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 white-Black 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 in total healthcare utilization. However, when place effects can vary by race, place plays a significant role in generating disparities. Crucially, we show that across a variety of measures of access, this 'place-by-race' component is largely due to Black and white beneficiaries facing very different, largely uncorrelated place effects in a given area, *not* due to 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 start by documenting Black-white racial disparities in a variety of measures of access to care. Across various measures of access – including log utilization, number of evaluation and management (E&M) visits, and receipt of colorectal cancer screenings – we show that Black patients access less care than white patients, conditional on demographic and health controls. We choose to focus on disparities in access to health*care* rather than disparities in actual underlying health for a few key reasons. First, access to healthcare 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). Finally, 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.

To understand the extent to which these estimated disparities are explained by place effects, we show 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; or, put differently, the place component represents how much the disparity would change if the Black and white populations were redistributed such that the share of Black beneficiaries living in a given place was identical to the share of white beneficiaries living in that place for all places. The person component represents the 'residual,' or the part of the national disparity that would remain if the Black and white geographic population distributions were made equivalent. We show that this decomposition can be performed assuming either that place effects are homogeneous or heterogeneous by race.

The key inputs to the decomposition are (1) data on where Black and white beneficiaries live and (2) estimates of causal place effects on access to care. We thus estimate causal effects of place on access to healthcare among Medicare beneficiaries. To do so, we use the now-standard 'movers' design previously used by Finkelstein et al. (2016) and others. Initially, we estimate a single set of place effects, assuming that place effects are homogeneous by race. We then extend the standard movers design to estimate race-specific place effects, separately for Black and white beneficiaries.

We start by documenting white-Black disparities in healthcare utilization and access. We show that while Black beneficiaries use more healthcare than white beneficiaries, that gap reverses when controlling for a demographics and a rich set of health conditions. Conditional on these observables, on average white beneficiaries use about 16.6% more healthcare services than Black beneficiaries. White beneficiaries also have one additional physician visit per year and are about one percentage point more likely to get a colorectal cancer screening in a given year. Overall, white-Black disparities in healthcare utilization and access appear real and significant.

We then use our movers design to estimate place effects on each of these measures of utilization and access. We show that place does matter for geographic variation in each

measure, replicating prior work by Finkelstein et al. (2016) that place explains around 50% of the geographic variation in each measure. We then use these place effects on each measure to construct our decomposition of the national disparity into place and person components. Interestingly, we find that when we assume that place effects are homogeneous by race, place effects explain only a small portion (5%) of the national disparity in healthcare utilization. Place matters a bit more for explaining the national disparity in the number of physician visits (11%), and it is fairly important for explaining national disparities in colorectal cancer screenings (46%). Across all measures, however, the majority of the national disparity is attributable to the person component rather than due to place. These results imply that traditional place-based policies that seek to just improve access to care in places where Black beneficiaries disproportionately live are unlikely to have major impacts on national disparities in healthcare utilization and access.

Allowing place effects to vary by race, however, reveals a somewhat different story. Here, the place component of the national disparity cannot just be thought of as the change in the national disparity that would occur if we equalized the fraction of the Black and white populations in a given area. Instead, the place component is the amount the national disparity would change if we shifted the Black and white geographic population distributions *and* equalized the Black and white place effects in all places. When we allow for race-specific place effects, places account for a considerably larger share of the national disparity in log utilization, reaching 26%. For the other measures, results are a bit more mixed, with the place component accounting for more than 100% of the national disparity in colorectal cancer screenings and still almost none of the national disparity in office visits.

We also show that, when place effects are allowed to differ by race, the place component itself can be further decomposed into two distinct components: the portion of the place component due to white beneficiaries *disproportionately living in places* that provide high-access to white beneficiaries versus (2) the portion of the place component due to Black and white beneficiaries facing *different place effects* in the same place. These two components amount to two distinct counterfactuals: (1) equalizing where Black and white beneficiaries live while allowing place effects to vary by race and (2) equalizing place effects by race while allowing the Black and white populations to be differently distributed across places. Ultimately, we find that the place component is mostly driven by Black and white beneficiaries facing different place effects for a given place, rather than by Black and white beneficiaries living in different places. For (log) utilization, different place effects by race explain 69% of the place component of the national disparity. For colorectal cancer screenings and the number of E&M visits, the shares are 74% and 306%, respectively.[1] These results imply that while

[1]The portion explained by a given component can exceed 100% if the other component pushes in the

traditional place-based policies may not do much to close national disparities, more targeted place-by-race-based policies could potentially make progress.

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 Black beneficiaries moving to a high-access area for *white* beneficiaries (and vice versa). 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 main 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 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

opposite direction of the overall place component national disparity. In the case of E&M visits, the overall place component is negative (equalizing where Black and white beneficiaries live *and* equalizing the Black and white place effects will lower the disparity). While (2), the portion due to Black and white beneficiaries facing different place effects is also negative, (1), the portion due to Black and white beneficiaries living in different places, is positive. Here, this would mean that equalizing the place effects closes the disparity, while shifting the geographic distribution of Black beneficiaries to match the distribution of white beneficiaries would actually cause the disparity to grow.

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 5 describe our empirical approach and results, respectively. Section 6 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, a wedge that may differ by race. 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 modeling y^*_{ijt} as consisting of a place component ψ_j and a person component y^*_i (suppressing t for simplicity):

$$y^*_{i,j} \equiv \underbrace{\psi_j}_{\text{place}} + \underbrace{y^*_i}_{\text{person}} \tag{2}$$

In practice, we compute the place component using causal place effects γ_j, which are estimated relative to some omitted area. Letting $j = 1$ be the omitted place in our estimation, we can define the relative place component as:

$$\gamma_j = \psi_j - \psi_1 \; \forall j \neq 1 \tag{3}$$

where γ_j the relative causal place effect for area j and ψ_j is the true place effect for area j.[2] Note that this implies that we can write individual utilization $y^*_{ij} = \gamma_j + \psi_1 + y^*_i$, and average utilization for individuals of race r in place j at time t as:

$$\bar{y}^r_{j,t} = \gamma_j + \psi_1 + \frac{1}{N^r_j} \sum_{i \in j,r} y^* = \gamma_j + \psi_1 + \bar{y}^{r*}_{j,t}$$

where N^r_j is the number of individuals of race r in area j. 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. For notational simplicity, we define disparity here as the unconditional difference in average utilization between white and Black beneficiaries. However, in Appendix B, we show that the choice of unconditional or conditional disparities has no effect on the decomposition formula that we derive, and in our empirical work we estimate disparities conditional on a variety of health and demographic factors.[3] Formally, we denote the disparity as $\bar{y}^w_t - \bar{y}^b_t$. Using Equation 2, we can write the disparity as:

$$\begin{aligned} \bar{y}^w_t - \bar{y}^b_t &= \sum_{j=1}^{J} (\sigma^w_{j,t} \bar{y}^w_{j,t} - \sigma^b_{j,t} \bar{y}^b_{j,t}) \\ &= (\sigma^w_{1,t} \bar{y}_{1,t} - \sigma^b_{1,t} \bar{y}_{1,t}) + \sum_{j=2}^{J} (\sigma^w_{j,t} (\gamma_j + \psi_1 + \bar{y}^{w*}_{j,t}) - \sigma^b_{j,t} (\gamma_j + \psi_1 + \bar{y}^{b*}_{j,t})) \end{aligned} \tag{4}$$

[2] This setup is motivated by the fact that our procedure for estimating the place effects – a two-way fixed effects specification with movers – recovers *differences* between place effects, not the true place effects themselves.

[3] This more accurately reflects disparities as measured elsewhere in the literature. For example, the Institute of Medicine (2003) defines disparities in health care quality 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).

where $j \in J$ indexes places, σ^r_{jt} is the fraction of the national population of race r in place j at time t, and $\sum_{j=1}^{J} \sigma^r_{j,t} = 1$.[4] 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.

1.2 Decomposition with Homogenous Place Effects

We start with a decomposition where we assume that place effects are homogeneous. Beginning from Equation 4, we have:

$$\begin{aligned}\bar{y}^w_t - \bar{y}^b_t &= (\sigma^w_{1,t}\bar{y}^w_{1,t} - \sigma^b_{1,t}\bar{y}^b_{1,t}) + \sum_{j=2}^{J}(\sigma^w_{j,t}(\gamma_j + \psi_1 + \bar{y}^{w*}_{j,t}) - \sigma^b_{j,t}(\gamma_j + \psi_1 + \bar{y}^{b*}_{j,t})) \\ &= (\sigma^w_{1,t}\bar{y}^w_{1,t} - \sigma^b_{1,t}\bar{y}^b_{1,t}) + \left(\sum_{j=2}^{J}\sigma^w_{j,t}\gamma_j + \psi_1\sum_{j=2}^{J}\sigma^w_{j,t} + \sum_{j=2}^{J}\sigma^w_{j,t}\bar{y}^{w*}_{j,t}\right) - \\ &\left(\sum_{j=2}^{J}\sigma^b_{j,t}\gamma_j + \psi_1\sum_{j=2}^{J}\sigma^b_{j,t} + \sum_{j=2}^{J}\sigma^b_{j,t}\bar{y}^{b*}_{j,t}\right)\end{aligned}$$

Now, note that we can write the omitted place term as follows:

$$\sigma^w_{1,t}\bar{y}_{1,t} - \sigma^b_{1,t}\bar{y}_{1,t} = \sigma^w_{1,t}(\psi_1 + \bar{y}^{w*}_1) - \sigma^b_{1,t}(\psi_1 + \bar{y}^{b*}_1)$$

Distributing the $\sigma^w_{1,t}$ and $\sigma^b_{1,t}$ terms and moving terms into the summations yields:

$$\bar{y}^w_t - \bar{y}^b_t = \left(\sum_{j=2}^{J}\sigma^w_{j,t}\gamma_j + \psi_1\underbrace{\sum_{j=1}^{J}\sigma^w_{j,t}}_{=1} + \sum_{j=1}^{J}\sigma^w_{j,t}\bar{y}^{w*}_{j,t}\right) - \left(\sum_{j=2}^{J}\sigma^b_{j,t}\gamma_j + \psi_1\underbrace{\sum_{j=1}^{J}\sigma^b_{j,t}}_{=1} + \sum_{j=1}^{J}\sigma^b_{j,t}\bar{y}^{b*}_{j,t}\right)$$

Rearranging terms yields the final decomposition:

[4] 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).

$$\bar{y}_t^w - \bar{y}_t^b = \underbrace{\sum_{j=2}^{J} \gamma_j (\sigma_{j,t}^w - \sigma_{j,t}^b)}_{\text{place component}} + \underbrace{\sum_{j=1}^{J} (\sigma_{j,t}^w \bar{y}_j^{w*} - \sigma_{j,t}^b \bar{y}_{j,t}^{b*})}_{\Gamma = \text{person component}} \tag{5}$$

The first 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 second component represents the residual person component, which we denote Γ.

The positive interpretation of this decomposition is straightforward: The place component represents how the national disparity would change if we equalized the white and Black geographic shares, σ_j^w and σ_j^b. Similarly, given that γ_j represents the *relative* place effect of j versus the omitted place, we could also interpret the place component as representing how the national disparity would change if we equalized all of the place effects ($\gamma_j = 0 \forall j$). This decomposition thus clearly speaks to the question of whether *place-based* policies (either policies that attempt to change place effects or policies that encourage migration) 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.

