The Geography of Health Disparities

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April 3, 2024

Roadmap

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Conceptual Framework

Empirical Strategy

Do Places Matter?

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The Importance of Place**-by-Race** Effects

Conclusion

Racial disparities in US health care

There are large racial disparities in access to medical care in the US. These are complex, far-reaching, and stem from myriad interpersonal and structural sources:

- Institutionally sanctioned racism and resulting mistrust (Alsan & Wanamaker, 2018; Alsan et al., 2019; Washington, 2006)
- *De jure* and *de facto* discrimination (Almond et al., 2006; Chay and Greenstone, 2000)
- Economic circumstance (Williams & Jackson, 2005)
- Biases in both human and algorithmic treatment choices (Obermeyer et al., 2019; Hoffman et al., 2016; Pierson et al., 2022)
- Geography (Baicker et al., 2004; Chandra et al., 2020)
- Countless others (Williams & Jackson, 2005; Bailey et al., 2017)

Geography and racial disparities

Today's focus is on the role of **geography**.

Geographic variation is a well-known and well-studied feature of the US health care system (Wennberg, 1973; Fisher, 2003; Finkelstein et al., 2016).

What does it mean for geography to drive a disparity? Two competing channels:

- Differential **geographic distribution** – access to health care varies across places, and Black patients are more likely to live in areas where access is lower (e.g., the American South)
- Differential **causal effects of place** on access – holding fixed where people live, places have different causal effects for Black patients than white patients (e.g., government-sanctioned discrimination in Tuskegee, AL)

Geography and racial disparities

Distinguishing between the two explanations is important for policymaking:

- Differences in geographic distribution → policies to reduce geographic variation
- Differences in causal place effects → policies to address specific sources of place effects (e.g., reducing air pollution, increasing economic opportunity, etc.)

Despite that, we have very little evidence on:

- The causal effects of place by race
- The relative contributions of differences in the geographic distribution and differences in place effects to disparities

Geography and racial disparities

Much of the existing work on geography on disparities has focused on how geographic variation in health care complicates the interpretation of disparities.

This work is largely focused on the **geographic distribution** of individuals.

Baicker, Chandra, and Skinner (2005):

> *"We show that where a patient lives can itself have a large impact on the level and quality of health care the patient receives. This matters in the measurement and interpretation of health (and health care) disparities, since black or Hispanic populations tend to live in different areas from non-Hispanic white populations."*

Geography and racial disparities

There is less work on this notion that places have **different causal effects by race**.

In part, this is because for a long time we didn't have credible ways to identify place effects. Recent methodological developments in economics have made this possible (Finkelstein, Gentzkow, Williams, 2016; Chetty and Hendren, 2018a,b)

Finkelstein, Gentzkow, and Williams (2016)

- New methods for estimating causal place effects using movers
- Identify the portion of geographic variation due to places (supply) and people (demand)

Our paper

Our paper builds on this work in a few ways:

1. Extend the FGW model of geographic variation to study disparities [today]
2. Use the movers design to separately estimate place effects for Black and white Medicare beneficiaries [today]
3. Decompose national disparities into a person component, the role of the geographic distribution, and the role of place effects heterogeneity [today]
4. Build a place effects “report card” [in the future]

Finkelstein, Gentzkow, and Williams (2016)

Sources of Geographic Variation in Health Care, *QJE*

Geographic variation in health care

Health care spending varies dramatically across areas.

The highest-spending areas in the map at right have more than double the spending of the lowest areas.

Spending is not correlated with outcomes in the cross-section.

Why so much variation?

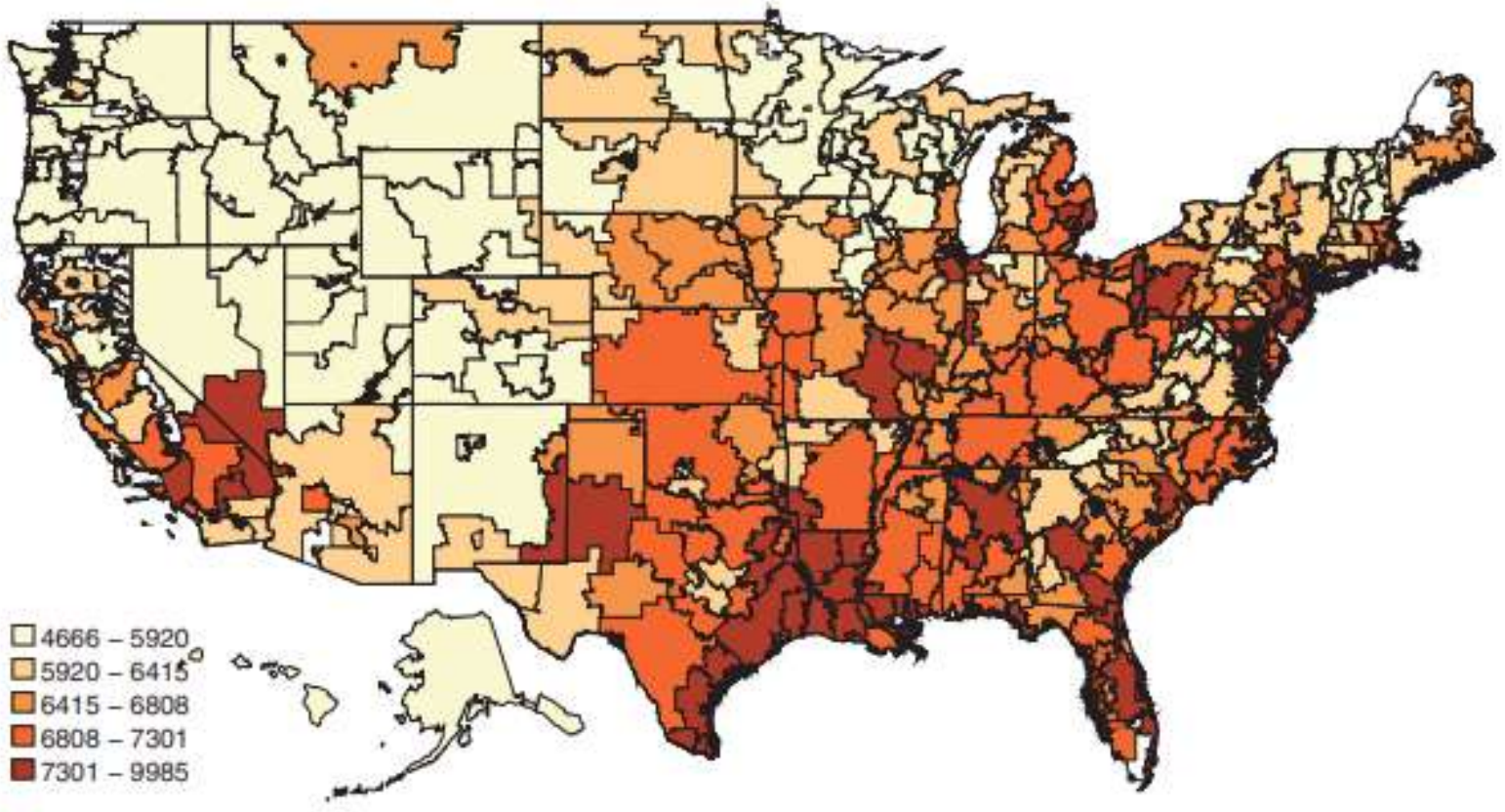


Figure. Utilization by HRR
(Finkelstein et al. 2016 Figure 1)

Geographic variation in health care

The goal of this paper is to understand how much of the observed geographic variation in medical spending is due to supply and how much is due to demand.

Differences in spending across areas may arise because of:

1. Differences in physician behavior (incentives, beliefs, treatment intensity) or other institutional features across areas (supply – the role of “place”)
2. Differences in the composition of patients (sickness, preferences, etc.) across areas (demand – the role of “people”)

Knowing the difference is important! If differences primarily come from (1), then policies available to reduce variation. If (2), then reducing variation may be inefficient.

Conceptual framework

There are individuals *i,* in places *j*, at time *t.* Model individual utilization as the sum of a place component and a person component (suppressing *t* for simplicity):

$$y_{ij} \equiv \gamma_j + y_i^*$$

- y_{ij} → utilization for individual *i*
- γ_j → place effect for beneficiaries in place *j* (place component)
- y_{ij}^* → privately optimal amount of utilization for individual *i* (patient component)

Then, write the difference in utilization between two areas *j,j'* as:

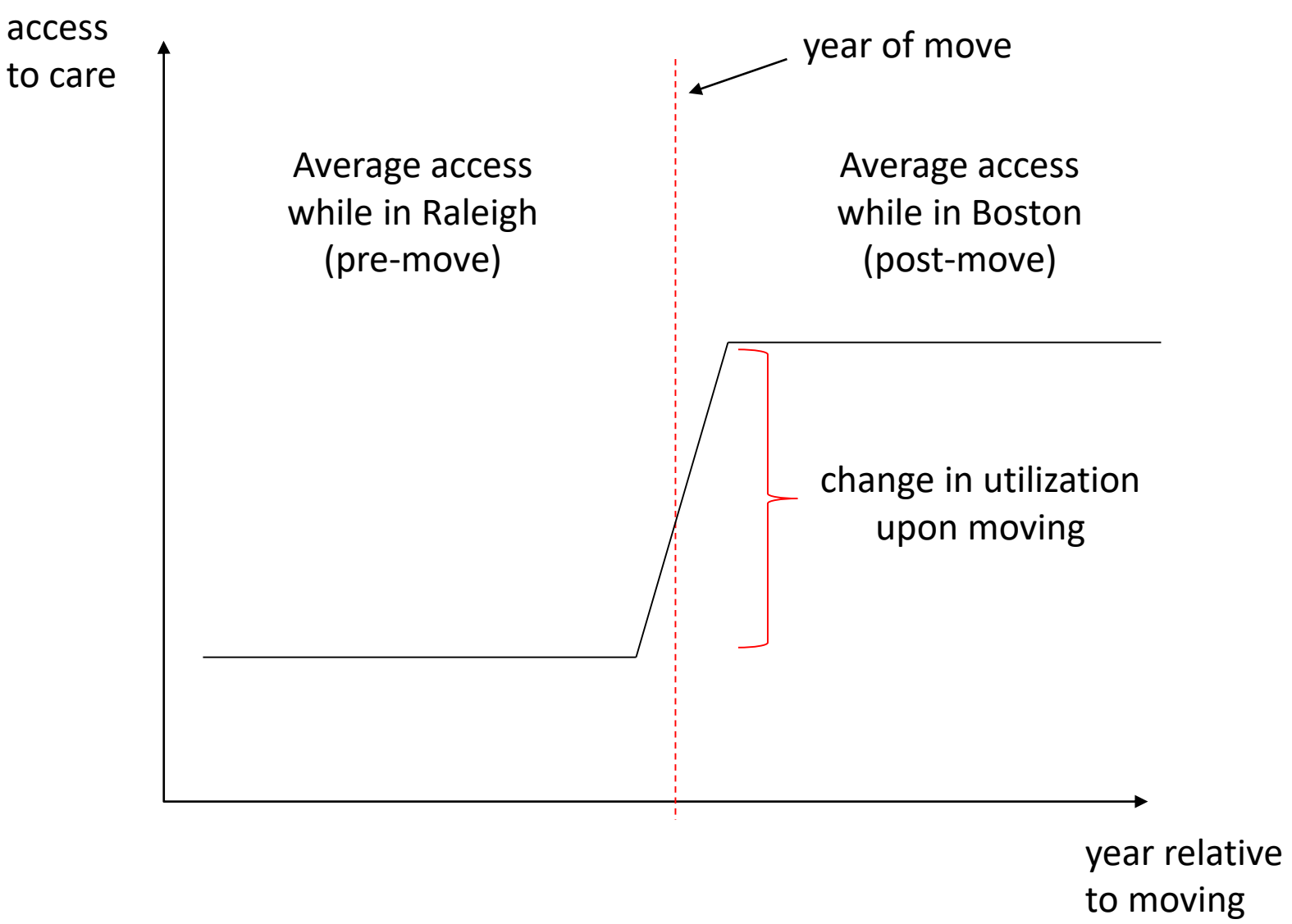
$$\bar{y}_j - \bar{y}_{j'} = \underbrace{\left(\gamma_j - \gamma_{j'}\right)}_{\text{place}} + \underbrace{\left(\overline{y_j^*} - \overline{y_{j'}^*}\right)}_{\text{person}}$$

Empirical strategy

Cross-sectional place effect estimates will combine causal effects of place with patient sorting. To disentangle these two, they use a **movers' design**.

Key underlying assumption: moving is not random, but trends in movers' untreated potential outcomes (i.e., their access if they hadn't moved) are unrelated to the difference in average access between their origin and destination.

Observed change in utilization on moving tell us the difference between origin and destination place effects. With many types of moves, we can estimate a place effect for each area *j*.



Empirical strategy

How much variation is due to place? Event study approach:

$$y_{it} = \alpha_i + \theta_{r(i,t)}\psi_i + \tau_t + \lambda_{r(i,t)} + X'_{it}\beta + \varepsilon_{it}$$

where:

- y_{it} → individual *i's* access measure in year *t*
- α_i → individual fixed effect
- ψ_i→ destination-origin difference in $\bar{y}$ for individual *i*
- τ_t → calendar year fixed effect
- X'_{it} → five-year age bins from ages 65-99
- $r(i,t) = t - t^*$ → indicator for year relative to move

The coefficients $\theta_{r(i,t)}$ measure the extent to which utilization converges to the origin-destination difference in utilization.

Estimation: causal place effects

Next, estimate the causal effect of each place itself:

$$y_{it} = \alpha_i + \gamma_{j(i,t)} + \lambda_{r(i,t)} + \tau_t + X'_{it}\beta + \nu_{it}$$

where:

- y_{it} → individual *i's* access measure in year *t*
- α_i → individual fixed effect
- $\gamma_{j(i,t)}$ → area *j* fixed effect
- $\lambda_{r(i,t)}$ → year relative to move fixed effect
- τ_t → calendar year fixed effect
- X'_{it} → five-year age bins from ages 65-99

Under the identifying assumptions, the vector of area fixed effects $\hat{\gamma}_{j(i,t)}$ captures the causal effects of each area *j* on access to care.

Places matter for health care utilization: event studies

When people move, their utilization converges to about half of the origin-destination difference.

Suggests that the role of places (vs. patients) is approximately 50%.

This is not a transient effect – utilization jumps sharply and stays high in the destination.

Small pre-trend prior to moving – could be picking up systematic differences in movers' utilization.

