Visits	0.273	0.488	-0.102	-0.113
SE			(0.160)	(0.160)
Colorectal Cancer Screen	0.002	0.005	-0.002	-0.001
SE			(0.002)	(0.002)

Notes: Table shows estimates of the decomposition outlined in Equation 5 using HRR as the level of geography. Column (1) shows the national white-Black disparity in the outcome, and column (2) is the disparity in the omitted HRR. Column (3) shows the person component of the decomposition. Column (4) shows the place component. Estimates are restricted to HRRs with 20 or more Black and white movers, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.

Appendix Table A4. HRR Decomposition, Heterogeneous Place Effects, 2018

					Decompose Place Component			
	National Disparity	Omitted Disparity	Person Component	Place Component	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Utilization)	-0.150	-0.226	0.002	0.073	0.085	116.30	-0.012	-16.30
SE			(0.019)	(0.019)	(0.012)		(0.011)	
Num. E&M Visits	0.273	0.488	0.486	-0.700	-0.586	83.61	-0.115	16.39
SE			(0.146)	(0.146)	(0.086)		(0.168)	
Colorectal Cancer Screen	0.002	0.005	0.005	-0.008	-0.007	83.51	-0.001	16.49
SE			(0.002)	(0.002)	(0.002)		(0.002)	

Notes: Table shows estimates of the decomposition outlined in Equation 8 using HRR as the level of geography. Column (1) shows the national white-Black disparity in the outcome, and column (2) is the disparity in the omitted HRR. Column (3) shows the person component of the decomposition. Column (4) shows the place component, and columns (5)-(8) show the portion of place component coming from different place effects by race (columns (5) and (6)) and the portion coming from differential geographic distribution by race (columns (7) and (8)). Estimates are restricted to HRRs with 20 or more Black and white movers, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.

Appendix Table A5. HRR-by-ZIP Income Quintile Decomposition, Homogenous Place Effects, 2018

	National Disparity (1)	Omitted Disparity (2)	Person Component (3)	Place Component (4)
Log(Utilization)	-0.139	-0.225	0.084	0.002
SE			(0.007)	(0.007)
Num. E&M Visits	0.265	0.414	-0.005	-0.144
SE			(0.094)	(0.094)
Colorectal Cancer Screen	0.002	-0.002	0.004	0.000
SE			(0.001)	(0.001)

Notes: Table shows estimates of the decomposition outlined in Equation 5 using HRR-by-ZIP income quintile as the level of geography. Column (1) shows the national white-Black disparity in the outcome, and column (2) is the disparity in the omitted HRR-by-ZIP Income Quintile. Column (3) shows the person component of the decomposition. Column (4) shows the place component. Estimates are restricted to HRR-by-ZIP income quintile areas with 20 or more Black and white movers, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.

Appendix Table A6. HRR-by-ZIP Income Quintile Decomposition, Heterogeneous Place Effects, 2018

					Decompose Place Component			
	National Disparity	Omitted Disparity	Person Component	Place Component	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Utilization)	-0.139	-0.225	0.393	-0.307	-0.308	100.60	0.002	-0.60
SE			(0.020)	(0.020)	(0.017)		(0.006)	
Num. E&M Visits	0.265	0.414	1.597	-1.745	-1.618	92.70	-0.127	7.30
SE			(0.149)	(0.149)	(0.092)		(0.087)	
Colorectal Cancer Screen	0.002	-0.002	0.011	-0.007	-0.007	93.33	-0.000	6.67
SE			(0.001)	(0.001)	(0.001)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 8 using HRR-by-ZIP income quintile as the level of geography. Column (1) shows the national white-Black disparity in the outcome, and column (2) is the disparity in the omitted HRR-by-ZIP Income Quintile. Column (3) shows the person component of the decomposition. Column (4) shows the place component, and columns (5)-(8) show the portion of place component coming from different place effects by race (columns (5) and (6)) and the portion coming from differential geographic distribution by race (columns (7) and (8)). Estimates are restricted to HRR-by-ZIP Income Quintile areas with 20 or more Black and white movers, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.

Appendix Table A7. HSA Decomposition, White Noise Sample, Heterogeneous Place Effects, 2018

					Decompose Place Component			
	National Disparity	Omitted Disparity	Person Component	Place Component	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Utilization)	-0.148	-0.070	0.007	-0.085	-0.088	103.99	0.003	-3.99
SE			(0.015)	(0.015)	(0.016)		(0.015)	
Num. E&M Visits	0.213	0.525	-0.290	-0.022	-0.024	110.46	0.002	-10.46
SE			(0.103)	(0.103)	(0.088)		(0.094)	
Colorectal Cancer Screen	0.002	0.004	-0.017	0.015	0.016	103.59	-0.001	-3.59
SE			(0.002)	(0.002)	(0.002)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 8 with place effects estimated on a restricted sample of white movers randomly chosen to equalize the number of Black and white movers in a give origin-destination HSA dyad. Estimates are restricted to HSAs with 20 or more Black and white movers in this restricted sample, and all place effects are adjusted using empirical Bayes shrinkage. Standard errors computed via bootstrap using 1,000 replicates.