Importantly, however, this decomposition assumes that place effects are uniform across white and Black beneficiaries. The only real policies that can be considered are ones that affect the overall place effects or that move the typical beneficiary in a place ("place-based policies"). This decomposition cannot be used to inform questions about "place-by-race-based policies" such as encouraging migration by one racial group but not the other, targeted access improvements in majority Black neighborhoods (within the 'place'), or efforts to reduce regional racial animus. Put differently, any place-based 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. We thus proceed next by considering heterogeneous place effects by race.

1.3 Place-by-Race Decomposition

In this section, we show how to decompose national disparities into place and person components when place effects are allowed to differ by race. As in the homogeneous place effects case, we model utilization as the sum of a person component and a place component, where the latter can now vary by race:

$$y_{i,j}^* = \psi_j^r + y_i^* \tag{6}$$

We now define race-specific relative place effects $\gamma_j^r = \psi_j^r - \psi_1^r \ \forall j \neq 1$, where place $j = 1$ is

the omitted area in our place effects estimation. Using this definition and the logic outlined in the homogeneous decomposition case, we can express average utilization for individuals of race r in place j at time t as:

$$\bar{y}^r_{j,t} = \gamma^r_j + \psi^r_1 + \bar{y}^{r*}_j \tag{7}$$

Plugging into Equation 4, we have:

$$\begin{aligned}
\bar{y}^w_t - \bar{y}^b_t &= (\sigma^w_{1,t}\bar{y}_{1,t} - \sigma^b_{1,t}\bar{y}_{1,t}) + \sum_{j=2}^{J}(\sigma^w_{j,t}(\gamma^w_j + \psi^w_1 + \bar{y}^{w*}_{j,t}) - \sigma^b_{j,t}(\gamma^b_j + \psi^b_1 + \bar{y}^{b*}_{j,t})) \\
&= (\sigma^w_{1,t}(\psi^w_1 + \bar{y}^{w*}_1) - \sigma^b_{1,t}(\psi^b_1 + \bar{y}^{b*}_1)) + \left(\sum_{j=2}^{J}\sigma^w_{j,t}\gamma^w_j + \psi^w_1\sum_{j=2}^{J}\sigma^w_{j,t} + \sum_{j=2}^{J}\sigma^w_{j,t}\bar{y}^{w*}_{j,t}\right) - \\
&\left(\sum_{j=2}^{J}\sigma^b_{j,t}\gamma^b_j + \psi^b_1\sum_{j=2}^{J}\sigma^b_{j,t} + \sum_{j=2}^{J}\sigma^b_{j,t}\bar{y}^{b*}_{j,t}\right)
\end{aligned}$$

Collecting terms and moving them inside the summations yields the final decomposition:

$$\bar{y}^w_t - \bar{y}^b_t = \underbrace{\left(\sum_{j=2}^{J}(\sigma^w_{j,t}\gamma^w_j - \sigma^b_{j,t}\gamma^b_j)\right)}_{\text{place-by-race component}} + \underbrace{(\psi^w_1 - \psi^b_1)}_{\substack{\text{diff. in omitted} \\ \text{place effects}}} + \underbrace{\sum_{j=1}^{J}(\sigma^w_{j,t}\bar{y}^{w*}_{j,t} - \sigma^b_{j,t}\bar{y}^{b*}_{j,t})}_{\Gamma = \text{ person component}} \tag{8}$$

The heterogeneous decomposition contains three terms. The first is a place-by-race term that captures both differences in where individuals of different races live and differences in relative place effects by race. The second is the difference in the true place effects in the omitted place. In practice, we cannot estimate these place effects, and they are absorbed in the residual person component. The final term is the residual person component.

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 8 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, one for each type of place-by-race-based policy – migration versus the elimination

of differential place effects by race. 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:

$$\bar{y}^w_t - \bar{y}^b_t = \underbrace{\underbrace{\sum_{j=2}^{J} \gamma^w_j(\sigma^w_{j,t} - \sigma^b_{j,t})}_{\text{diff. geo. dist.}} + \underbrace{\sum_{j=2}^{J} \sigma^b_{j,t}(\gamma^w_j - \gamma^b_j)}_{\text{diff. place effects}}}_{\text{place-by-race}} + \underbrace{(\psi^w_1 - \psi^b_1)}_{\substack{\text{diff. in omitted} \\ \text{place effects}}} + \underbrace{\Gamma}_{\text{person}} \tag{9}$$

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 first term) and how much is due to differential place effects (the second 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 encouraging migration or reducing overall geographic variation may have promise for closing disparities. If, however, the place-by-race component arises because of differential place effects, then policies to eliminate differences in place effects by race may be necessary.

The decompositions in Equations 5, 8, and 9 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 8 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 9). 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.[5] 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

[5]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.[6] 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

[6]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:

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

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 10 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 10 and estimate the following:

$$y_{it} = \alpha_i + \gamma_j + \theta_{r(i,t)} + x'_{it}\beta + \tau_t + \varepsilon_{it} \tag{11}$$

All of the components of Equation 11 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.[7]

For the decomposition, we need a set of race-specific place effects for each area. To recover these, we estimate Equation 11 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.

[7] 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.

A natural concern with this estimation approach is that HSA place effects for Black movers will be estimated with considerably more noise than HSA place effects for white movers. 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. We discuss these robustness checks in more detail in Section 5.4.

4 Disparities in Access to Medical Care

Before moving to our causal evidence and decomposition, we estimate racial disparities in access to medical care in our data. We take several different approaches to characterizing disparities. First, we consider *unconditional* disparities in access to medical care, that is, raw differences between Black and white beneficiaries in average access. Next, we consider how these estimates of disparity change as we add controls. To do so, we restrict the sample to Black and white beneficiaries only and estimate regressions of the following form:

$$y_{i,t} = \alpha_0 + \alpha_1 White_i + X'_{i,t}\beta + \varepsilon_{i,t} \tag{12}$$

where $y_{i,t}$ is the outcome of interest, $X'_{i,t}$ is a vector of time-varying characteristics that include 5-year age-sex cells and a set of 28 indicators for various chronic conditions, and $White_i$ is an indicator for a beneficiary being white. Our estimates $\hat{\alpha_1}$ reflect differences in utilization controlling for differences in health and demographics.

In Table 2, we provide estimates of these disparities, reporting the α_1 coefficient from the regression above with successively more controls. Column (1) shows unconditional disparities, showing the α_1 coefficient from a simple regression of the outcome on an indicator for a beneficiary being white. In column (2), we add demographic controls: 5-year age cells, an indicator for beneficiary sex, and all two-way interactions. Finally, in column (3), we add a set of indicators for 28 different chronic conditions.

We start by examining unconditional disparities. When restricting our attention to raw differences in means between white and Black beneficiaries, we find mixed results in terms of the direction and magnitude of disparities. Log utilization, for example, has a negative disparity, indicating that Black beneficiaries receive more care, on average, than white beneficiaries. By contrast, we observe positive disparities in the number of E&M visits and colorectal cancer screenings, suggesting that Black beneficiaries have lower access on these dimensions.

As we add controls, however, the picture becomes clearer. Column (3) shows our esti-

mates of disparities conditional on demographic and health controls. When accounting for differences in individual health needs, the white-Black disparity in access to care is stark: white patients have significantly more overall utilization, more E&M visits, and more regular receipt of colorectal cancer screenings. For patients with comparable levels of health need, white patients have greater access to care across the board.

Finally, we explore the extent of within-race variation in access across HSAs, then examine how correlated that variation is for white and Black beneficiaries. This allows us to examine, for example, the extent to which places with lower average access (conditional on health and demographics) for individuals of one race also have lower average access for another race. These estimates also help provide motivation for our causal place effects estimates below. We start by estimating these cross-sectional "place effects" using regressions of the following form, estimated separately for white and Black beneficiaries who never move:

$$y_{it} = \kappa_j + \tau_t + X'_{it}\beta + \nu_{it} \tag{13}$$

where κ_j is an HSA fixed effect, τ_t is a year fixed effect, and X'_{it} contains the demographic and health controls used to estimate disparities in Equation 12. 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, sex, chronic conditions, and secular trends in utilization. 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.

Figure 1 shows the estimates, with the cross-sectional HSA estimates for white beneficiaries on the y-axis and Black beneficiaries on the x-axis. 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. We also explore these cross-sectional differences for our remaining outcomes and find similar results (Appendix Figure A1).

These results provide useful motivation for our study. Our disparities estimates underscore that disparities are sizable and persistent across several measures of access. The scatter plots make clear that there is not only geographic variation in access to medical care, but also that this variation 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.

5 Results

5.1 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 10 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 11 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 11.

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. The fact that each distribution is centered slightly to the left of zero indicates that our omitted place (the same place for Black and white specifications) is generally in the middle of the distribution of true place effects (ψ_j from Section 1.1).

5.2 Decompositions

With these place effects in hand, we next turn to our decompositions. We begin with a decomposition that assumes place effects are constant across individuals. The results of this decomposition are shown in Table 3. Column (1) shows the national disparity. Conditional on our health and demographic controls, Black beneficiaries have lower utilization, receive fewer

E&M visits, and have fewer colorectal cancer screenings than white beneficiaries. Columns (2) and (3) show our estimates of the person and place components, respectively. Column (4) shows the key object: the percent of the national disparity that is explained by the place component. For log utilization and E&M visits, our estimates of the place component are small and statistically indistinguishable from zero, accounting for approximately 5-10% of the national disparity in these outcomes. We find a larger role for place in the case of colorectal cancer screenings, though the person component of the decomposition still accounts for the majority of the national disparity. 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, and standard place-based policies are unlikely to be successful in closing national disparities.

Next, we relax the assumption that place effects are homogeneous across groups in a given HSA and estimate the decomposition outlined in Equation 9. The results are shown in Table 4. This decomposition returns strikingly different results on the importance of place. When place effects are allowed to vary by race, places play a markedly larger role in driving disparities. For our purposes, the primary result of interest is how the place component in column (4) of Table 4 compares to the place component in column (4) of Table 3. For log utilization, the place component explains more than 25% of the national disparity when place effects are allowed to vary by race, nearly a five-fold increase compared to the homogeneous decomposition in Table 3. Similarly, while the homogeneous place component accounts for slightly less than half of the national disparity in colorectal cancer screenings, the place-by-race component explains more than 100% in Table 4. We find less evidence for E&M visits, where the place-by-race component is small and statistically indistinguishable from zero. For our other outcomes, however, the broader lesson is 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 explore this result further, we use Equation 9 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 4 show the key result. We find that the majority 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. For log utilization, 69% of the place component is driven by differential place effects across areas. These differential place effects explain nearly 18% of the total national disparity in log utilization. For colorectal cancer screenings, the pattern

is even more pronounced: differential place effects account for more than 100% of the place component, and by themselves drive approximately 81% of the national disparity. Across all outcomes, the role of the geographic distribution of individuals is small and generally statistically indistinguishable from zero, while the role of differential place effects is large 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 4 and 5 shows the results. Improving the Black place effects for bottom quartile HSAs has large effects on disparities. The disparity in log utilization declines by 43%, the disparity in E&M visits by 44%, and the disparity in colorectal cancer screenings by 180%. In the last case, the resulting disparity is negative, suggesting that, all else equal, such a place effect reallocation would result in higher utilization of colorectal cancer screenings among Black beneficiaries.