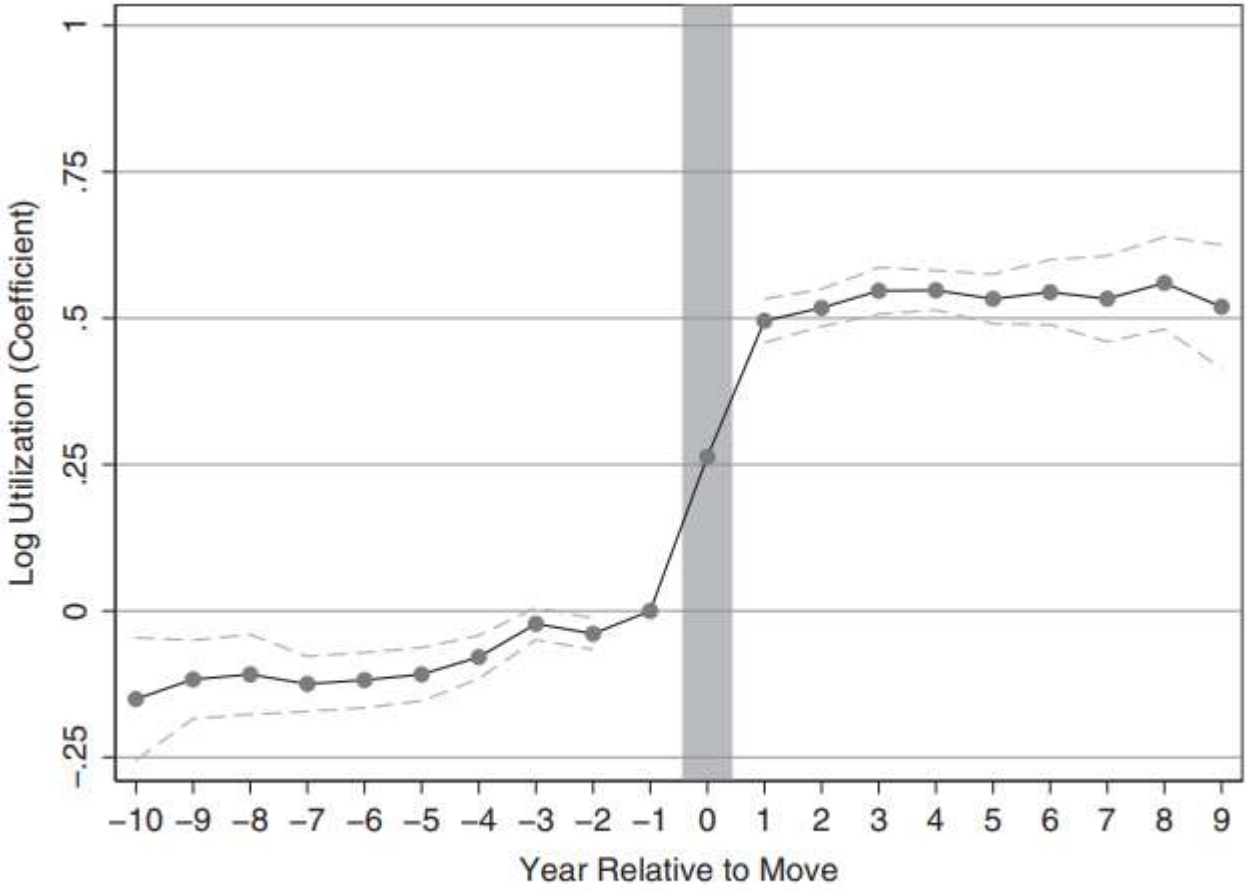


FIGURE VI

Event Study

Places matter for health care utilization: decomposition

Then use the estimated causal place effects ($\widehat{\gamma_j}$) to estimate the conceptual framework:

$$Share_{place}(j, j') = \frac{(\gamma_j - \gamma_{j'})}{\overline{y_j} - \overline{y_{j'}}}$$

Share of differences in utilization due to place is about 50-60%, while share due to patients is about 40-50%.

TABLE II

ADDITIVE DECOMPOSITION OF LOG UTILIZATION

	(1) Above/ below median	(2) Top & bottom 25%	(3) Top & bottom 10%	(4) Top & bottom 5%	(5) McAllen & El Paso	(6) Miami & Minneapolis
Difference in average log utilization						
Overall	0.283	0.456	0.664	0.817	0.587	0.667
Due to place	0.151	0.271	0.406	0.461	0.374	0.466
Due to patients	0.132	0.185	0.258	0.356	0.213	0.200
Share of difference due to						
Patients	0.465	0.405	0.388	0.435	0.363	0.300
	(0.027)	(0.029)	(0.026)	(0.025)	(0.161)	(0.088)
Place	0.535	0.595	0.612	0.565	0.638	0.700

Baicker, Chandra, and Skinner (2005)

Geographic Variation in Health Care and the Problem of Measuring Racial Disparities, *Perspectives in Biology and Medicine*

Broad overview

The takeaway from the Finkelstein et al. (2016) paper is that places are important drivers of observed variation in health care.

This paper makes the cases that these place-based differences are an important driver of racial disparities in the United States health care system.

The logic is that places vary considerably in terms of utilization and quality, and Black and white people in the United States are not distributed equally across those places.

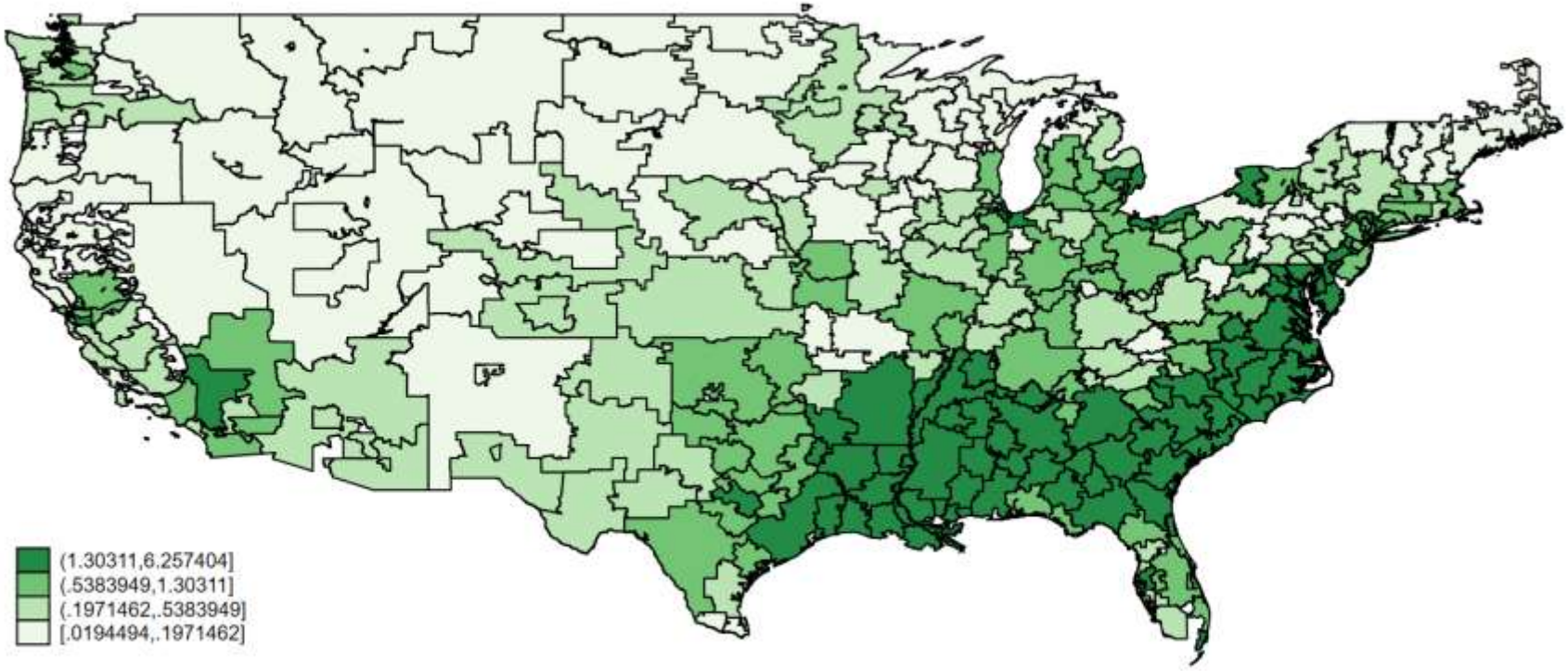


Figure. Fraction of Medicare Beneficiaries in an HRR who are Black Relative to National Average, 2021

Between-area variation in utilization

Broad argument: places that have lower utilization have lower utilization *for everyone*, but Black patients are more likely to live in these areas.

Figure at right: areas with larger percentage of Black patients have lower rates of annual eye exams for diabetics of both races.

Estimate that about 56% of observed disparity in this outcome is due to differences in where people live ("between-market" variation).

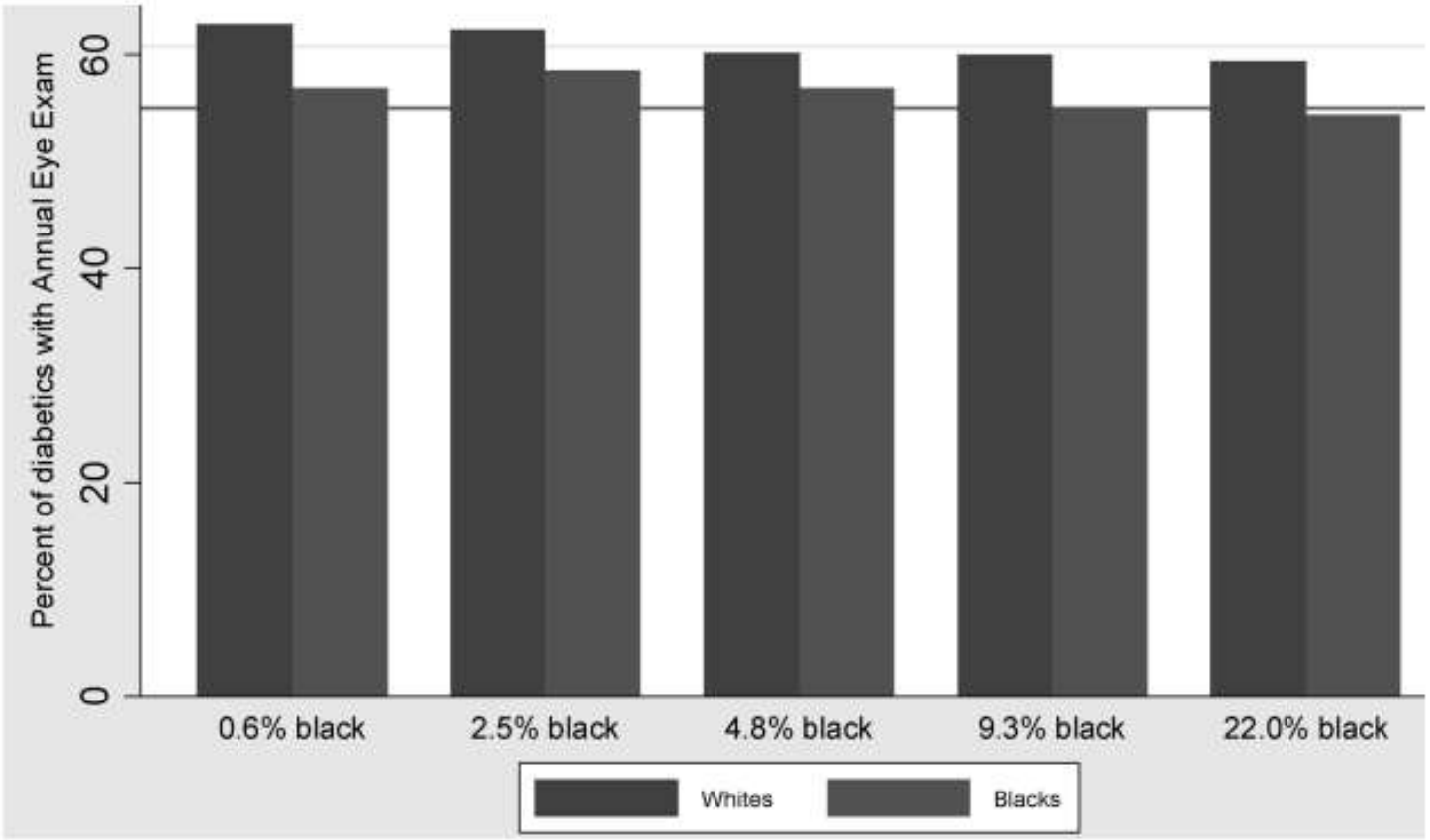


Figure. Percent of Diabetics Receiving an Annual Eye Exam by Black Population Quintile (Baicker, Chandra, Skinner, 2005, Figure 3)

Between-area variation in utilization

There is also evidence of within-area variation driving disparities, however.

Even conditional on where people live, Black patients are less likely to have an annual eye exam than white patients.

Estimate that ~44% of observed disparity in this outcome due to differential treatment within markets.

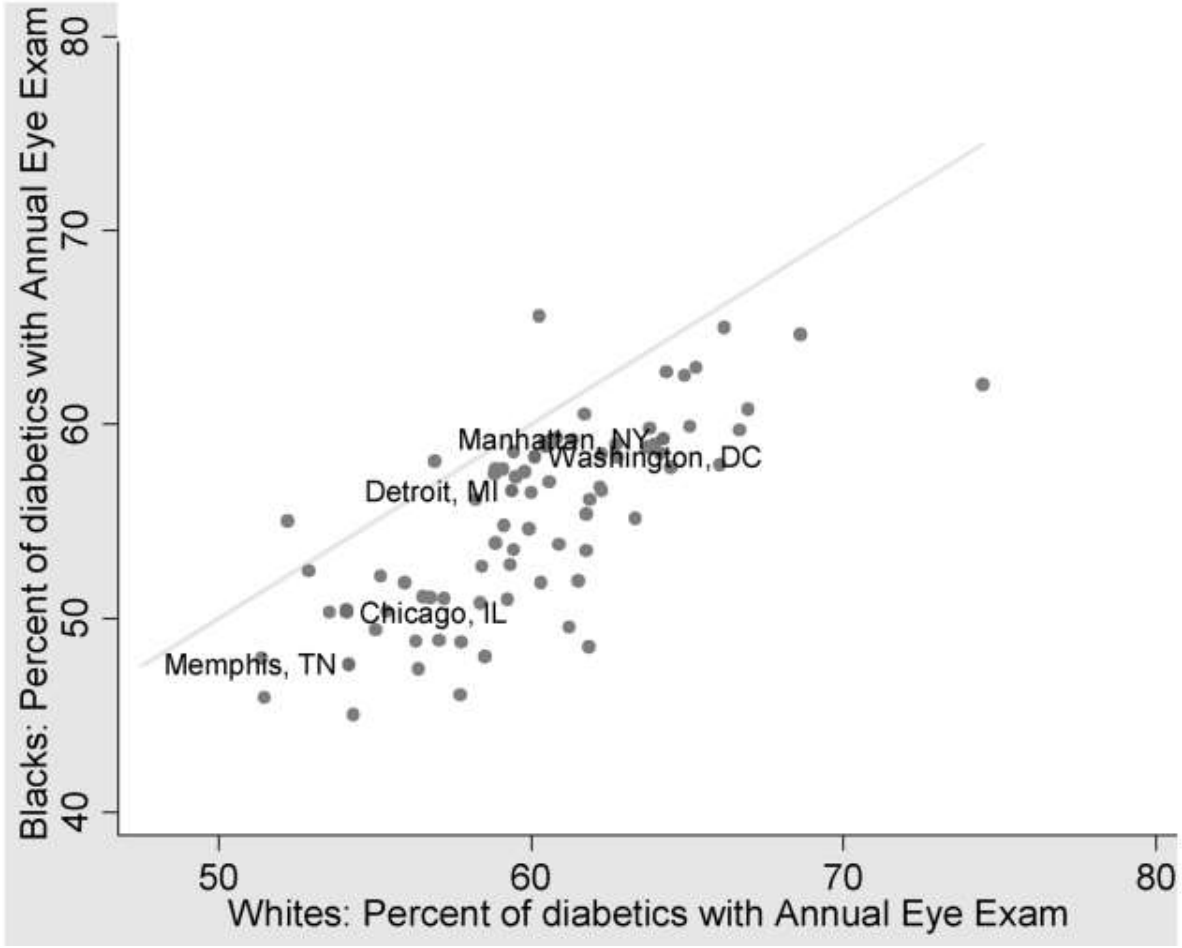


Figure. Percent of Diabetics Receiving an Annual Eye Exam by Black Population Quintile (Baicker, Chandra, Skinner, 2005, Figure 5)

Baicker et al. (2005) policy prescriptions

In the presence of these kinds of geographic disparities, interventions at the level of the provider will be necessary but not sufficient to close disparities.

Policies that reduce geographic variation – i.e., bring areas with disproportionately low-quality care into alignment with high-quality areas – will be important:

> *"What is necessary to erase health care disparities is to implement national policies designed to improve the overall quality of treatment or health of all patients, which in turn will have a disproportionate effect on reducing racial, ethnic, and geographic disparities in health care and health outcomes. Interventions focused on the overall quality of hospitals in a few regions of the country (where a disproportionate share of minorities communities are located) could dramatically reduce racial disparities in care."*

Tim Layton’s and my paper

The Geography of Health Disparities

Today’s focus

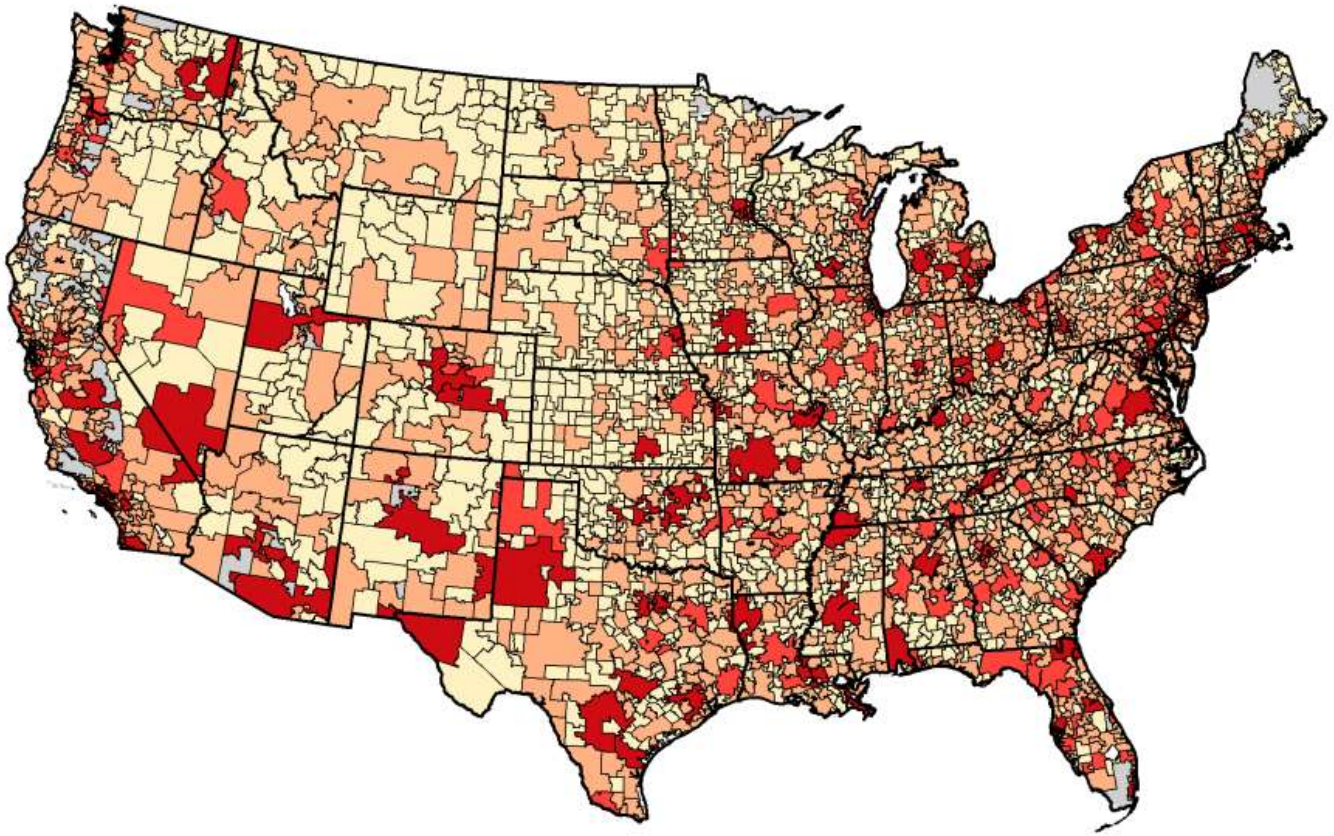
Our paper starts from the Finkelstein et al. (2016) conceptual framework, which we then use to study the role of place in driving disparities, similar to Baicker et al. (2005).

We restrict our focus to disparities in **access to medical care**. To do so, we focus on the utilization of different types of medical care to proxy for access:

- Total utilization
- Visits for evaluation and management (“primary care” visits)
- Receipt of recommended screenings (e.g., for colorectal cancer)

Today's focus

Our unit of geography is the **Hospital Service Area (HSA).** These are local markets for hospital care. There are 3,436 in the United States.



Map 1.3. Hospital Service Areas According to Population Size

According to the 1990 census, about 10% of the population of the United States lived in areas with populations of fewer than 30,000; about 50% lived in areas with fewer than 180,000 residents. Only 32% of Americans lived in hospital service areas with populations greater than 360,000.

Population of Hospital Service Areas

360,000 or more	(104 HSAs)
180,000 to <360,000	(171)
30,000 to <180,000	(1,344)
866 to <30,000	(1,817)
Not Populated	

Source: The Dartmouth Atlas

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Conceptual framework

We import the conceptual framework of Finkelstein, Gentzkow, and Williams (2016) and use it to study disparities.

There are individuals *i,* in places *j*, at time *t.* Following FGW, we model our utilization-based measures of access as the sum of a place component and a person component (suppressing *t* for simplicity):

$$y_{ij} \equiv \gamma_j + y_i^*$$

- y_{ij} → utilization for individual *i*
- γ_j → place effect for beneficiaries in place *j* (place component)
- y_{ij}^* → privately optimal amount of utilization for individual *i* (patient component)

Conceptual framework

We use this setup to divide the national 'disparity' in utilization between Black and white beneficiaries into place and non-place factors.

We define the disparity as $\delta^{w,b} \equiv \bar{y}^w - \bar{y}^b$ and write:

$$\begin{aligned}
\delta^{w,b} &= \frac{1}{N_w}\sum_{i\in w} y_{ij} - \frac{1}{N_b}\sum_{i\in b} y_{ij} \\
&= \left(\sum_{j\in J} \sigma_j^w \gamma_j + \frac{1}{N_w}\sum_{i\in w} y_i^*\right) - \left(\sum_{j\in J} \sigma_j^b \gamma_j + \frac{1}{N_b}\sum_{i\in b} y_i^*\right) \\
&= \underbrace{\sum_{j\in \mathrm{J}} (\sigma_j^w - \sigma_j^b)\gamma_j}_{\text{place component}} + \underbrace{\left(\frac{1}{N_w}\sum_{i\in w} y_i^* - \frac{1}{N_b}\sum_{i\in b} y_i^*\right)}_{\text{person component}}
\end{aligned}$$

where σ_j^r is the share of the national population of race *r* that lives in area *j*.

Conceptual framework

We then consider a decomposition that allows place effects to differ by race. For individuals of race *r* we define average utilization as:

$$\bar{y}^r = \sum_{j \in \mathrm{J}} \sigma_j^r \gamma_j^r + \frac{1}{N_r} \sum_{i \in r} y_i^*$$

Plugging this in for $r \in \{w, b\}$ and rearranging yields the following:

$$\delta^{w,b} = \bar{y}^w - \bar{y}^b = \underbrace{\sum_{j \in \mathcal{J}} \left(\sigma_j^w \gamma_j^w - \sigma_j^b \gamma_j^b \right)}_{\text{place-by-race component}} + \underbrace{\left(\frac{1}{N_w} \sum_{i \in w} y_i^* - \frac{1}{N_b} \sum_{i \in b} y_i^* \right)}_{\text{person component}}$$

which we further decompose as:

$$\delta^{w,b} = \underbrace{\sum_{j \in \mathcal{J}} \gamma_j^b \left(\sigma_j^w - \sigma_j^b \right)}_{\text{diffs. due to geo. dist.}} + \underbrace{\sum_{j \in \mathcal{J}} \sigma_j^w \left(\gamma_j^w - \gamma_j^b \right)}_{\text{diffs. due to place effects}} + \underbrace{\left(\frac{1}{N_w} \sum_{i \in w} \hat{y}_i^* - \frac{1}{N_b} \sum_{i \in b} \hat{y}_i^* \right)}_{\text{person component}}$$

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Measures of access to care

We construct measures of access to care using the Medicare claims as follows:

- Log(Utilization), stripped of geographic variation in prices (Finkelstein, Gentzkow, & Williams, 2016)
- Receipt of any primary care visit (0/1) and number of primary care visits (Carey et al., 2020; Zheng et al., 2016)
- Receipt of USPSTF-recommended screenings for elderly adults, including:
  - Colorectal cancer screening
  - Depression screening
  - Diabetes screening

Empirical objects of interest

There are a few objects from the decomposition that we want to estimate:

1. National Black-white disparity for access measure *Y* in year *t* ($\hat{\delta}^{w,b}$)
2. Share of the national population of race *r* living in area *j* at time *t* ($\hat{\sigma}_{jt}^{w}, \hat{\sigma}_{jt}^{b}$)
3. Causal place effects for white and Black beneficiaries ($\hat{\gamma}_{j}^{w}, \hat{\gamma}_{j}^{b}$)

We estimate (1) and (2) using the Medicare claims and the Master Beneficiary Summary File from 2008-2018, which allows us to construct the disparity at the national level and population shares for each HSA.

We estimate (3) using a movers design estimated separately for Black and white Medicare beneficiaries.

Identification

- To estimate causal place effects, we leverage beneficiary migration across areas (a ‘mover design’).
- The core intuition underlying our approach is that changes over time in access to care are independent of the difference in average access to care in the origin and destination.
- A key implication of our approach is that our results are generalizable to non-movers:
  - In practice, we find that movers and non-movers are quite similar on observable characteristics
  - Also show that Black and white movers are quite similar on observables

Movers and Non-Movers

Black and White Movers

Estimation: the importance of place

We start by examining whether places matter for access to care for Black and white beneficiaries. To do so, we follow Finkelstein, Gentzkow, and Williams (2016) and estimate event studies:

$$y_{it} = \alpha_i + \theta_{r(i,t)}\psi_i + \tau_t + \lambda_{r(i,t)} + X'_{it}\beta + \varepsilon_{it}$$

where:

- y_{it} → individual *i's* access measure in year *t*
- α_i → individual fixed effect
- ψ_i → destination-origin difference in $\bar{y}$ for individual *i*
- τ_t → calendar year fixed effect
- X'_{it} → five-year age bins from ages 65-99
- $r(i,t) = t - t^*$ → indicator for year relative to move

The coefficients $\theta_{r(i,t)}$ measure changes in access to care by year relative to move *r(i,t)* and reflect convergence to the origin-destination difference in access.

Estimation: causal place effects

We then estimate causal place effects using the following specification, estimated separately by race:

$$y_{it} = \alpha_i + \gamma_{j(i,t)} + \lambda_{r(i,t)} + \tau_t + X'_{it}\beta + \nu_{it}$$

where:

- y_{it} → individual *i's* access measure in year *t*
- α_i → individual fixed effect
- $\gamma_{j(i,t)}$ → area *j* fixed effect
- $\lambda_{r(i,t)}$ → year relative to move fixed effect
- τ_t → calendar year fixed effect
- X'_{it} → five-year age bins from ages 65-99

Under our identifying assumption, the vector of area fixed effects $\hat{\gamma}_{j(i,t)}$ captures the causal effects of each area *j* on access to care.