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. 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.

5.3 Importance of Place-by-Race Effects

In the previous section, we established that place-by-race effects are 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 this, 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.

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:

$$y_{it} = \alpha_i + \delta^{vent}_{h(i,t)} + x'_{it}\beta + \tau_t + \theta_{r(i,t)} + \varepsilon_{it} \tag{14}$$

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 bins; 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 quite 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 log utilization considerably. 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 log 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 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 14. Figure 6 shows the results. Consistent with the results of our decomposition in Table 4, 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 areas that deliver higher access for white beneficiaries are not the same areas that deliver higher access for Black beneficiaries.

5.4 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. 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 considerably more, 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 5.3, 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.

6 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.

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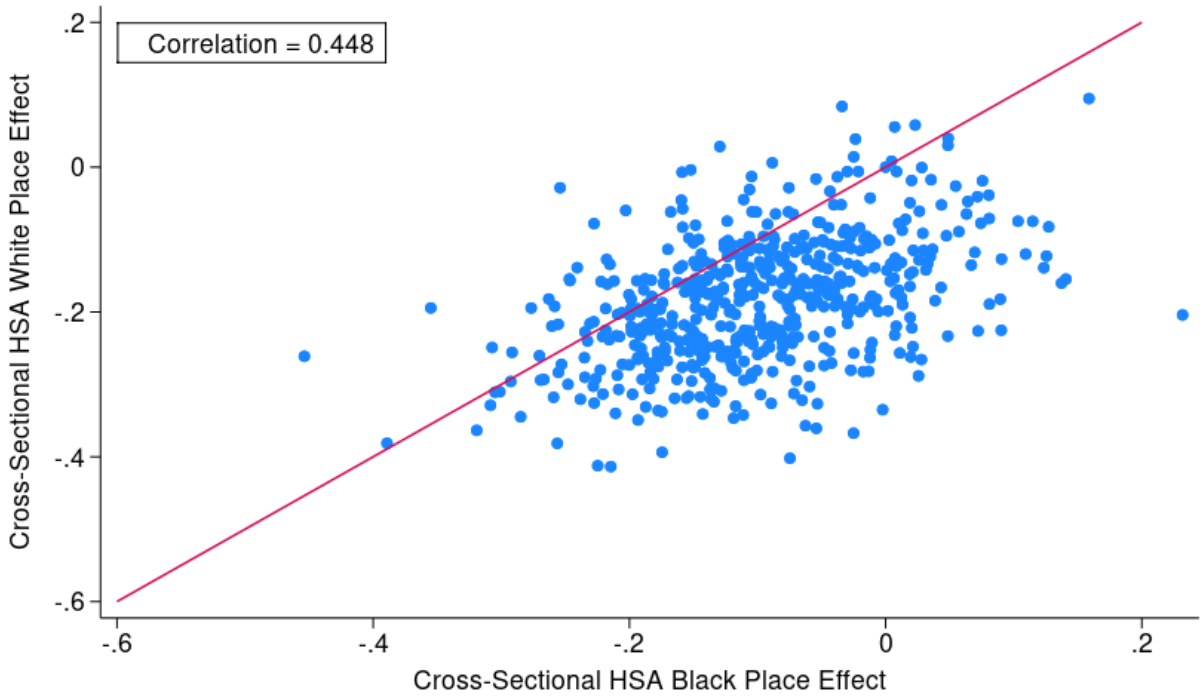
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Figures and Tables

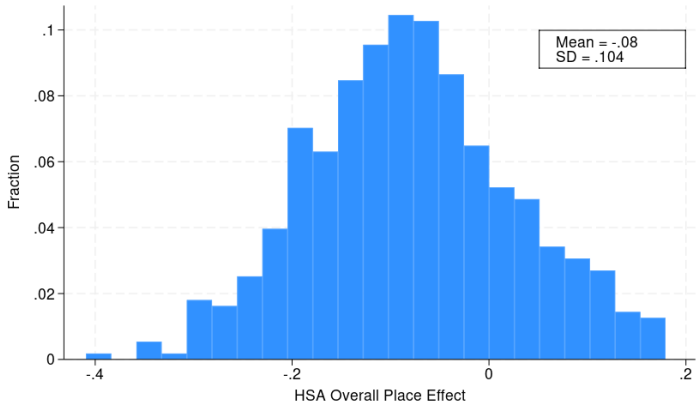
Figure 1. Cross-Sectional HSA "Place Effects" by Race



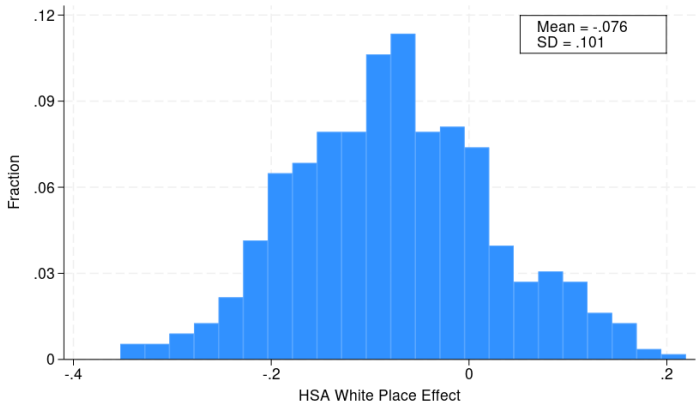
Notes: Figure shows estimates of cross-sectional HSA "place effects" by race. We construct these by estimating Equation 13 on a sample of non-movers.

Figure 2. Distribution of HSA Place Effects, Log Utilization

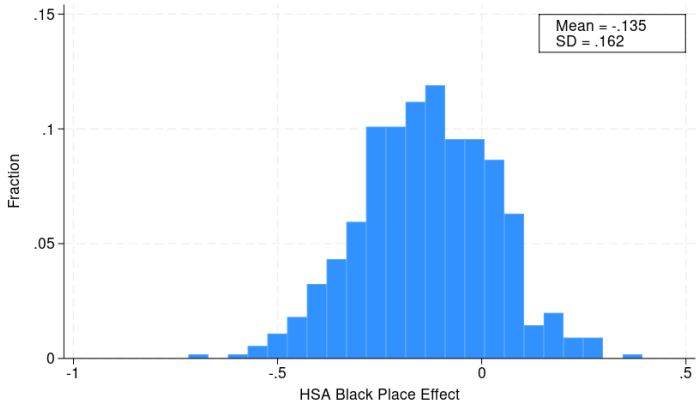
(A) Overall Place Effects



(B) White Place Effects



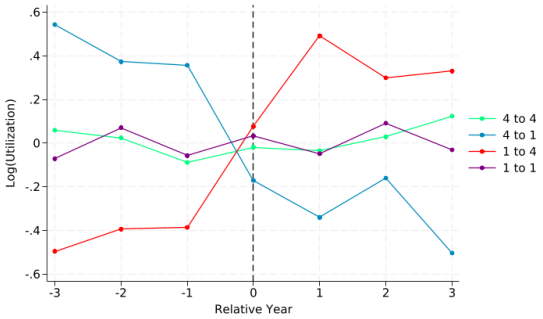
(C) Black Place Effects



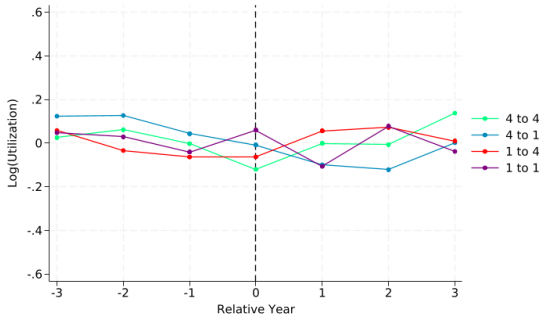
Notes: Figure depicts the distribution of HSA place effects for log utilization, estimated using the specification in Equation 11. Panel A shows the distribution of overall HSA place effects $\hat{\gamma}_j$. Panel B shows the distribution of white HSA place effects $\hat{\gamma}_j^w$. Panel C shows the distribution of Black HSA place effects $\hat{\gamma}_j^b$.

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

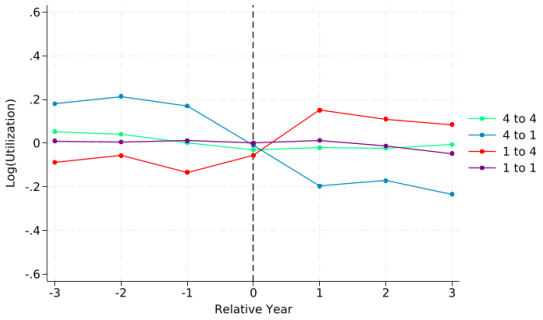
(A) Black Movers, Black Place Effects



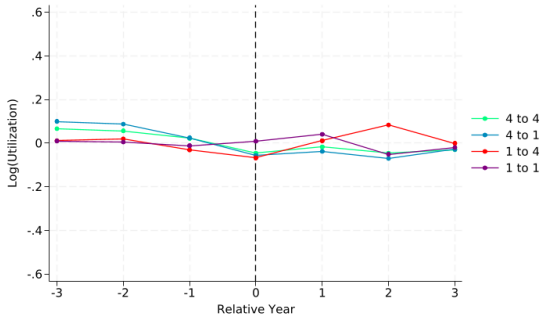
(B) Black Movers, White Place Effects



(C) White Movers, White Place Effects



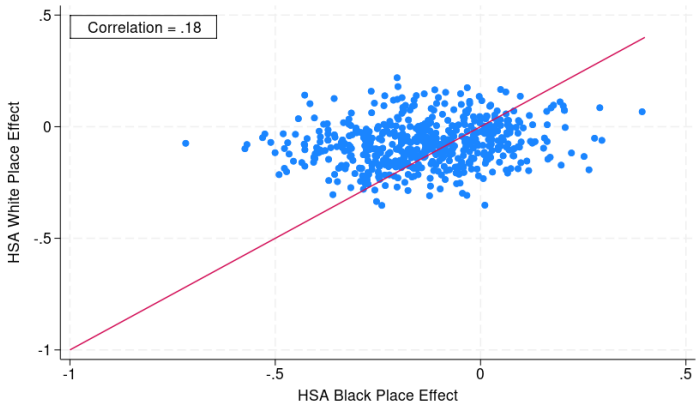
(D) White Movers, Black Place Effects



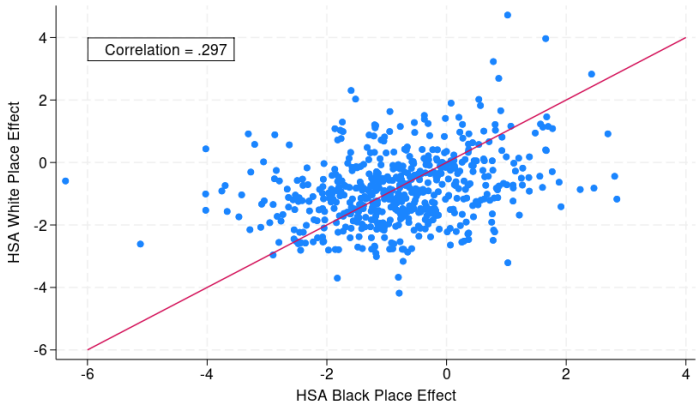
Notes: Figures show average log utilization by year relative to moving for different types of moves. Panel A shows averages for Black HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Panel B shows averages for Black HSA movers whose moves are classified by 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