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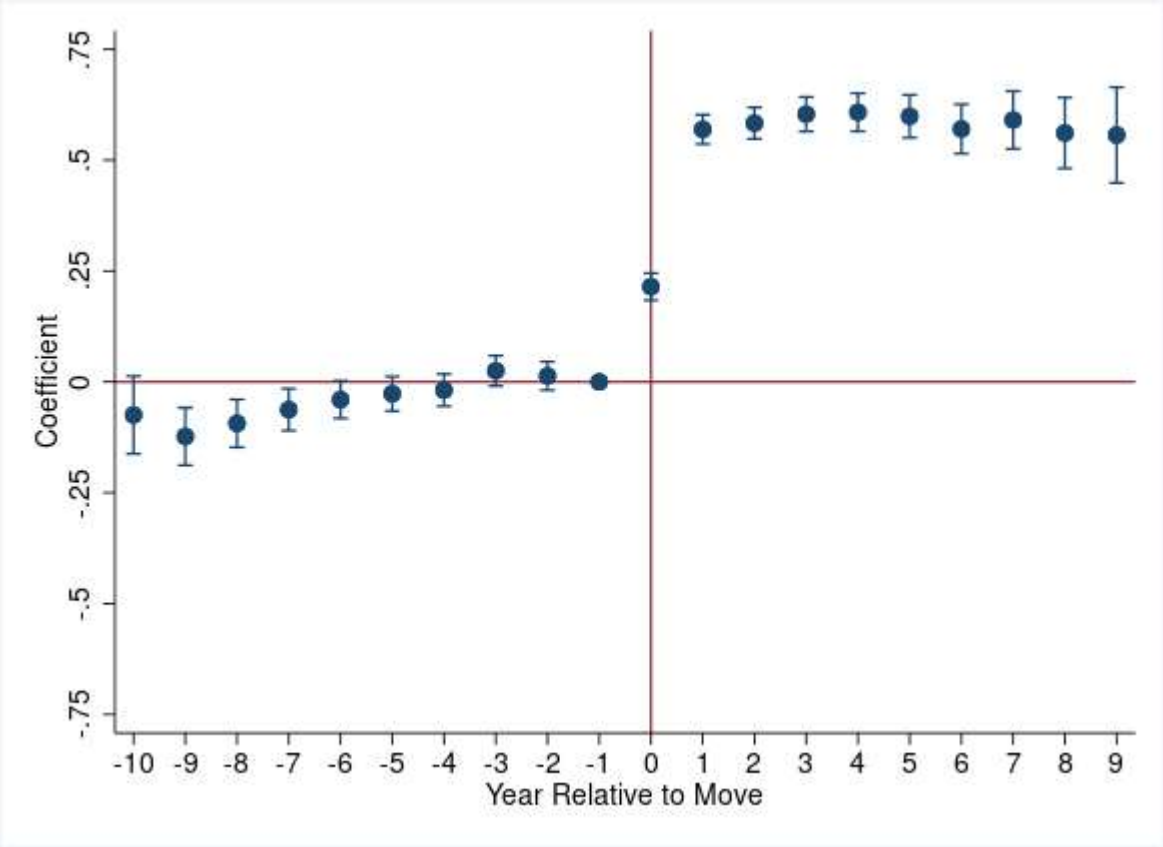
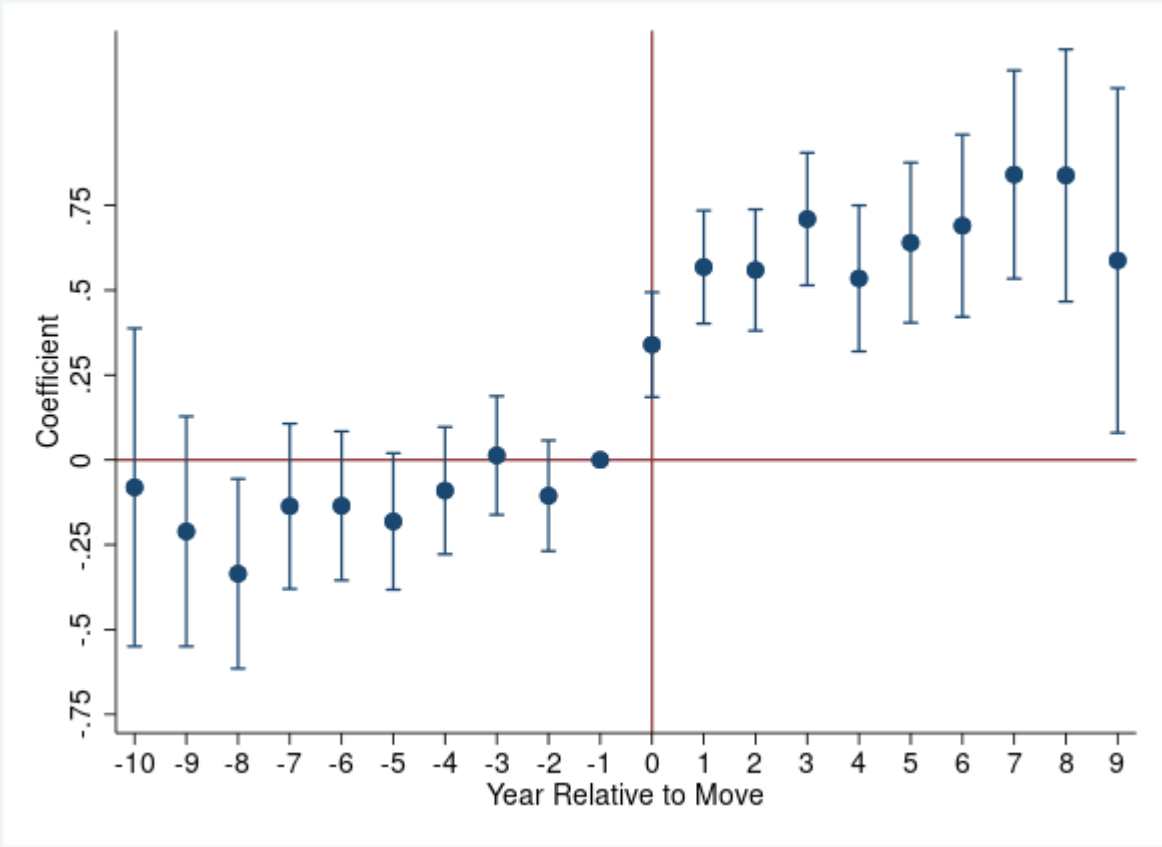
Places matter for access to care



(a) Effect of HSA Move on Log(Utilization), White Movers



(b) Effect of HSA Move on Log(Utilization), Black Movers

Figure: Effect of Moving on Log(Utilization), White and Black HSA Movers

Any PC Visit

Num. PC Visits

Distribution of place effects

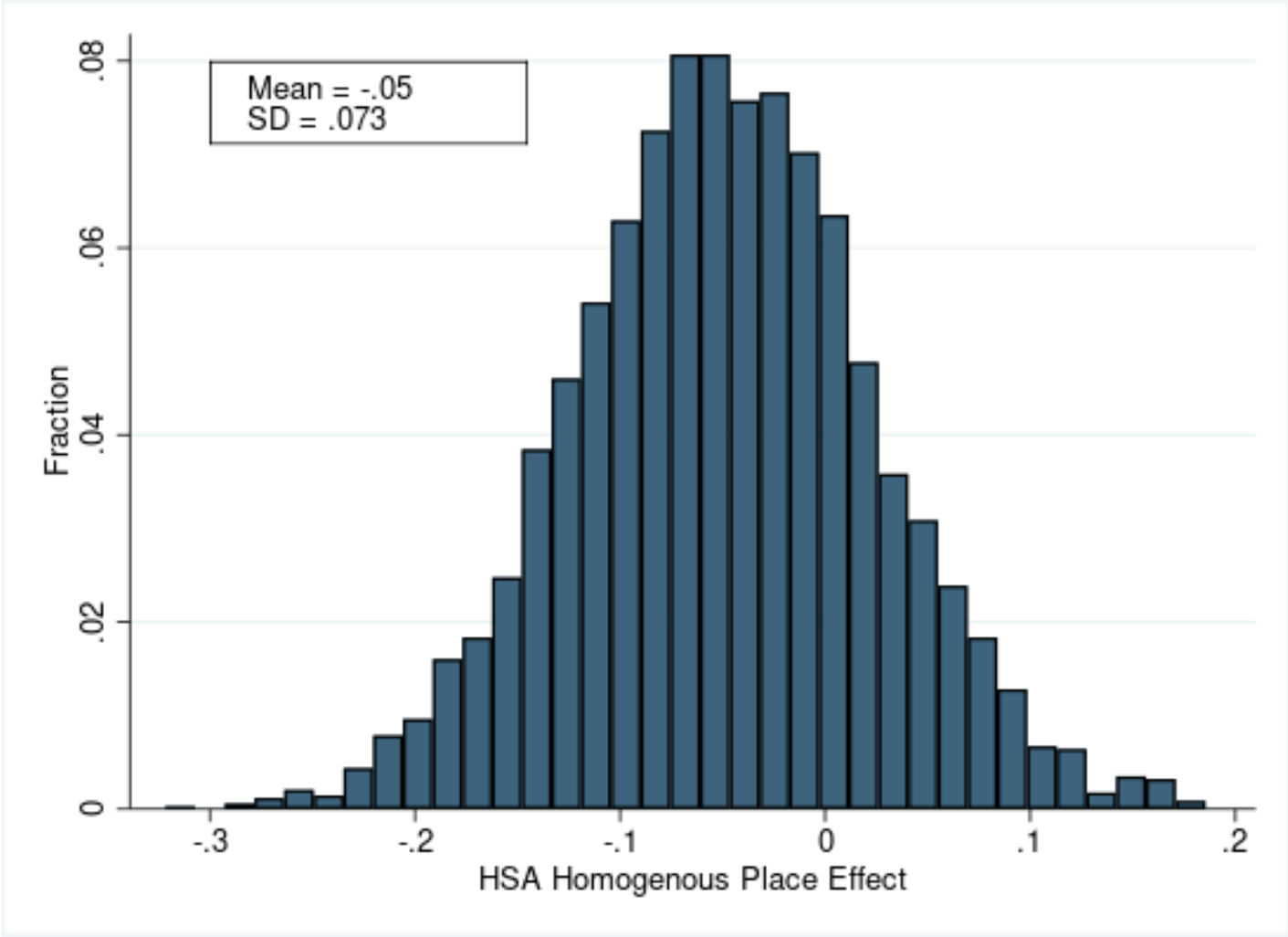
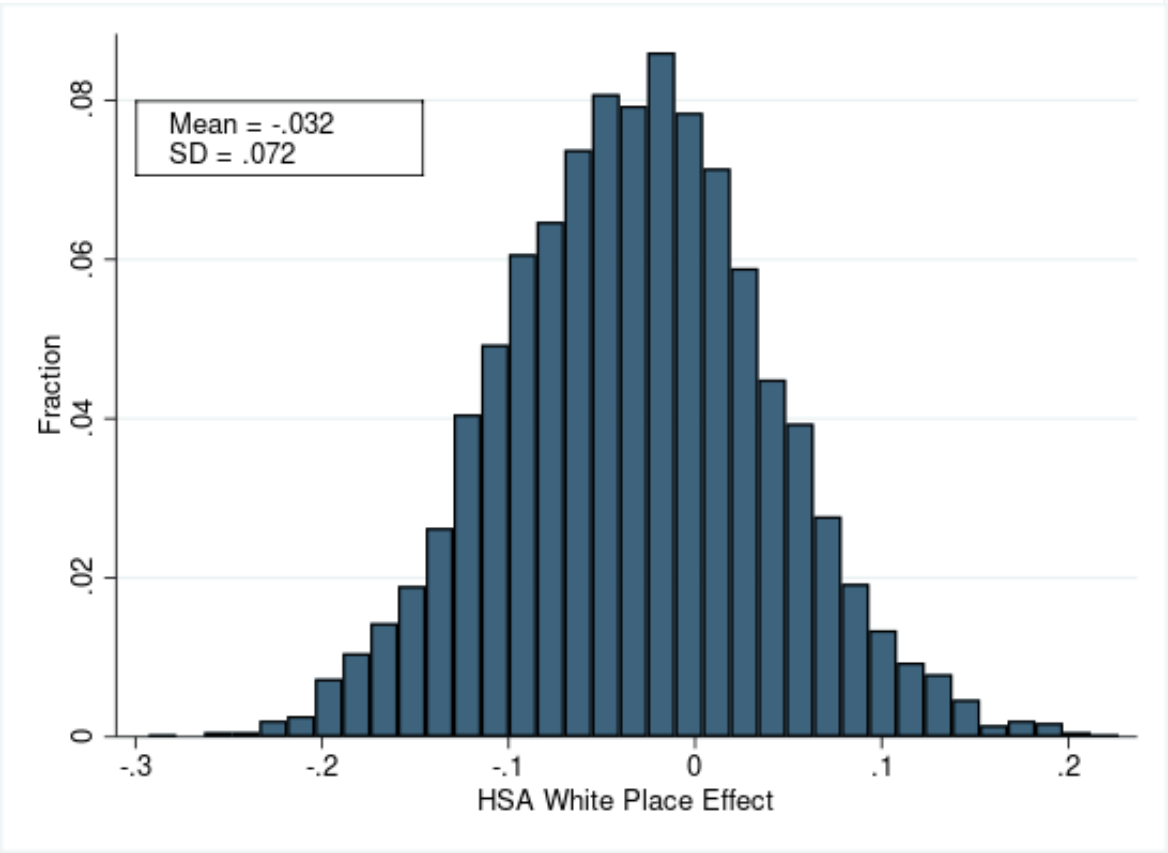
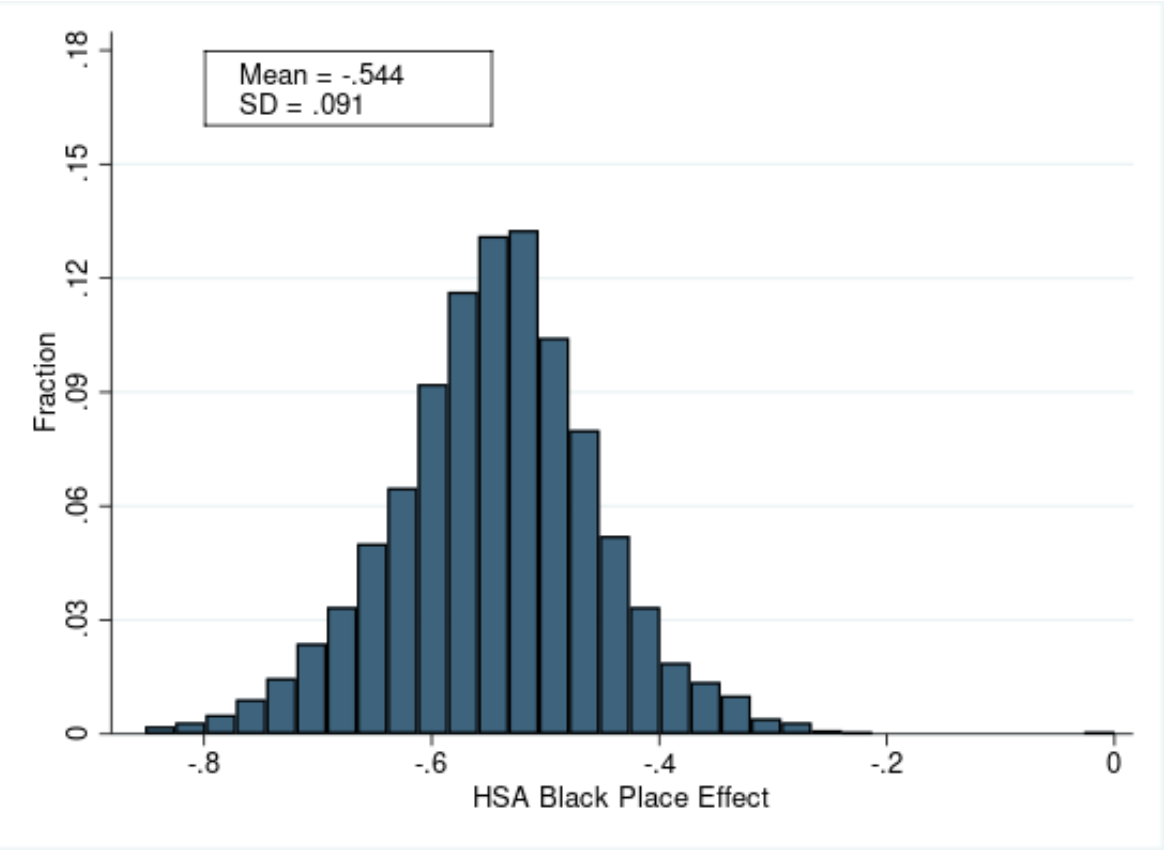