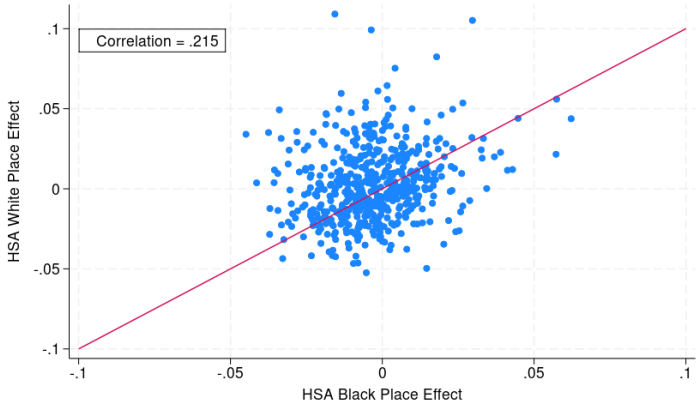
(A) Log Utilization



(B) Number of E&M Visits



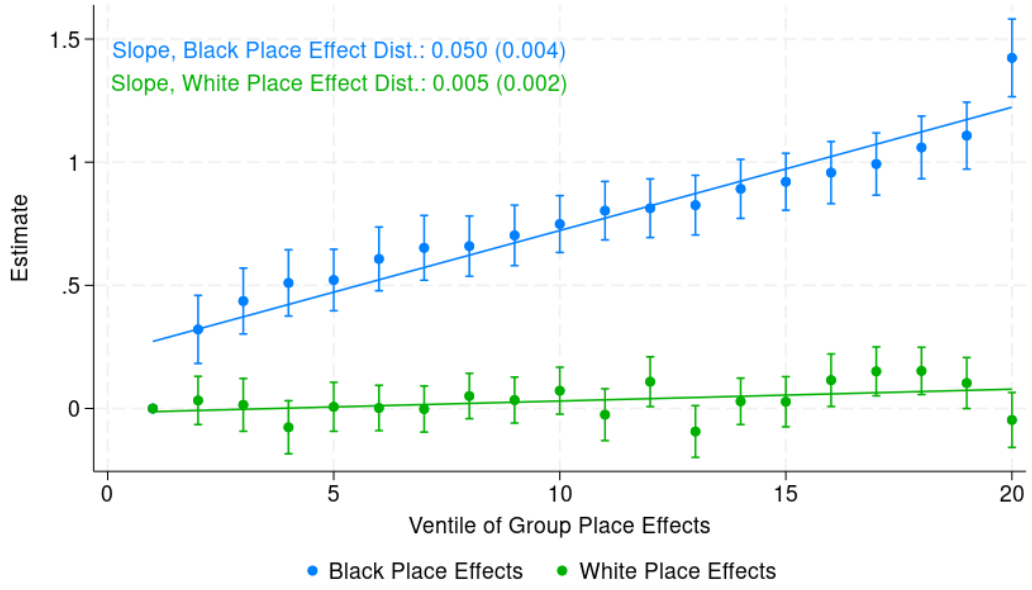
(C) Colorectal Cancer Screening



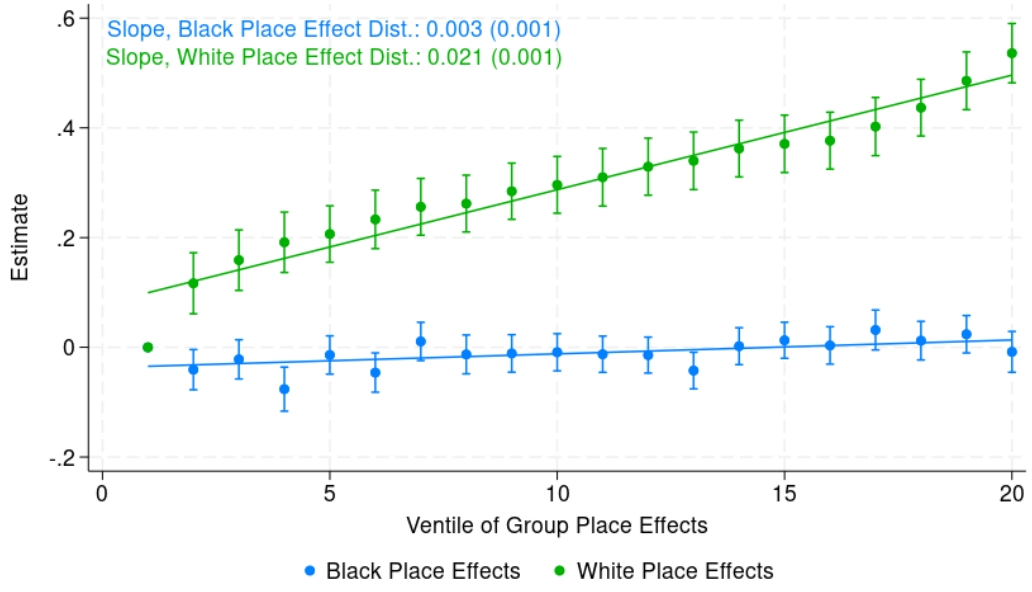
Notes: Scatter plots show the relationship between estimated HSA white place effects ($\hat{\gamma}_j^w$) and estimated HSA Black place effects ($\hat{\gamma}_j^b$). Panel A shows place effects on log utilization, Panel B on number of evaluation and management visits, and Panel C on receipt of colorectal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

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

(A) Black HSA Movers

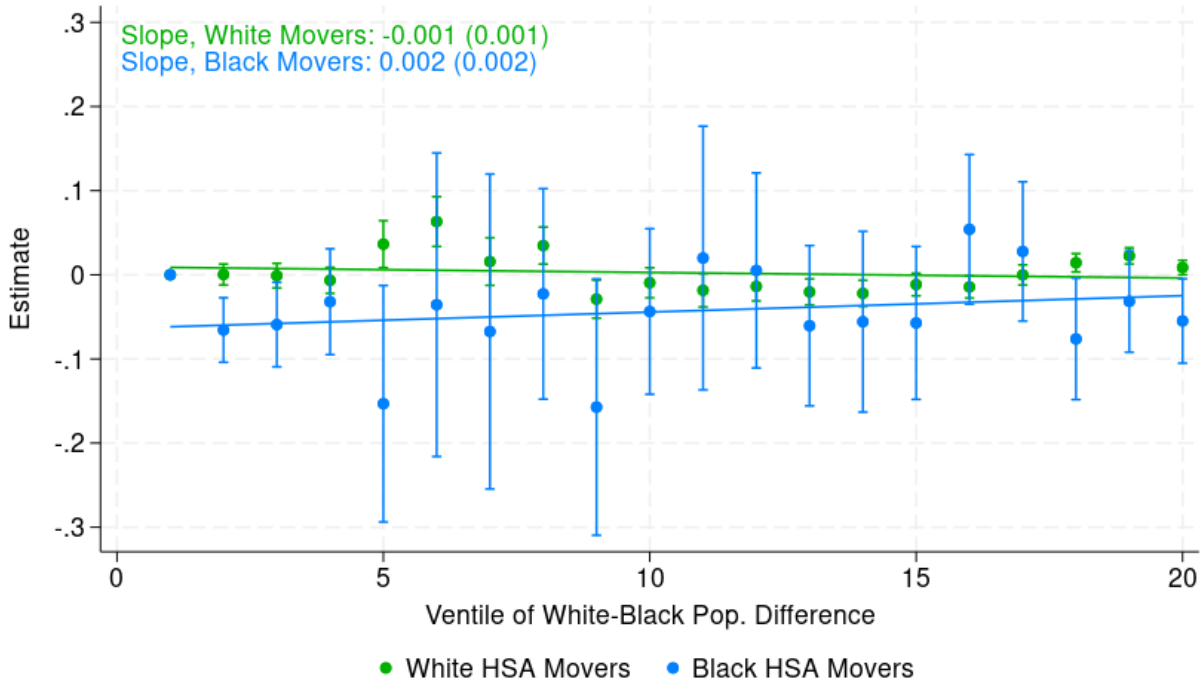


(B) White HSA Movers



Notes: Figures show estimates of Equation 14 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 14 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. Estimated White-Black Disparities in Access to Care

	(1)	(2)	(3)
Log Utilization			
White-Black Disparity	–0.013***	–0.041***	0.166***
SE	(0.002)	(0.002)	(0.001)
R^2	0.000	0.018	0.447
Num. E&M Visits			
White-Black Disparity	0.604***	0.513***	1.065***
SE	(0.009)	(0.009)	(0.007)
R^2	0.000	0.013	0.293
Colorectal Cancer Screening			
White-Black Disparity	0.010***	0.011***	0.011***
SE	(0.000)	(0.000)	(0.000)
R^2	0.000	0.002	0.010
Demographic Controls		✓	✓
Demographic + Health Controls			✓
N	47,309,197	47,309,197	47,309,197

Notes: Table shows estimated disparities (white - Black) in access to medical care for three outcomes: log utilization, number of evaluation and management visits, and colorectal cancer screening. Column (1) shows the unconditional disparity. Column (2) shows the estimated disparity controlling for demographics (five-year age cells, sex, and all two way interactions between the two). Column (3) shows the estimated disparity controlling for demographics and health (28 indicators for various chronic conditions).