Figure. Distribution of Homogenous HSA Place Effects, Log(Utilization)

Distribution of place effects



(a) HSA Place Effects on Log(Utilization), White Movers



(b) HSA Place Effects on Log(Utilization), Black Movers

Figure: Distribution of HSA Place Effects on Log(Utilization), White and Black HSA Movers

Any PC Visit

Num. PC Visits

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Decomposing disparities in access

We use the estimated place effects ($\hat{\gamma}_{j(i,t)}$) to conduct our decomposition. The different pieces are as follows:

- White place effect for area *j* → $\hat{\gamma}^{w}_{j(i,t)}$, estimated using movers
- Black place effect for area *j* → $\hat{\gamma}^{b}_{j(i,t)}$, estimated using movers
- Share of white population in area *j* at time *t* → $\hat{\sigma}^{w}_{jt}$, estimated using full Traditional Medicare population
- Share of Black population in area *j* at time *t* → $\hat{\sigma}^{b}_{jt}$, estimated using full Traditional Medicare population
- Disparity in access measure *Y* at time *t* → $\hat{\delta}^{w,b}$, estimated using full Traditional Medicare population

Homogenous decomposition

- When we conduct our decomposition with homogenous place effects, we find that places matter very little.
- This suggests that place-based policies designed to resolve disparities would do little to close these gaps.
- Our result is consistent across a variety of measures of access.

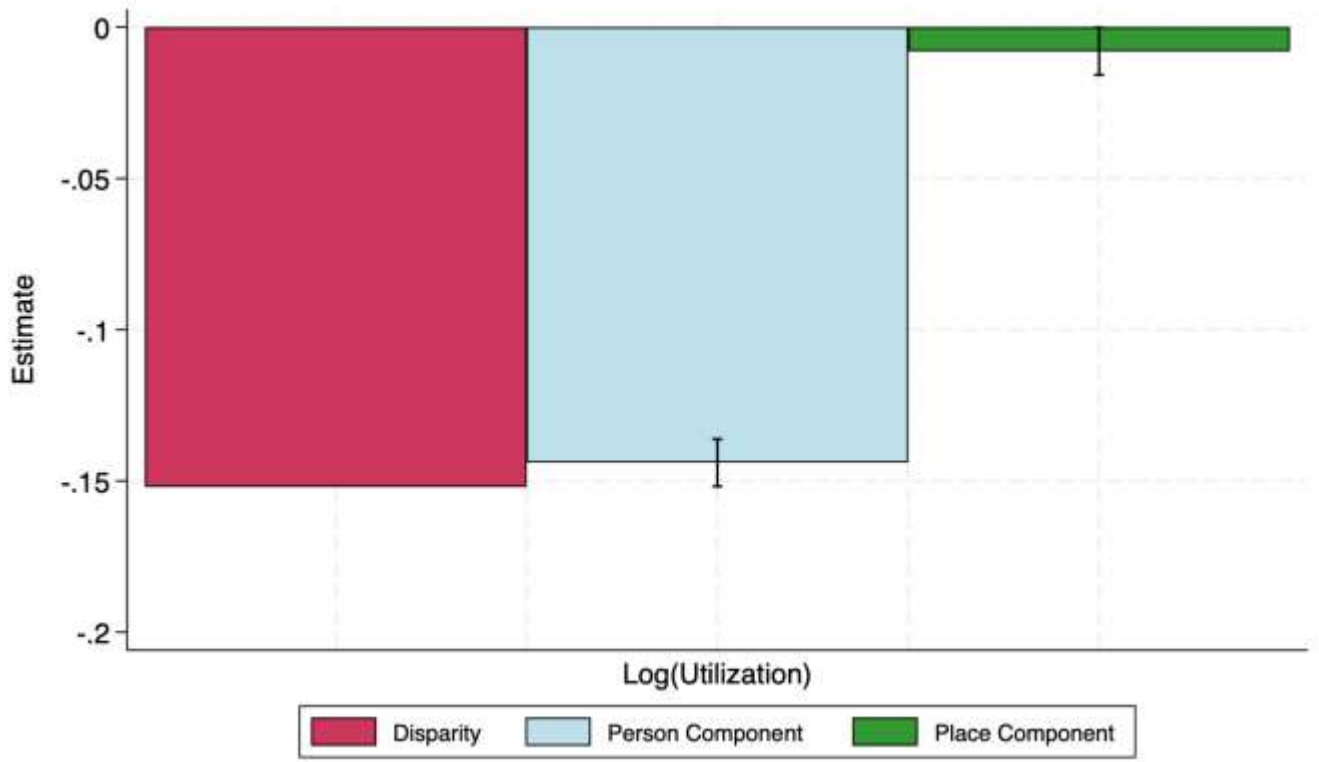

Figure. Homogenous HSA Decomposition, Log(Utilization)

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Heterogeneous decomposition

- When we allow place effects to vary by race, however, places matter enormously for disparities
- This suggests that place-*by*-*race*-based policies may be more effective at closing these gaps.
- Again, our result is consistent across a variety of measures of access.

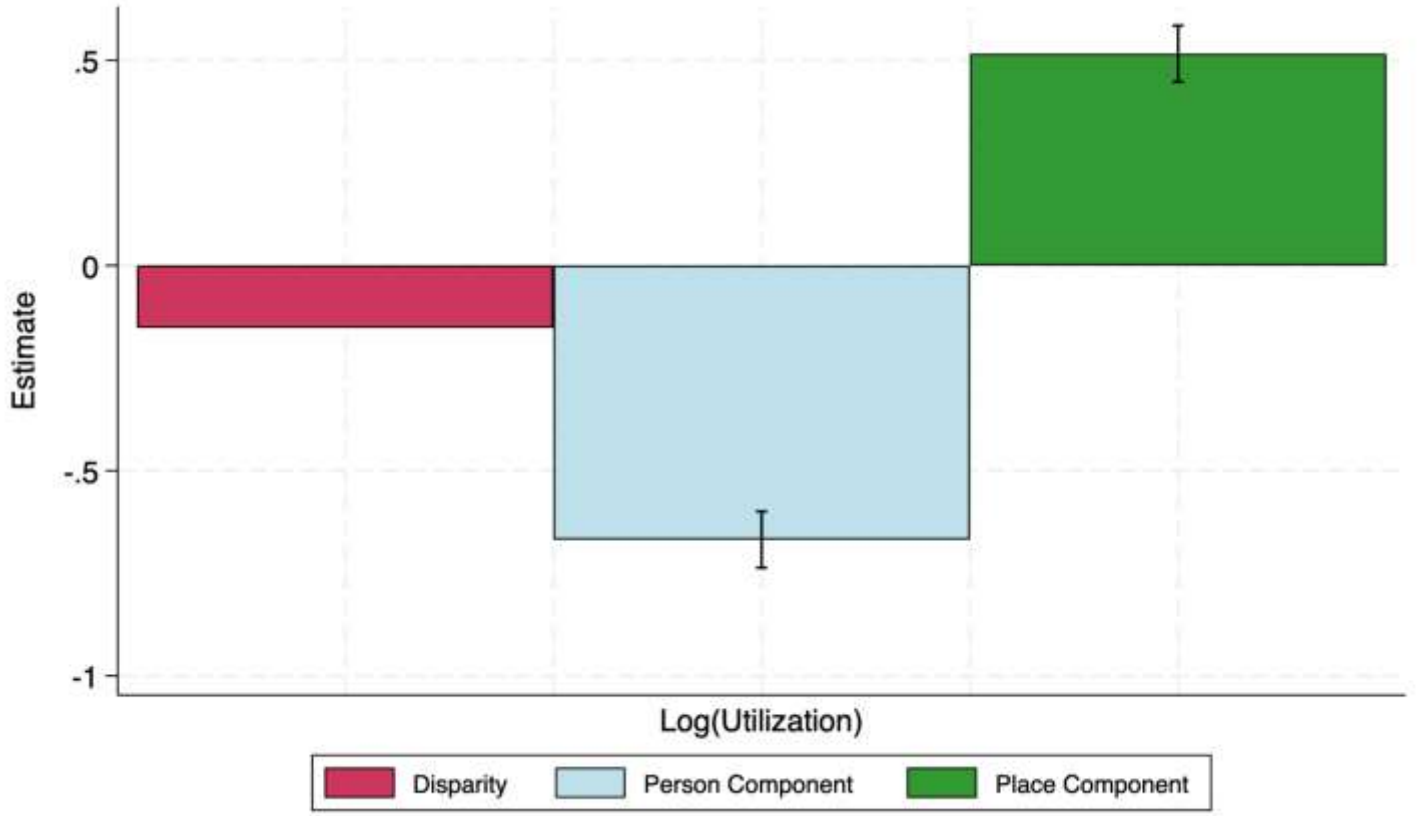

Figure. Heterogeneous Decomposition, Log(Utilization)

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Decomposing the place component

- What drives the place component?
- When we break the place component down, we find that essentially all of it is driven by **differential place effects by race**, not geographic sorting.
- In other words, simply moving Black beneficiaries to areas with better access for white beneficiaries would do little to close disparities.

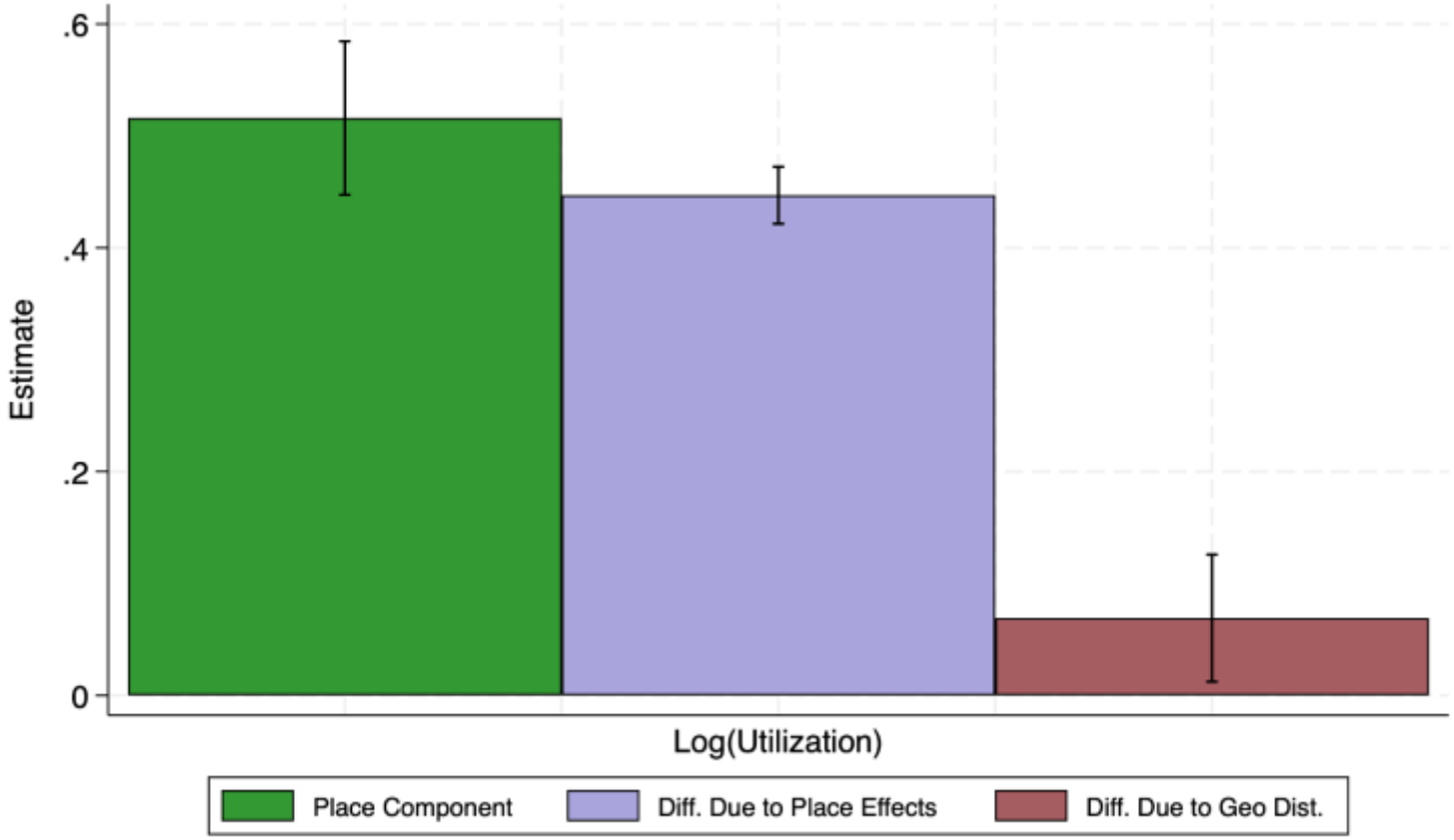

Figure. HSA Place Component Decomposition, Log(Utilization)

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Places matter considerably for disparities

How much would changing place effects change disparities? We conduct the following exercise:

1. Hold fixed the ”person” component
2. Divide the place effects for Black beneficiaries into quartiles
3. Assign the places with the bottom quartile place effects the average place effect for the top quartile
4. Recompute the place component under these alternative place effects
5. Recompute the disparity as the sum of the fixed person component and the new place component

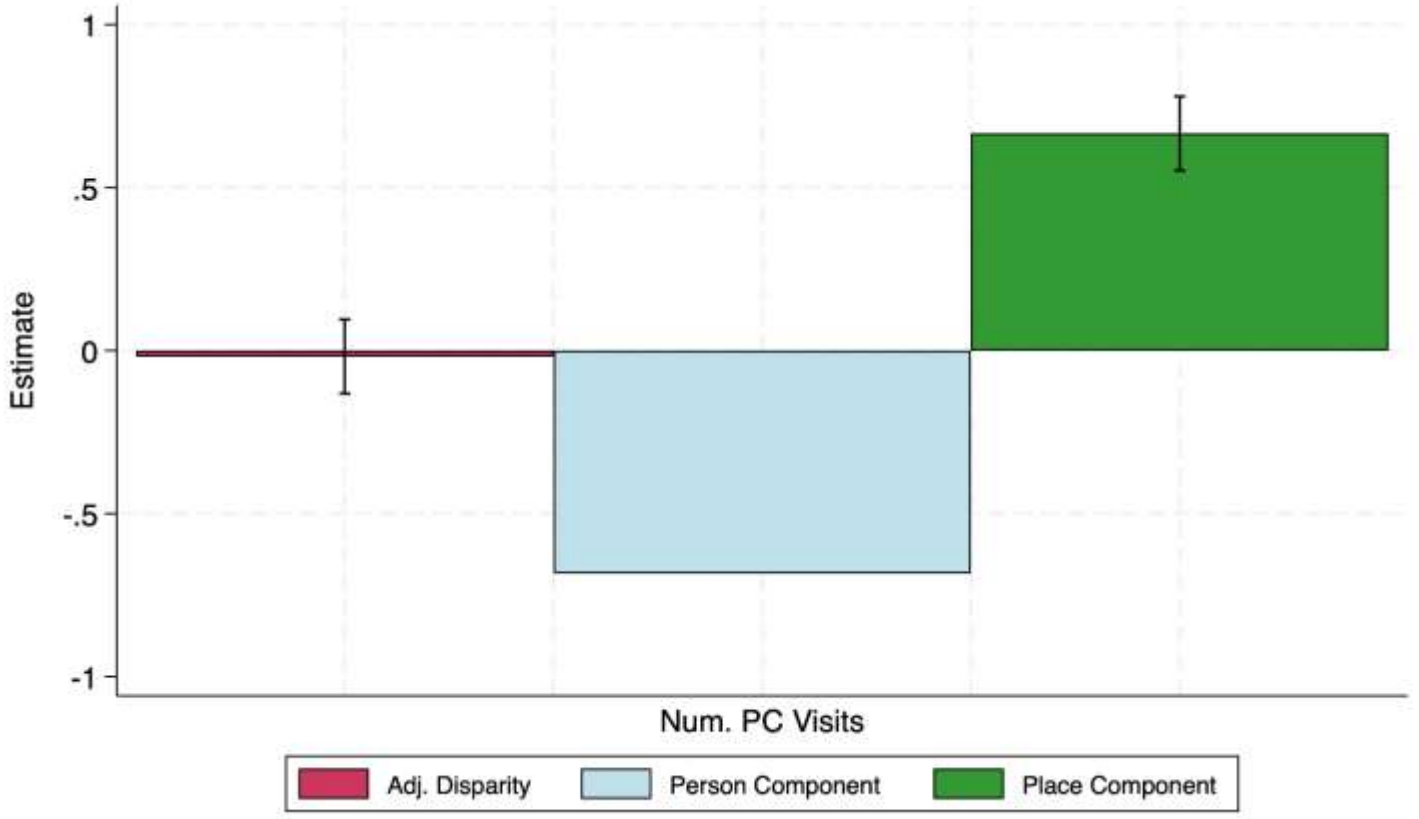

Figure: Reallocation Exercise, Number of PC Visits, 2018

Log(Utilization)

Any PC Visit

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Decomposition

The Importance of Place**-by-Race** Effects

Conclusion

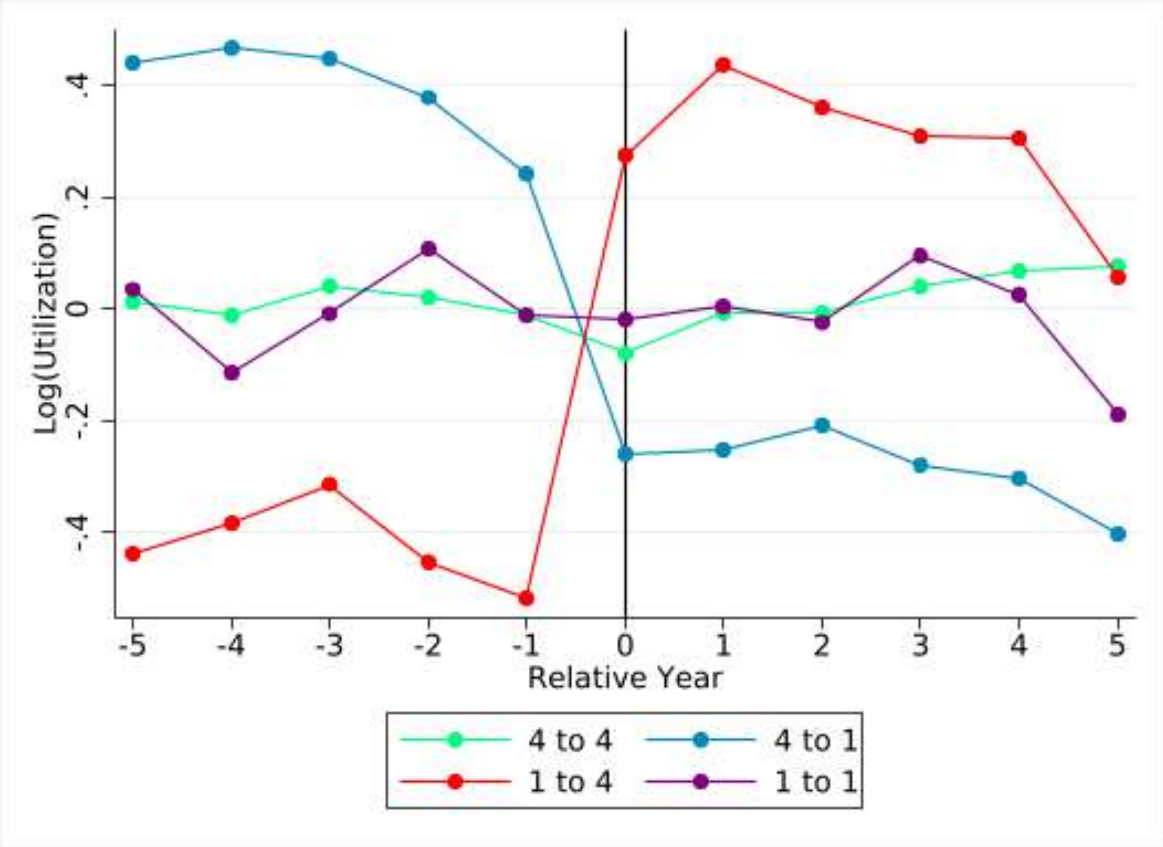
The importance of place-by-race effects

Why does the geographic distribution of individuals have such a limited impact?

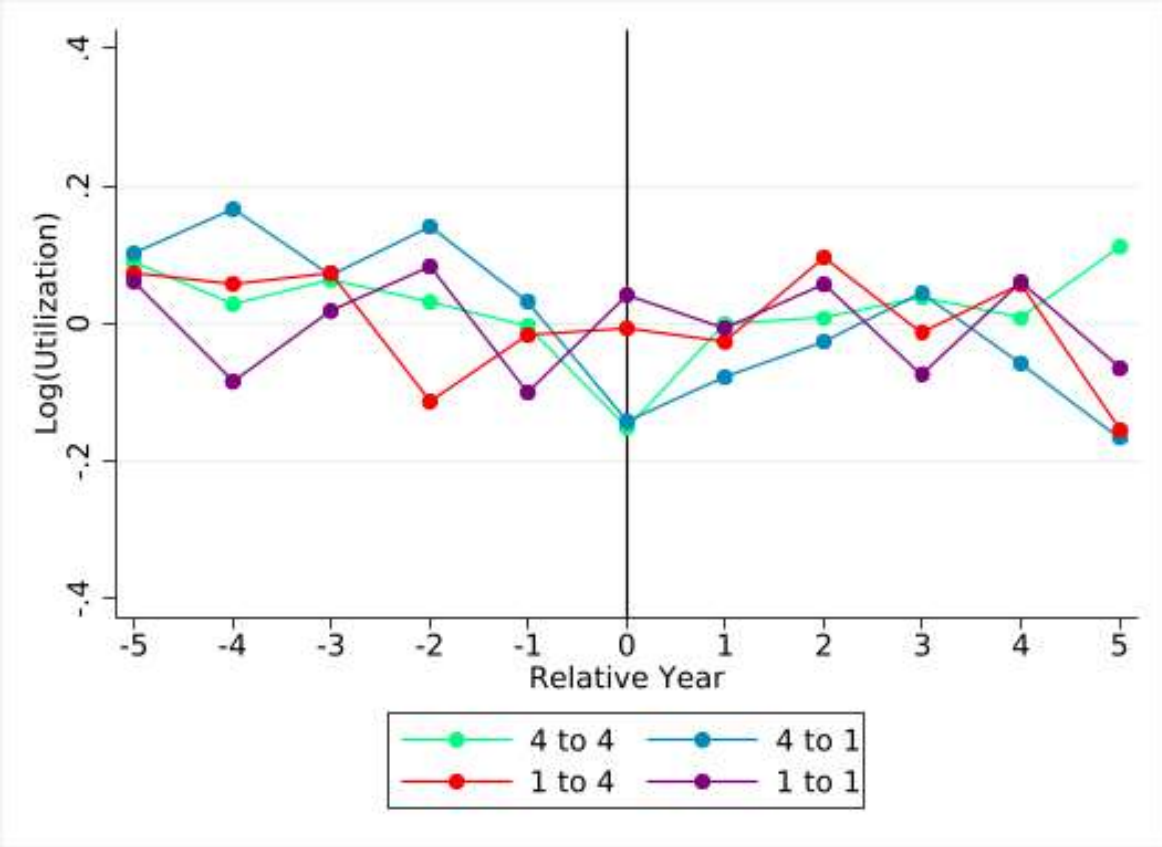
$$\delta^{w,b} = \underbrace{\sum_{j \in \mathcal{J}} \gamma_j^b \left(\sigma_j^w - \sigma_j^b\right)}_{\text{diffs. due to geo. dist.}} + \underbrace{\sum_{j \in \mathcal{J}} \sigma_j^w \left(\gamma_j^w - \gamma_j^b\right)}_{\text{diffs. due to place effects}} + \underbrace{\left(\frac{1}{N_w} \sum_{i \in w} \hat{y}_i^* - \frac{1}{N_b} \sum_{i \in b} \hat{y}_i^*\right)}_{\text{person component}}$$

1. **Place effects for Black beneficiaries and white beneficiaries are uncorrelated**
2. Place effects for Black beneficiaries are uncorrelated with the differential geographic distribution

The importance of place-by-race effects



(a) Black Place Effect Moves, Black Movers



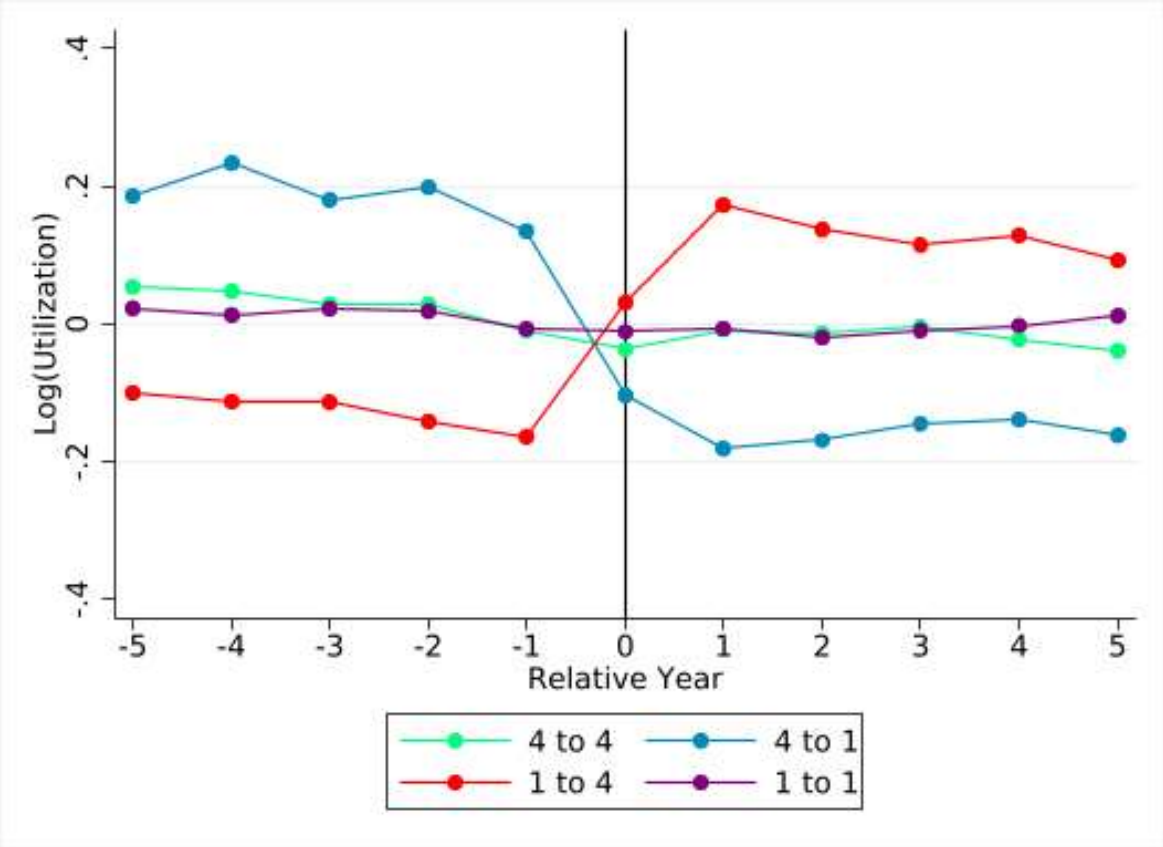
(b) White Place Effect Moves, Black Movers