Table 3. HSA Decomposition, Homogenous Place Effects, 2018

	National Disparity (1)	Person Component (2)	Place Component (3)	% Natl. Disparity (4)
Log Utilization	0.168	0.158	0.010	5.77
SE		(0.007)	(0.007)	
Num. E&M Visits	1.371	1.220	0.151	11.04
SE		(0.094)	(0.094)	
Colorectal Cancer Screen	0.006	0.003	0.003	45.64
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 Column (2) shows the person component of the decomposition. Columns (3) and (4) show the place component and the percent of the national disparity explained by the place component, respectively. 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, Heterogenous Place Effects, 2018

					Decompose Place Component			
	National Disparity	Person Disparity	Place Component	% Natl. Disparity	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Utilization	0.168	0.124	0.044	26.05	0.030	17.91	0.014	8.14
SE		(0.012)	(0.012)		(0.010)		(0.008)	
Num. E&M Visits	1.371	1.456	-0.085	-6.21	-0.261	-19.03	0.176	12.82
SE		(0.086)	(0.086)		(0.076)		(0.098)	
Colorectal Cancer Screen	0.006	-0.001	0.007	109.45	0.005	81.09	0.002	28.36
SE		(0.002)	(0.002)		(0.001)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 9. Column (1) shows the national white-Black disparity in the outcome, and column (2) shows the person component of the decomposition. Columns (3) and (4) show the place component and the percent of the national disparity explained by the place component. Columns (5)-(8) show the portion of the national disparity 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 5. HSA Decomposition, Reallocation Exercise, 2018

					Decompose Place Component			
	National Disparity	Person Disparity	Place Component	% Natl. Disparity	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Utilization	0.096	0.124	-0.029	-29.88	-0.042	-44.17	0.014	14.29
SE	(0.010)		(0.010)		(0.009)		(0.007)	
Num. E&M Visits	0.772	1.456	-0.685	-88.72	-0.860	-111.50	0.176	22.78
SE	(0.100)		(0.100)		(0.096)		(0.095)	
Colorectal Cancer Screen	-0.005	-0.001	-0.004	88.45	-0.006	123.10	0.002	-34.65
SE	(0.002)		(0.002)		(0.002)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 9. For each HSA, we replace the Black place effect with the average Black place effect of top quartile HSAs. Column (1) shows the national white-Black disparity in the outcome, and column (2) shows the person component of the decomposition. Columns (3) and (4) show the place component and the percent of the national disparity explained by the place component. Columns (5)-(8) show the portion of the national disparity 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

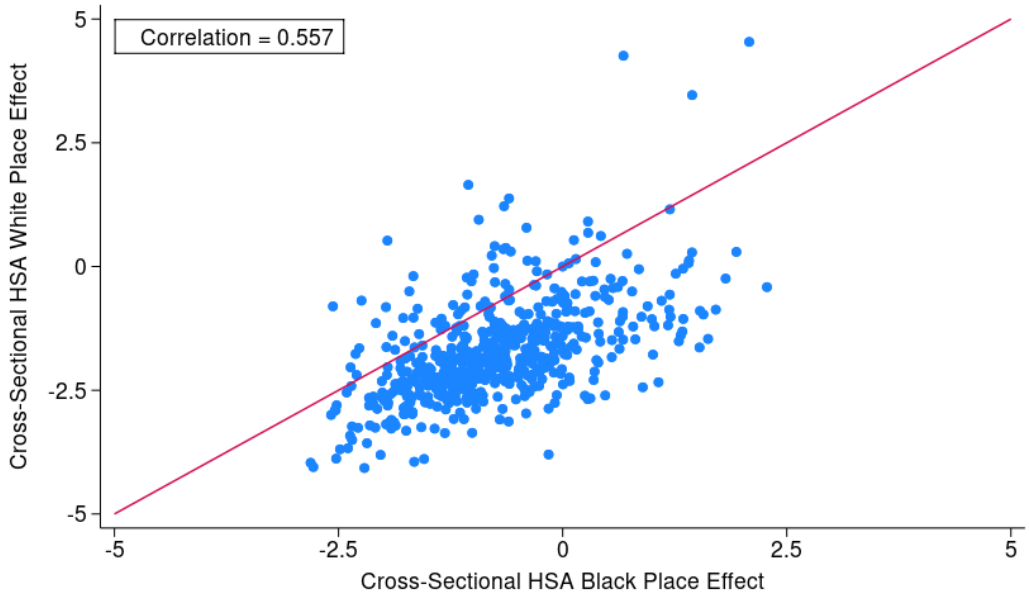
Layton and Peterson

May 8, 2025

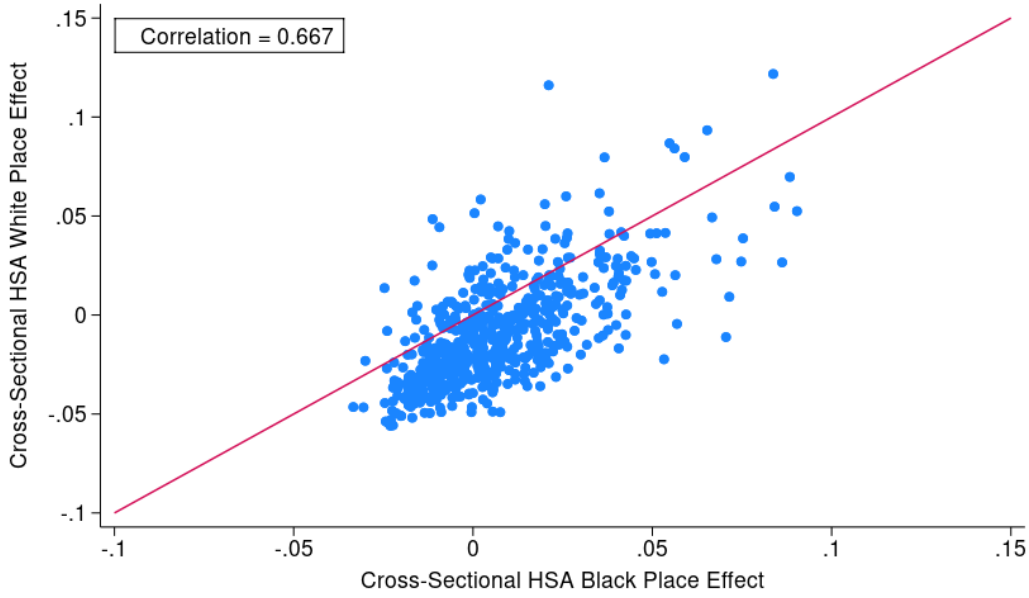
A Appendix Figures and Tables

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

(A) Number of E&M Visits



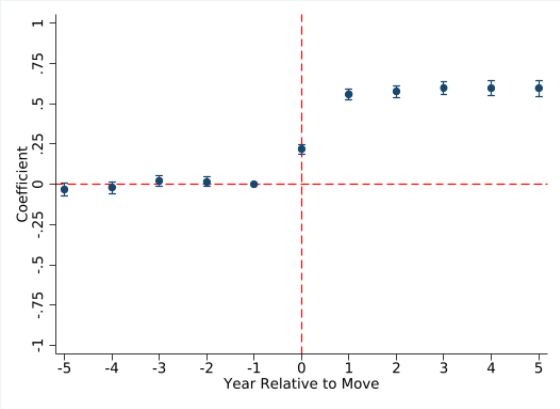
(B) Colorectal Cancer Screening



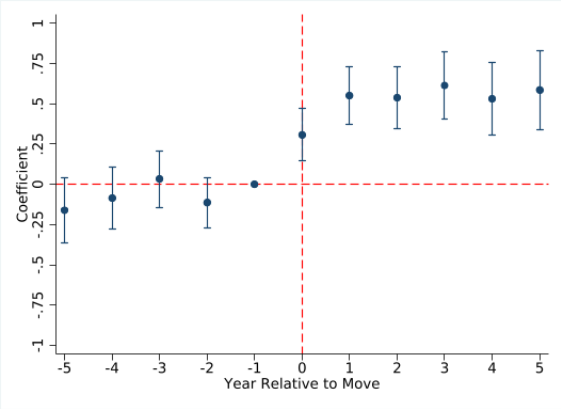
Notes: Figures show estimates of Equation 13 using a sample of non-movers and the number of evaluation and management visits (Panel A) and receipt of any colorectal cancer screening (Panel B) as the outcomes.

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

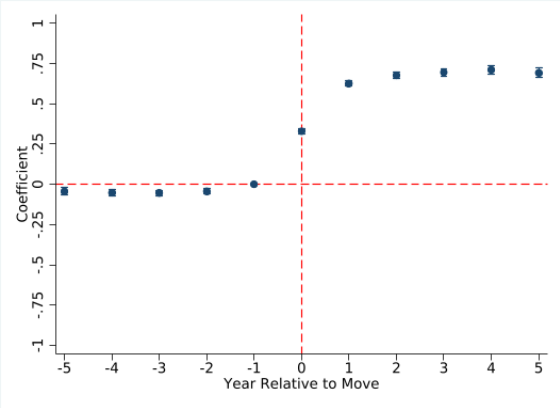
(A) Log Utilization, White Movers



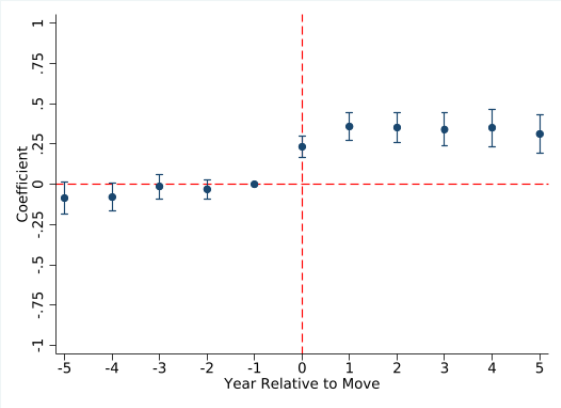
(B) Log Utilization, Black Movers



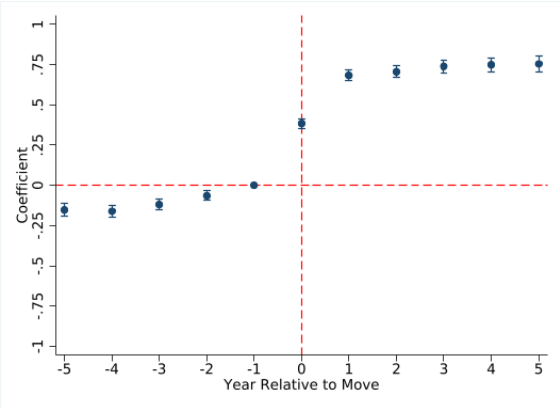
(C) Num. E&M Visits, White Movers



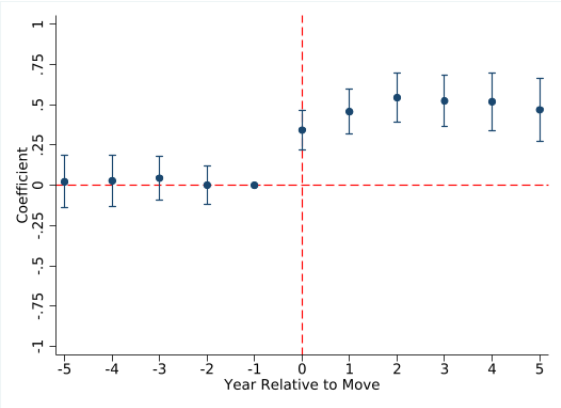
(D) Num. E&M Visits, Black Movers



(E) Colorectal Cancer Screening, White Movers



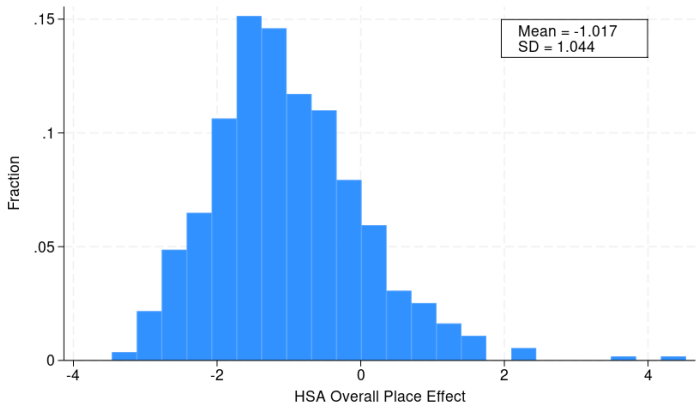
(F) Colorectal Cancer Screening, Black Movers



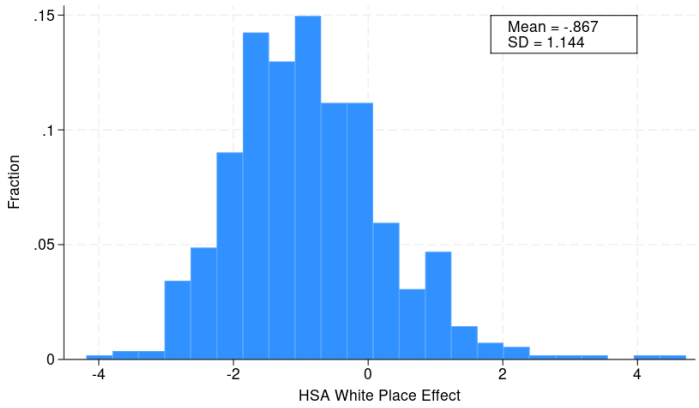
Notes: Figures plot the $\hat{\theta}_{r(i,t)}$ coefficients from Equation 10, estimated separately for white and Black HSA movers. Panels (A) and (B) use log utilization as the outcome. Panels (C) and (D) use number of evaluation and management visits as the outcome. Panels (E) and (F) use receipt of colorectal cancer screening as the outcome.

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

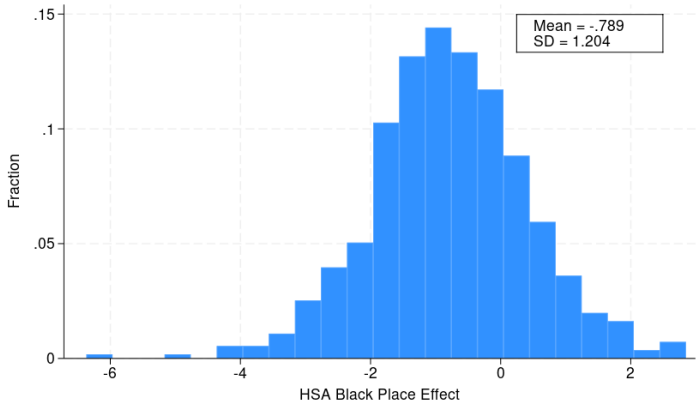
(A) Overall Place Effects



(B) White Place Effects



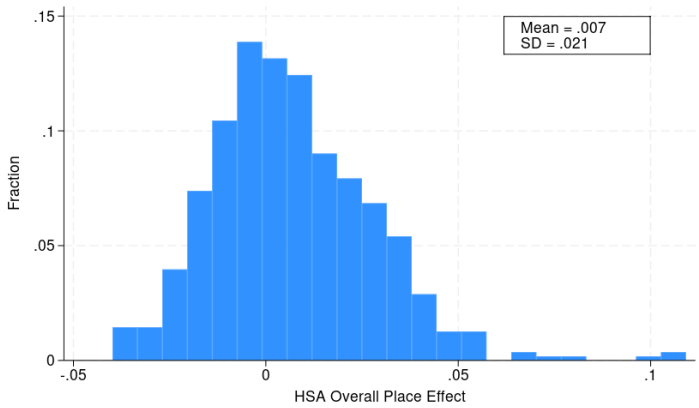
(C) Black Place Effects



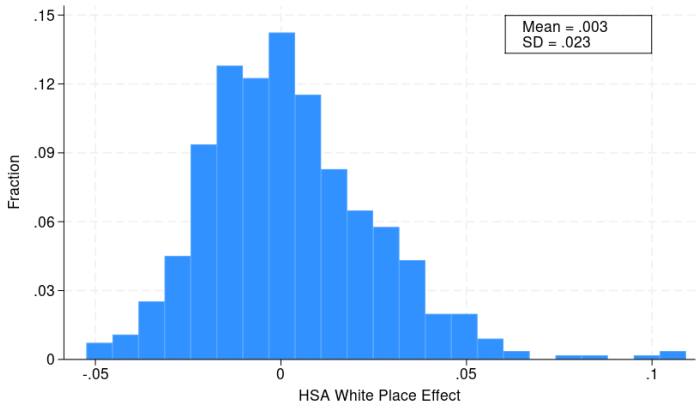
Notes: Figure depicts the distribution of HSA place effects for number of E&M visits, estimated using the specification in Equation 11. Panel A shows the distribution of overall HSA place effects $\hat{\gamma}_j$. Panel B shows the distribution of white HSA place effects $\hat{\gamma}_j^w$. Panel C shows the distribution of Black HSA place effects $\hat{\gamma}_j^b$.

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

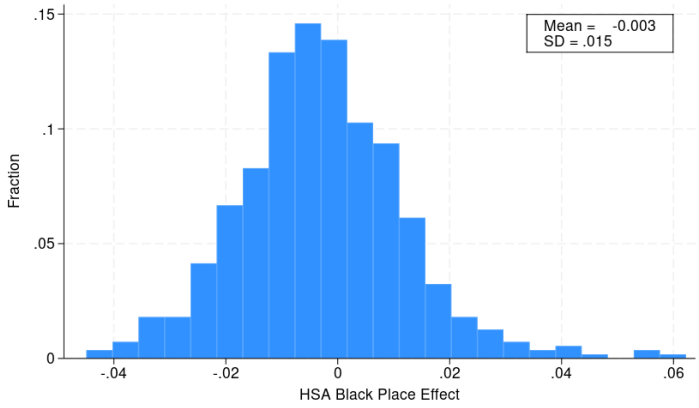
(A) Overall Place Effects



(B) White Place Effects



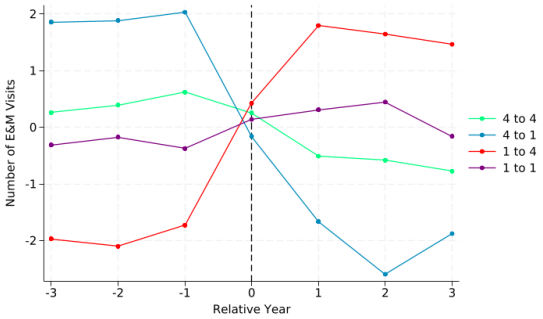
(C) Black Place Effects



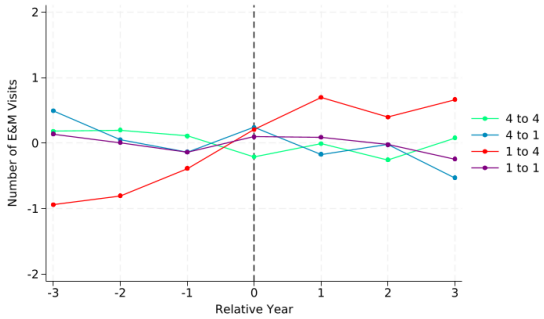
Notes: Figure depicts the distribution of HSA place effects for receipt of a colorectal cancer screening, estimated using the specification in Equation 11. Panel A shows the distribution of overall HSA place effects $\hat{\gamma}_j$. Panel B shows the distribution of white HSA place effects $\hat{\gamma}_j^w$. 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

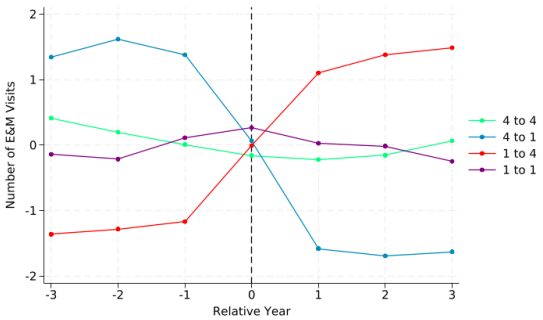
(A) Black Movers, Black Place Effects



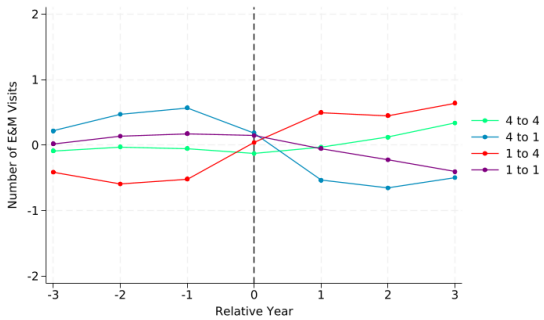
(B) Black Movers, White Place Effects



(C) White Movers, White Place Effects



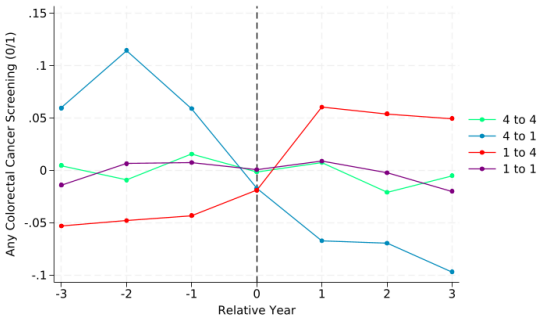
(D) White Movers, Black Place Effects



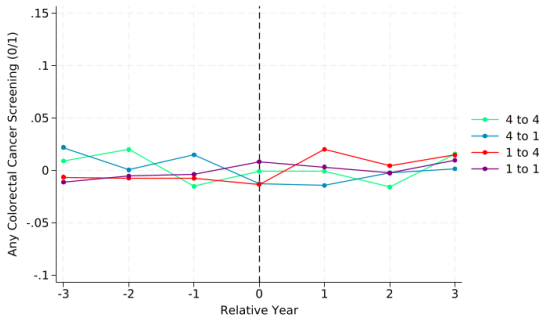
Notes: Figures show average number of E&M vists by year relative to moving for different types of moves. Panel A shows averages for Black HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Panel B shows averages for Black HSA movers whose moves are classified 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

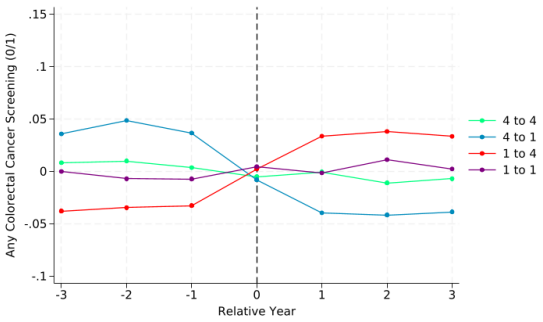
(A) Black Movers, Black Place Effects



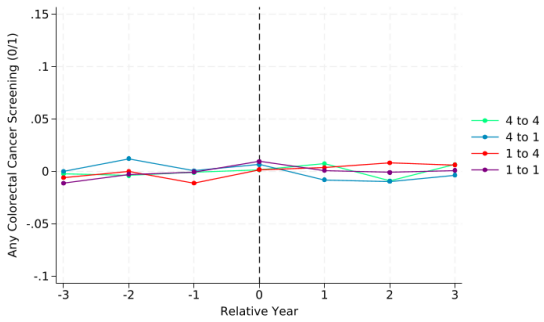
(B) Black Movers, White Place Effects



(C) White Movers, White Place Effects



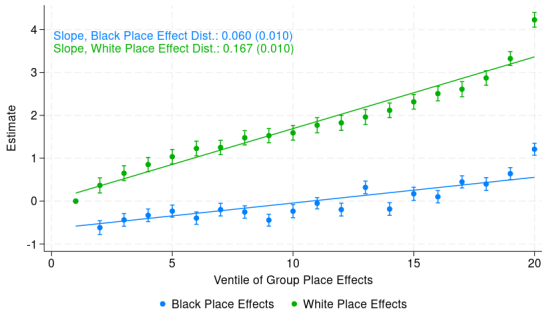
(D) White Movers, Black Place Effects



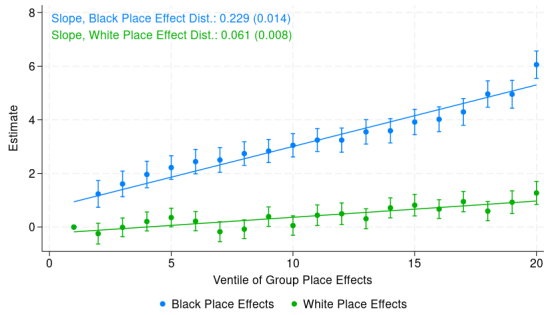
Notes: Figures show probability of receiving a colorectal cancer screening by year relative to moving for different types of moves. Panel A shows averages for Black HSA movers whose moves are classified by the origin-destination Black place effects quartiles. Panel B shows averages for Black HSA movers 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