Figure. Changes in Log(Utilization) by Move Type, Black Movers

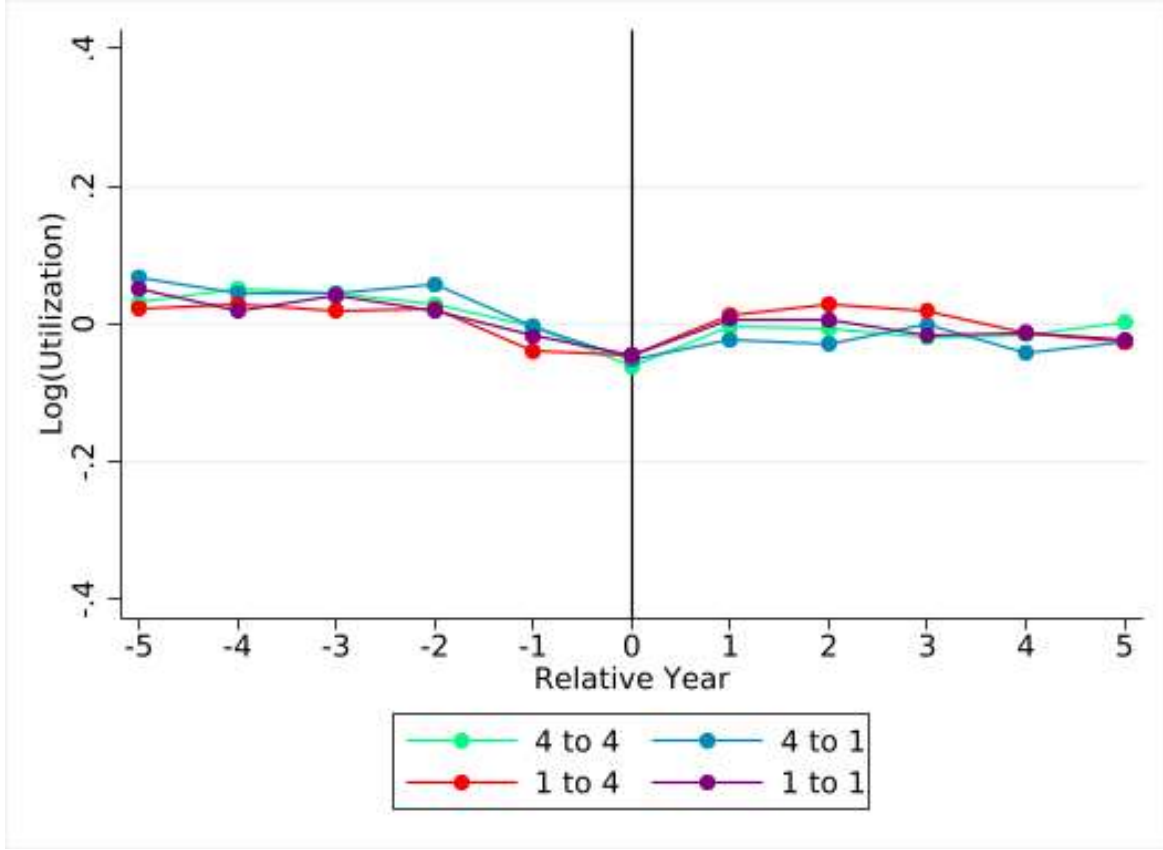
Any PC Visit

Num. PC Visit

The importance of place-by-race effects



(a) White Place Effect Moves, White Movers



(b) Black Place Effect Moves, White Movers

Figure. Changes in Log(Utilization) by Move Type, White Movers

Any PC Visit

Num. PC Visit

How correlated are place effects?

- Why do we observe these patterns?
- Across all access measures, Black and white place effects are only weakly correlated in a given HSA
- Conduct various robustness tests:
  - Broader geographies (HRRs)
  - Narrower geographies (HRRxZIP income quintile)
  - Randomly dropping white beneficiaries to equalize number of movers by race in an origin-destination dyad
  - Varying the omitted place in our place effects regressions

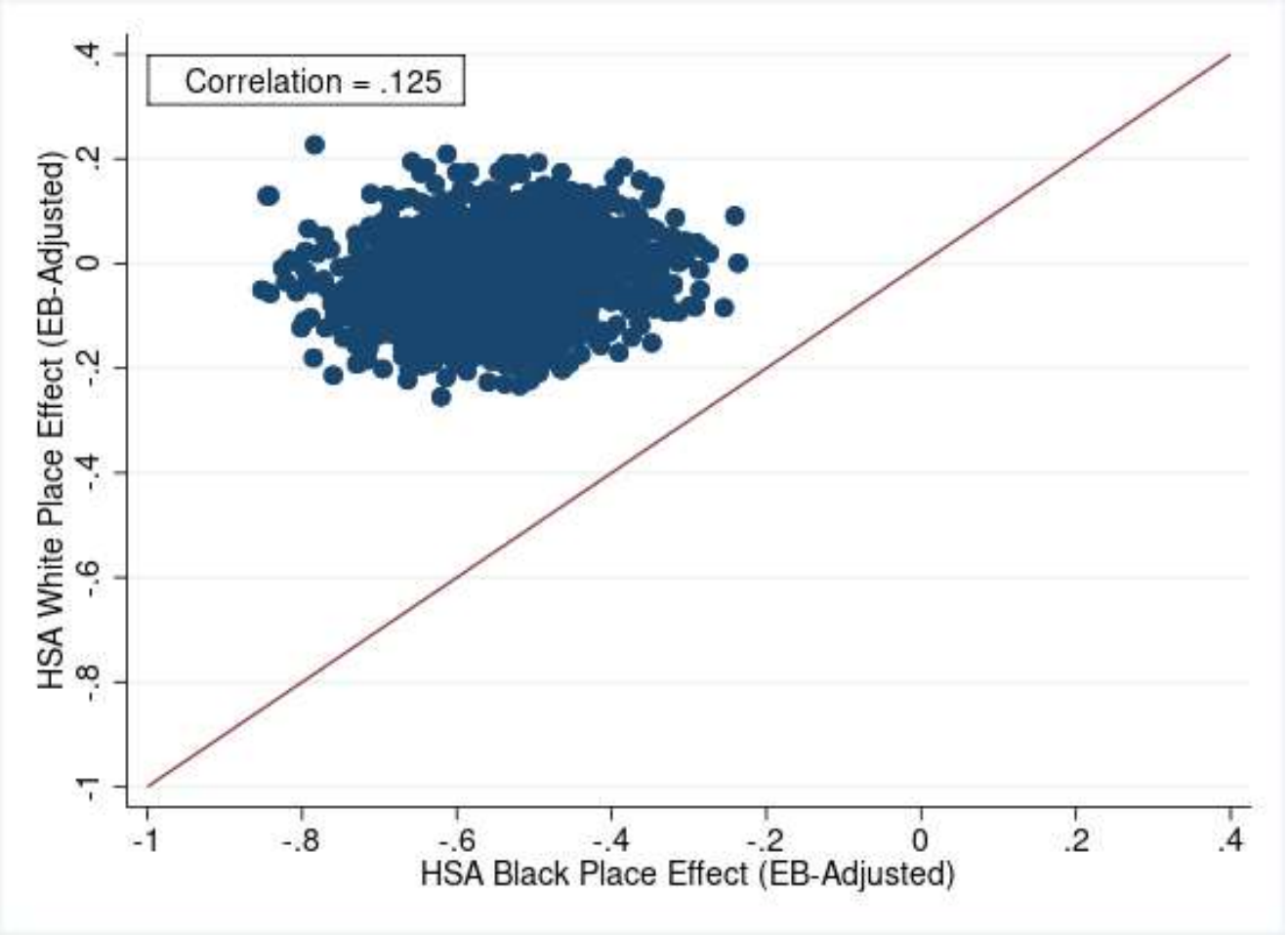


Figure. Correlation between Black and White HSA Place Effects

How correlated are place effects?

To test this further, we divide the estimated place effects ($\hat{\gamma}^{w}_{j(i,t)}$ and $\hat{\gamma}^{b}_{j(i,t)}$) into race-specific ventiles *v*, then estimate the following:

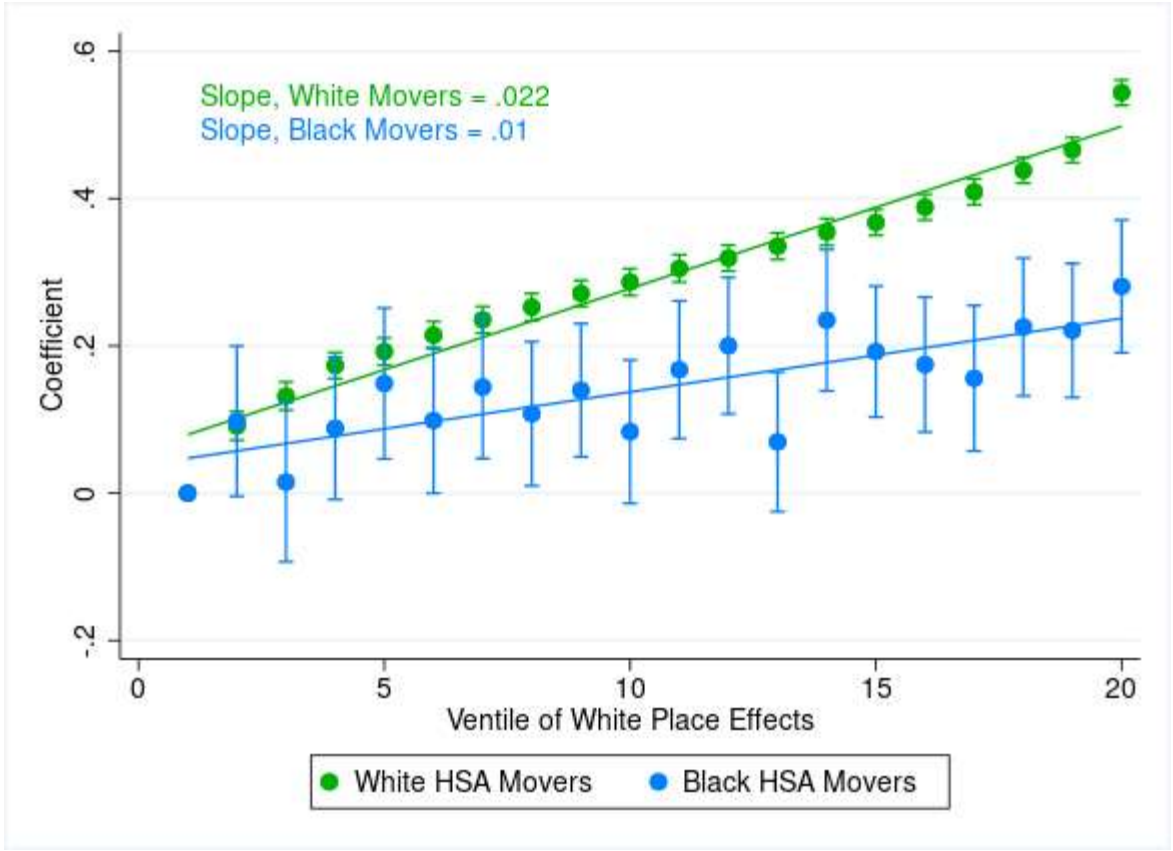
$$y_{it} = \alpha_i + \theta^{r}_{v(i,t)} + \lambda_{r(i,t)} + \tau_t + X'_{it}\beta + \nu_{it}$$

$\theta^{r}_{v(i,t)}$ is a set of indicators for an individual *i* residing in the place effects ventile *v* of race *r* at time *t*.

We estimate this separately for white and Black movers, testing how access changes when:

1. White beneficiaries move from low white place effects ventiles to higher white place effects ventiles
2. Black beneficiaries move from low Black place effects ventiles to higher Black place effects ventiles
3. Beneficiaries move from low to high ventiles for place effects of the opposite race

How correlated are place effects?



(a) Effect of White Place Effects Ventile on Log(Utilization)

(b) Effect of Black Place Effects Ventile on Log(Utilization)

Figure. Causal Effect of Moving Up Place Effects Distribution by Race, Log(Utilization)

Any PC Visit | Num. PC Visits

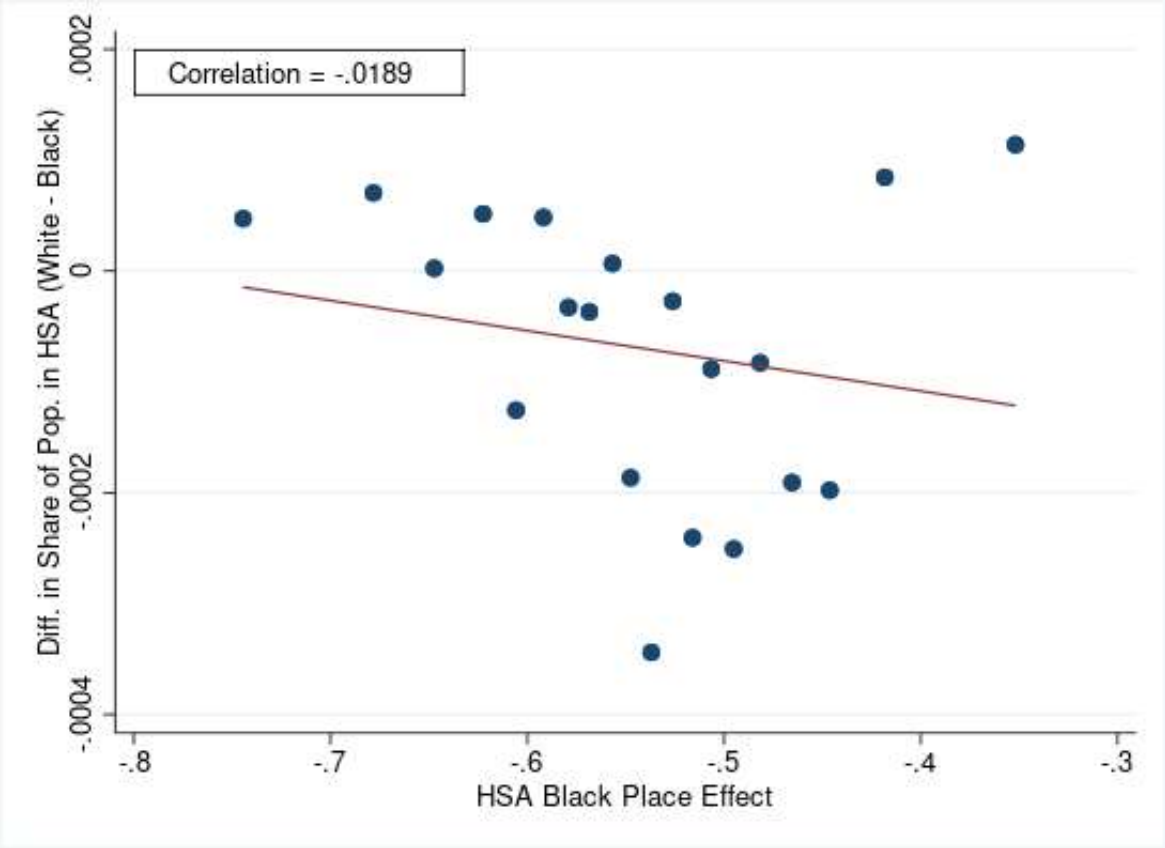
Examining the geographic distribution

Why does the geographic distribution of individuals have such a limited impact?