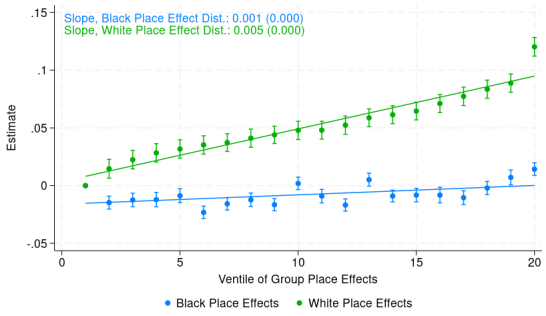
(A) Num. E&M Visits, White Movers



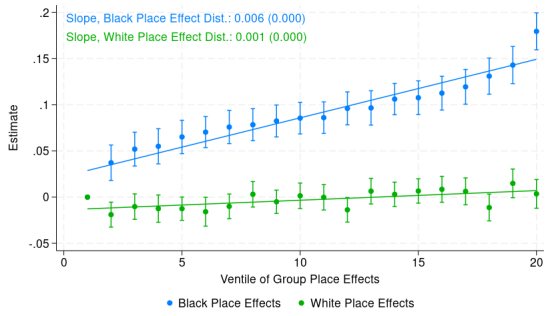
(B) Num. E&M Visits, Black Movers



(C) Colorectal Cancer Screening, White Movers



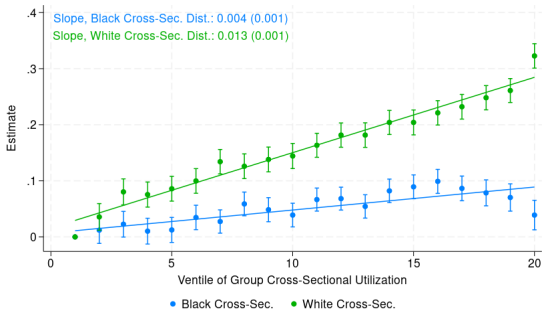
(D) Colorectal Cancer Screening, Black Movers



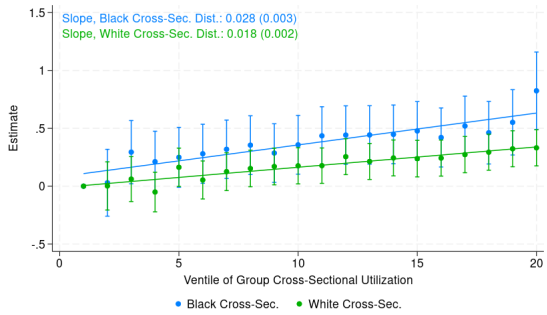
Notes: Figures plot the $\hat{\delta}^{vent}_{h(i,t)}$ coefficients from Equation 14, estimated separately for white and Black HSA movers. Panels (A) and (B) use number of evaluation and management visits as the outcome. Panels (C) and (D) use receipt of colorectal cancer screening as the outcome.

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

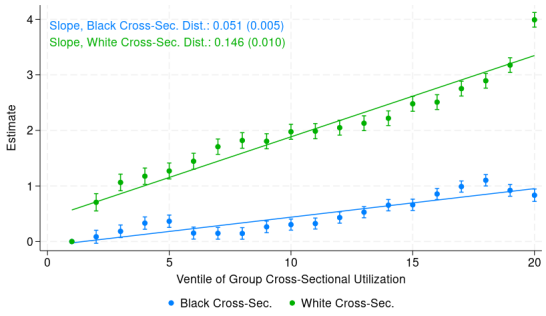
(A) Log Utilization, White Movers



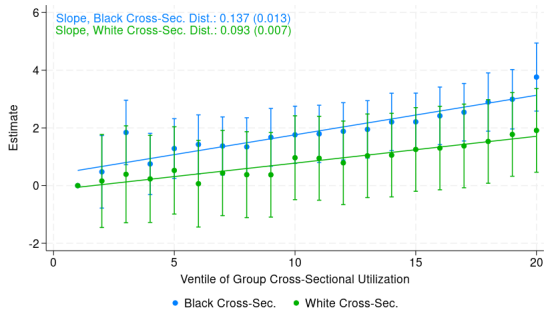
(B) Log Utilization, Black Movers



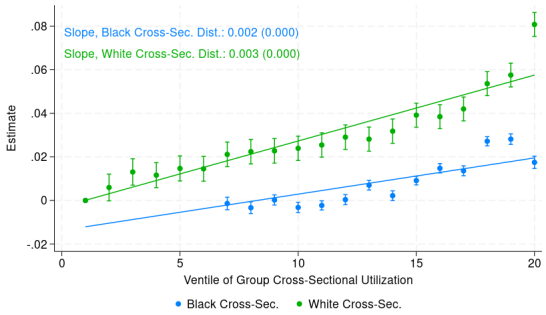
(C) Num. E&M Visits, White Movers



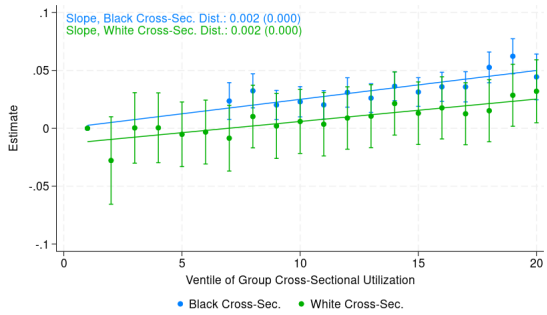
(D) Num. E&M Visits, Black Movers



(E) Colorectal Cancer Screening, White Movers



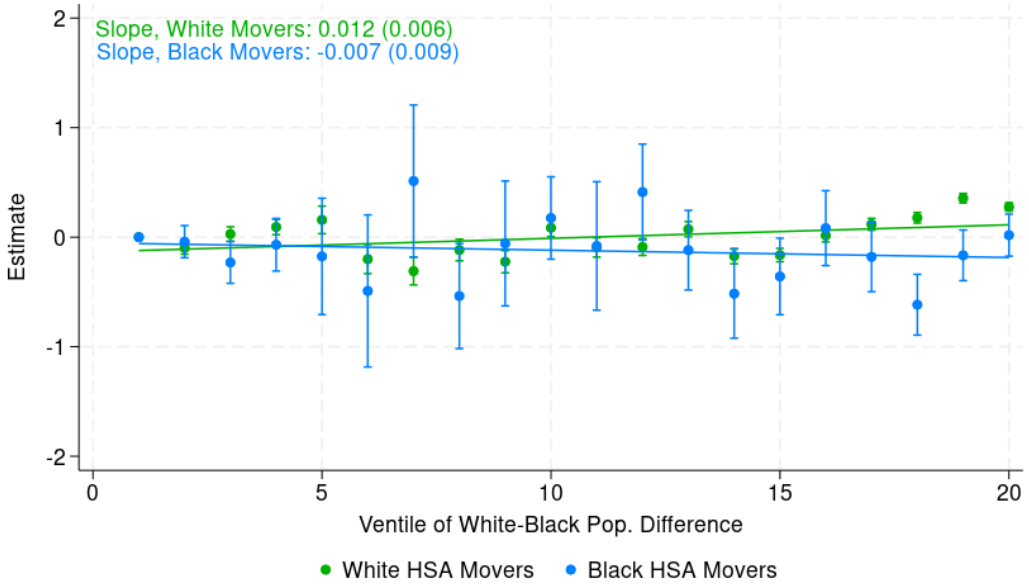
(F) Colorectal Cancer Screening, Black Movers



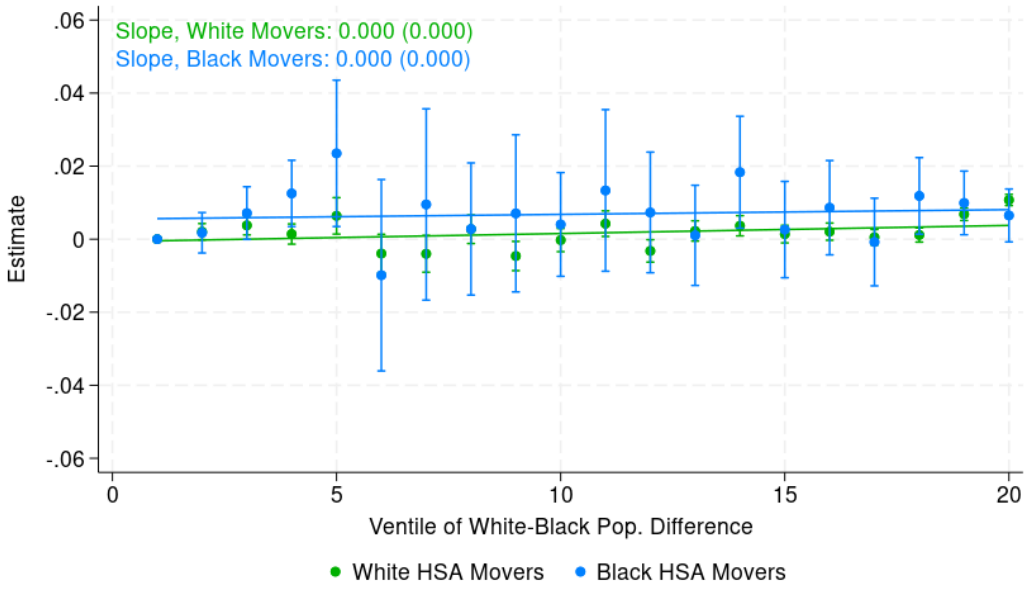
Notes: Figures plot the $\hat{\delta}^{vent}_{h(i,t)}$ coefficients from Equation 14, estimated separately for white and Black HSA movers and using ventiles based on the cross-sectional distribution of utilization. Panels (A) and (B) use log utilization as the outcome. Panels (C) and (D) use number of 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 14 and using ventiles based on the differential white-Black population share. Each point estimate reflects the causal effect of moving up the distribution of differential white-Black population share.

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)	Person Component (2)	Place Component (3)	% Natl. Disparity (4)
Log Utilization	0.169	0.172	-0.004	-2.10
SE		(0.013)	(0.013)	
Num. E&M Visits	1.201	1.227	-0.027	-2.23
SE		(0.178)	(0.178)	
Colorectal Cancer Screen	0.005	0.005	-0.000	-2.75
SE		(0.003)	(0.003)	

Notes: Table shows estimates of the decomposition outlined in Equation 5. Column (1) shows the national white-Black disparity in the outcome Column (2) shows the person component of the decomposition. Columns (3) and (4) show the place component and the percent of the national disparity explained by the place component, respectively. 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	Person Disparity	Place Component	% Natl. Disparity	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Utilization	0.169	0.091	0.077	45.90	0.080	47.55	-0.003	-1.65
SE		(0.018)	(0.018)		(0.010)		(0.012)	
Num. E&M Visits	1.201	1.851	-0.650	-54.16	-0.624	-52.00	-0.026	-2.15
SE		(0.141)	(0.141)		(0.093)		(0.177)	
Colorectal Cancer Screen	0.005	0.012	-0.007	-150.28	-0.007	-138.98	-0.001	-11.30
SE		(0.002)	(0.002)		(0.002)		(0.002)	

Notes: Table shows estimates of the decomposition outlined in Equation 9. Column (1) shows the national white-Black disparity in the outcome, and column (2) shows the person component of the decomposition. Columns (3) and (4) show the place component and the percent of the national disparity explained by the place component. Columns (5)-(8) show the portion of the national disparity 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)	Person Component (2)	Place Component (3)	% Natl. Disparity (4)
Log Utilization	0.178	0.168	0.010	5.60
SE		(0.006)	(0.006)	
Num. E&M Visits	1.249	1.301	-0.053	-4.22
SE		(0.086)	(0.086)	
Colorectal Cancer Screen	0.005	0.004	0.001	17.89
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 Column (2) shows the person component of the decomposition. Columns (3) and (4) show the place component and the percent of the national disparity explained by the place component, respectively. 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	Person Disparity	Place Component	% Natl. Disparity	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Utilization	0.178	0.481	-0.304	-170.93	-0.312	-175.70	0.008	4.76
SE		(0.019)	(0.019)		(0.017)		(0.005)	
Num. E&M Visits	1.249	2.949	-1.701	-136.18	-1.654	-132.48	-0.046	-3.70
SE		(0.142)	(0.142)		(0.089)		(0.078)	
Colorectal Cancer Screen	0.005	0.012	-0.007	-140.83	-0.007	-147.35	0.000	6.53
SE		(0.001)	(0.001)		(0.001)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 9. Column (1) shows the national white-Black disparity in the outcome, and column (2) shows the person component of the decomposition. Columns (3) and (4) show the place component and the percent of the national disparity explained by the place component. Columns (5)-(8) show the portion of the national disparity 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	Person Disparity	Place Component	% Natl. Disparity	Diff. PEs	%	Diff. Geo.	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Utilization	0.168	0.254	-0.086	-51.07	-0.091	-54.44	0.006	3.38
SE		(0.014)	(0.014)		(0.014)		(0.014)	
Num. E&M Visits	1.373	1.369	0.004	0.32	-0.061	-4.44	0.065	4.76
SE		(0.106)	(0.106)		(0.088)		(0.103)	
Colorectal Cancer Screen	0.006	-0.009	0.015	255.08	0.016	258.75	-0.000	-3.67
SE		(0.002)	(0.002)		(0.002)		(0.001)	

Notes: Table shows estimates of the decomposition outlined in Equation 9 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.

B Additional Decomposition Derivations

Here, we derive additional results related to our decompositions.

B.1 Decomposition with Conditional Disparities

To adapt the conceptual framework to accommodate conditional disparities, we rederive the main decomposition equation allowing the person-level components of the decomposition to depend on individual characteristics $X_{i,t}$.

B.1.1 Homogeneous Place Effects

We start with the homogeneous place effects case. As in Section 1, we model utilization as:

$$y_{i,j} = \psi_j + y_i^* \ \forall j$$

Let $\gamma_j = \psi_j - \psi_1 \implies \psi_j = \gamma_j + \psi_1$, where $j = 1$ is the omitted place in our estimation. Note that this implies that we can write:

$$y_{i,j} = \gamma_j + \psi_1 + y_i^* \tag{15}$$

We can write the conditional white-Black disparity as:

$$\delta_t = \mathbb{E}[y_{i,t} \mid r = w, X_{i,t}] - \mathbb{E}[y_{i,t} \mid r = b, X_{i,t}]$$

Plugging in, we have

$$\begin{aligned}
\delta_t &= \sum_{j=1}^{J} (\sigma_{j,t}^w \bar{y}_{j,t}^w - \sigma_{j,t}^b \bar{y}_{j,t}^b) \\
&= (\sigma_{j,t}^w \bar{y}_{1,t}^w - \sigma_{j,t}^b \bar{y}_{1,t}^b) + \sum_{j=2}^{J} (\sigma_{j,t}^w \bar{y}_{j,t}^w - \sigma_{j,t}^b \bar{y}_{j,t}^b) \\
&= (\sigma_{j,t}^w \bar{y}_{1,t}^w - \sigma_{j,t}^b \bar{y}_{1,t}^b) + \sum_{j=2}^{J} \left(\sigma_{j,t}^w (\gamma_j + \psi_1 + \mathbb{E}[y_i^* \mid r = w, X_{i,t}]) - \sigma_{j,t}^b (\gamma_j + \psi_1 + \mathbb{E}[y_i^* \mid r = b, X_{i,t}])\right)
\end{aligned} \tag{16}$$

By Equation 15, we can write the first term as:

$$\sigma_{j,t}^w \bar{y}_{1,t}^w - \sigma_{j,t}^b \bar{y}_{1,t}^b = \sigma_{j,t}^w (\psi_1 + \mathbb{E}[y_i^* \mid r = w, X_{i,t}]) - \sigma_{j,t}^b (\psi_1 + \mathbb{E}[y_i^* \mid r = b, X_{i,t}])$$

Distributing the $\sigma_{j,t}^r$ terms in the first term and moving everything into the summations yields the following:

$$\delta_t = \left(\sum_{j=2}^{J} \sigma_{j,t}^{w} \gamma_j + \psi_1 \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^{w}}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^{w} \mathbb{E}[y_i^* \mid r = w, X_{i,t}] \right) - \left(\sum_{j=2}^{J} \sigma_{j,t}^{b} \gamma_j + \psi_1 \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^{w}}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^{b} \mathbb{E}[y_i^* \mid r = b, X_{i,t}] \right)$$

$$= \underbrace{\sum_{j=2}^{J} \gamma_j (\sigma_{j,t}^{w} - \sigma_{j,t}^{b})}_{\text{place component}} + \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^{w} \mathbb{E}[y_i^* \mid r = w, X_{i,t}] - \sigma_{j,t}^{b} \mathbb{E}[y_i^* \mid r = b, X_{i,t}]}_{\text{person component}} \tag{17}$$

Intuitively, because the place component is invariant to individual characteristics (i.e., is indexed by j, not i), estimating the decomposition for conditional disparities only influences the (residual) conditional person component. There is no effect on the estimated place component and no effect on the fraction of the overall disparity explained by place.

B.1.2 Heterogeneous Place Effects

It is straightforward to show that this generalizes to the case where place effects can vary with individuals' race. We now model utilization as:

$$y_{i,j} = \psi_j^r + y_i^* \ \forall j$$

Let $\gamma_j^r = \psi_j^r - \psi_1^r \implies \psi_j^r = \gamma_j^r + \psi_1^r$, where $j = 1$ is the omitted place in our estimation. Note that this implies that we can write:

$$y_{i,j} = \gamma_j^r + \psi_1^r + y_i^* \tag{18}$$

Amending Equation 16 to allow for heterogeneous place effects in this framework yields:

$$\delta_t = (\sigma_{j,t}^{w} \bar{y}_{1,t}^{w} - \sigma_{j,t}^{b} \bar{y}_{1,t}^{b}) + \sum_{j=2}^{J} \left(\sigma_{j,t}^{w} (\gamma_j^w + \psi_1 + \mathbb{E}[y_i^* \mid r = w, X_{i,t}]) - \sigma_{j,t}^{b} (\gamma_j^b + \psi_1 + \mathbb{E}[y_i^* \mid r = b, X_{i,t}]) \right)$$

By Equation 18, we can write the first term as:

$$\sigma_{j,t}^{w} \bar{y}_{1,t}^{w} - \sigma_{j,t}^{b} \bar{y}_{1,t}^{b} = \sigma_{j,t}^{w} (\psi_1^w + \mathbb{E}[y_i^* \mid r = w, X_{i,t}]) - \sigma_{j,t}^{b} (\psi_1^w + \mathbb{E}[y_i^* \mid r = b, X_{i,t}])$$

Distributing the $\sigma_{j,t}^r$ terms in the first term and moving everything into the summations yields the following:

$$\delta_t = \left(\sum_{j=2}^{J} \sigma_{j,t}^{w} \gamma_j^{w} + \psi_1^{w} \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^{w}}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^{w} \mathbb{E}[y_i^* \mid r = w, X_{i,t}] \right) - \left(\sum_{j=2}^{J} \sigma_{j,t}^{b} \gamma_j^{b} + \psi_1^{b} \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^{w}}_{=1} + \sum_{j=1}^{J} \sigma_{j,t}^{b} \mathbb{E}[y_i^* \mid r = b, X_{i,t}] \right)$$

$$= \underbrace{\sum_{j=2}^{J} (\gamma_j^{w} \sigma_{j,t}^{w} - \gamma_j^{b} \sigma_{j,t}^{b})}_{\text{place component}} + \underbrace{(\psi_1^{w} - \psi_1^{b})}_{\substack{\text{diff. in omitted} \\ \text{place effects}}} + \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^{w} \mathbb{E}[y_i^* \mid r = w, X_{i,t}] - \sigma_{j,t}^{b} \mathbb{E}[y_i^* \mid r = b, X_{i,t}]}_{\text{person component}} \tag{19}$$

As above, adding and subtracting $\sigma_{j,t}^{b} \gamma_j^{w}$ yields the heterogeneous decomposition equation:

$$\delta_t = \underbrace{\underbrace{\sum_{j=2}^{J} \gamma_j^{w} (\sigma_{j,t}^{w} - \sigma_{j,t}^{b})}_{\text{diff. geo. dist.}} + \underbrace{\sum_{j=2}^{J} \sigma_{j,t}^{b} (\gamma_j^{w} - \gamma_j^{b})}_{\text{diff. place effects}}}_{\text{place component}} + \underbrace{(\psi_1^{w} - \psi_1^{b})}_{\substack{\text{diff. in omitted} \\ \text{place effects}}} + \underbrace{\sum_{j=1}^{J} \sigma_{j,t}^{w} \mathbb{E}[y_i^* \mid r = w, X_{i,t}] - \sigma_{j,t}^{b} \mathbb{E}[y_i^* \mid r = b, X_{i,t}]}_{\text{person component}}$$