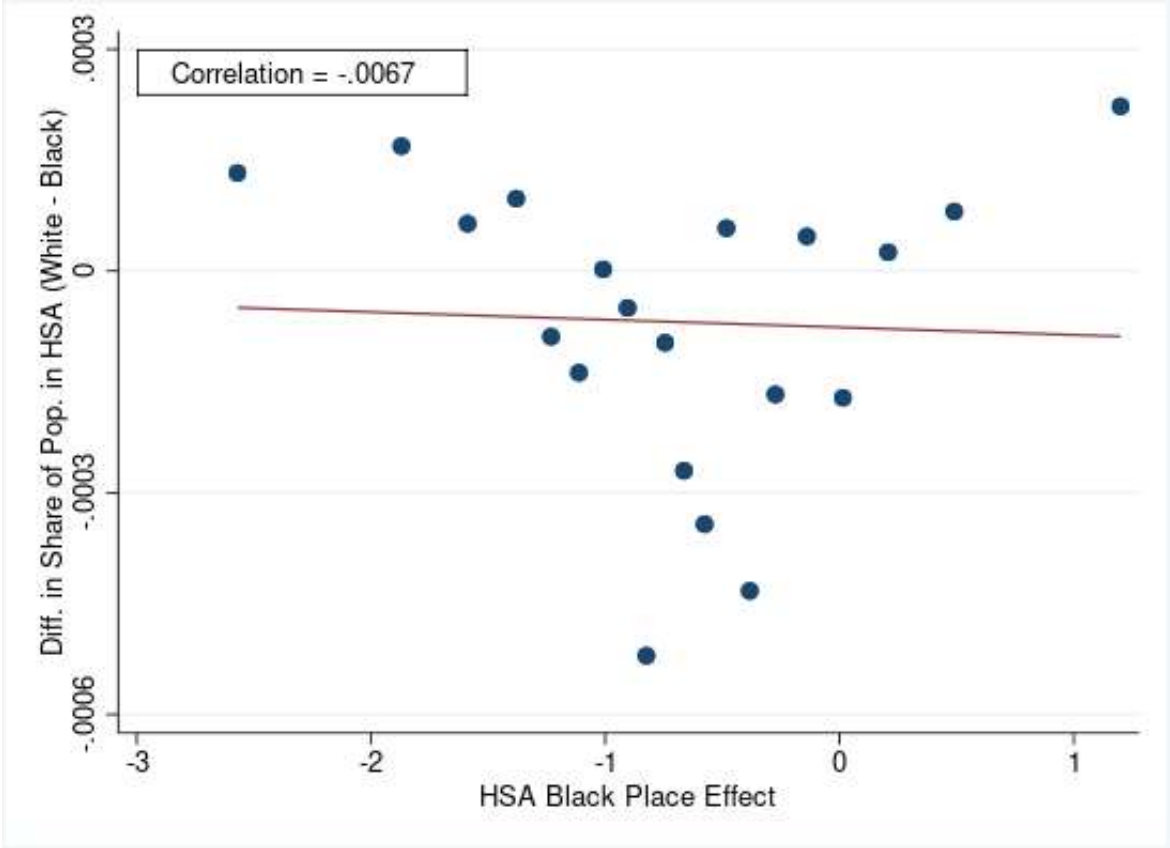
$$\delta^{w,b} = \underbrace{\sum_{j \in \mathcal{J}} \gamma_j^b \left(\sigma_j^w - \sigma_j^b\right)}_{\text{diffs. due to geo. dist.}} + \underbrace{\sum_{j \in \mathcal{J}} \sigma_j^w \left(\gamma_j^w - \gamma_j^b\right)}_{\text{diffs. due to place effects}} + \underbrace{\left(\frac{1}{N_w} \sum_{i \in w} \hat{y}_i^* - \frac{1}{N_b} \sum_{i \in b} \hat{y}_i^*\right)}_{\text{person component}}$$

1. Place effects for Black beneficiaries and white beneficiaries are uncorrelated
2. **Place effects for Black beneficiaries are uncorrelated with the differential geographic distribution**

Black place effects and the geographic distribution are uncorrelated



(a) Log(Utilization)



(b) Number of PC Visits

Figure. Correlation between Estimated Black Place Effects and Differential Geographic Distribution

Examining the geographic distribution

We divide places based on their differential population distribution ($\hat{\sigma}_{jt}^{w}$ and $\hat{\sigma}_{jt}^{b}$) into race-specific ventiles *v*, then estimate the following:

$$y_{it} = \alpha_i + \kappa_{v(i,t)} + \lambda_{r(i,t)} + \tau_t + X_{it}'\beta + \nu_{it}$$

$\kappa_{v(i,t)}$is a set of indicators for an individual *i* residing in the differential population distribution ventile *v* at time *t*.

We estimate this separately for white and Black movers, testing how access changes when:

1. White beneficiaries move from areas that have a larger share of the white population to those with a larger share of the Black population
2. Black beneficiaries move from areas that have a larger share of the white population to those with a larger share of the Black population

Access unchanged by moves across the geographic distribution

- Our estimates of these ventile regressions do not rely at all on estimates of the place effects for Black beneficiaries
- **Reinforce earlier finding**: differential geographic distribution of individuals plays little role in driving disparities
- For both white and Black beneficiaries, moves to higher ventiles of the differential population distribution have no effect on access across all of our measures.

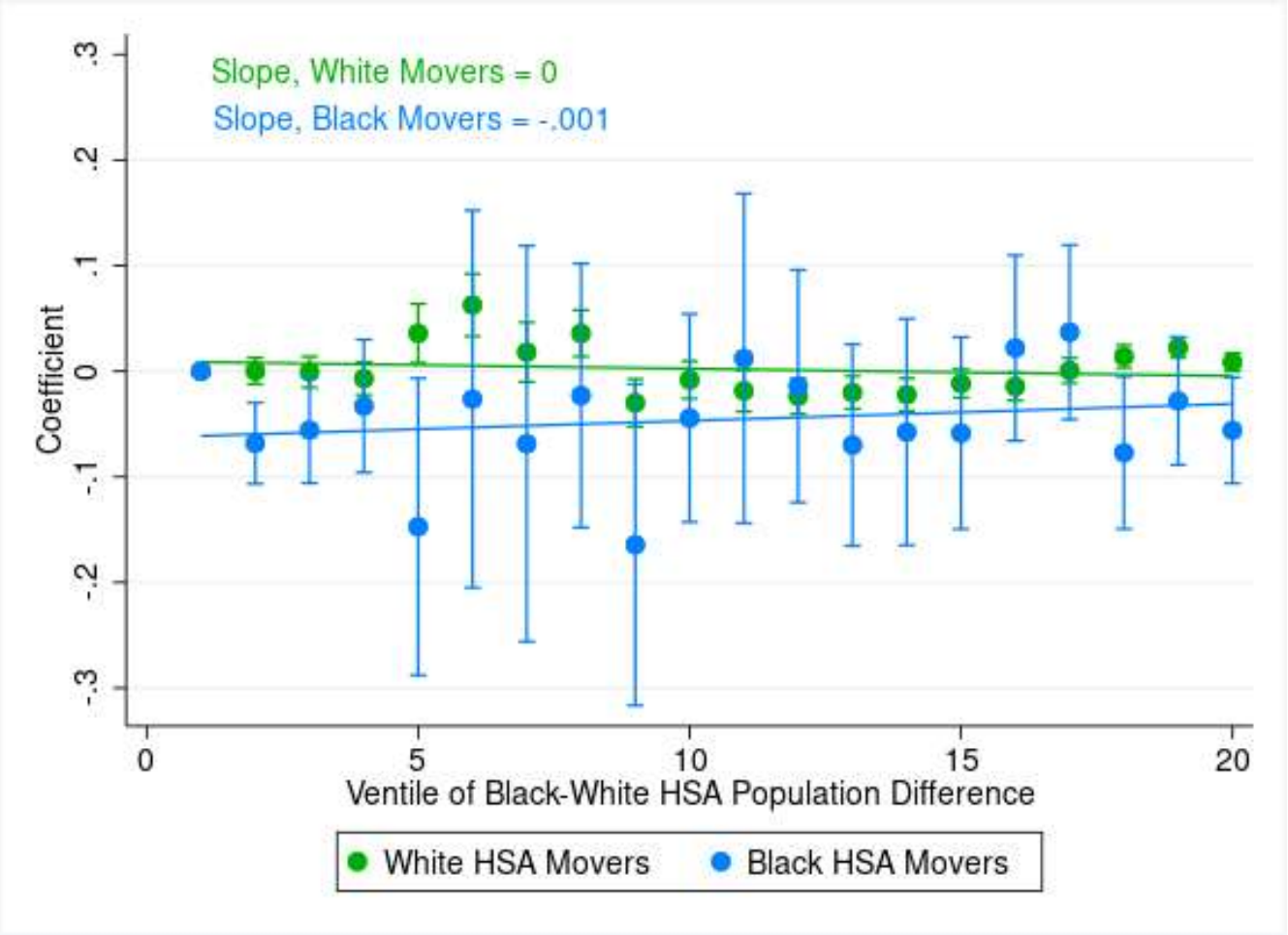


Figure: Effect of Moving to Higher Differential Population Ventile by Race, Log(Utilization)

Other Outcomes

What is the right level of geography?

We replicate all of these analyses for both broader regions (Hospital Referral Regions) and more narrow, granular geographies (HRR x ZIP Code Income Quintile). At each level, we find that:

1. Places matter for access to care
2. Places matter for disparities in access to care
3. Differential place effects by geography drive the place component of our decomposition
4. Place effects for Black beneficiaries are uncorrelated with the geographic distribution of individuals and uncorrelated with place effects for white beneficiaries

Importance of causal place effects

- We would not have reached the same conclusions using observational estimates of place effects.
- Observational estimates of decomposition either understate role of place or give opposite sign altogether.

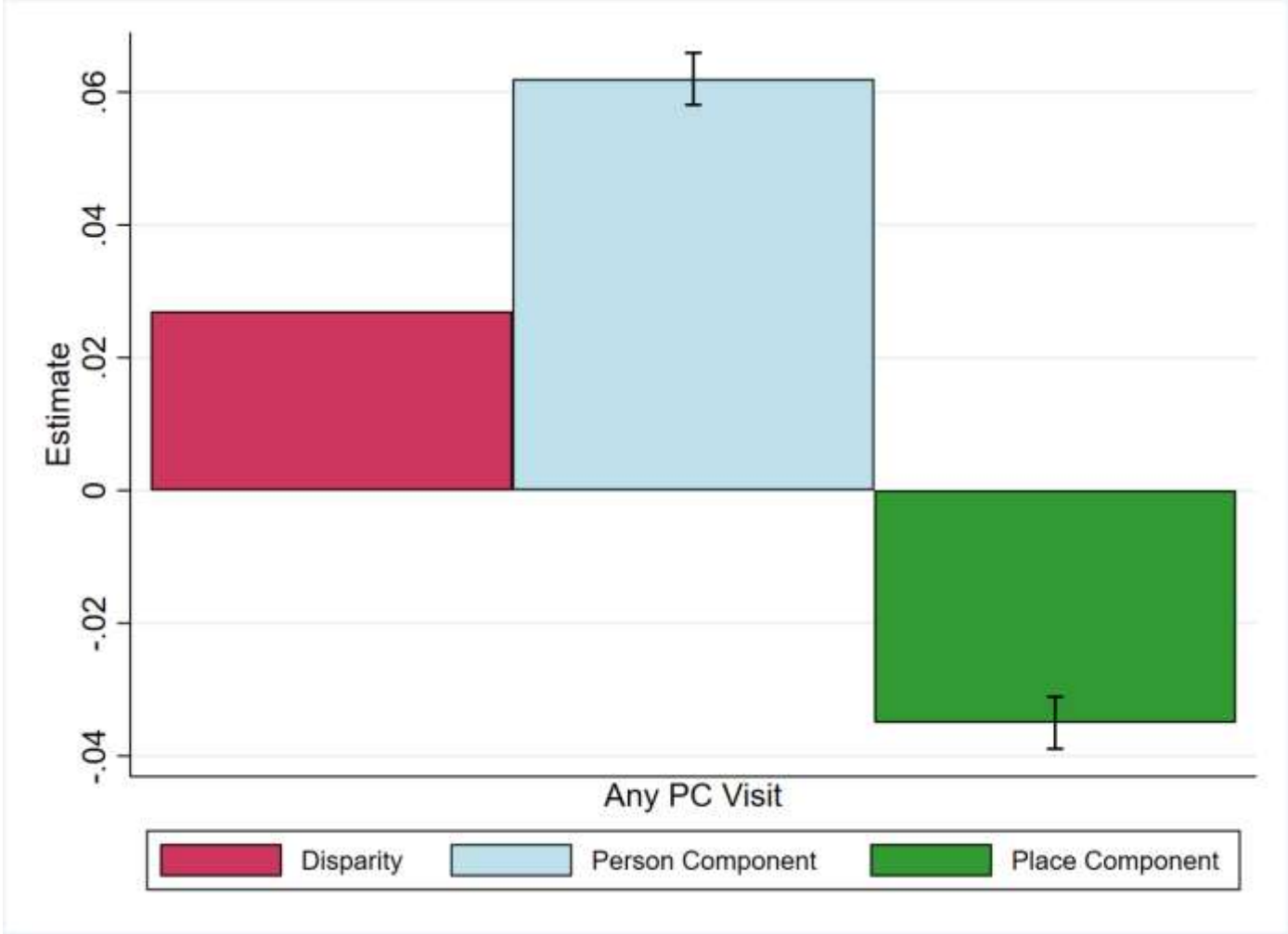


Figure. Decomposition Estimates, Observational HSA Place Effects, Any PC Visit

Other Measures

Roadmap

Background

Conceptual Framework

Empirical Strategy

Do Places Matter?

Decomposition

The Importance of Place**-by-Race** Effects

Conclusion

Summing up

How should we read these results?

1. Places matter for access to care and for racial disparities in access to care at both broad (HRR) and narrow (HRR x ZIP Code income quintile) levels.

2. We show that place effects **heterogeneity** is critical for uncovering the importance of place. Assuming constant place effects indicates that places matters very little.

3. Places matter for disparities because areas have **differential place effects** for Black and white beneficiaries, **not** because Black and white beneficiaries tend to live in different areas.

4. The places that do the best at delivering access to medical care for white beneficiaries do not do as well as delivering access for Black beneficiaries, and vice versa.

What does this mean for public policy?

1. Policies to target access poor areas more generally (place-based policies) will have less impact on disparities than policies that specifically target areas with poor access for Black beneficiaries (place-*by-race*-based policies).

Thank you!

We are grateful for any feedback or further thoughts you may have!
Please feel free to email me at **gpeterson@g.harvard.edu**.

Thank you for your time!

Appendix Figures

Movers vs. Non-Movers

	Non-Movers		ZIP Movers		HSA Movers		HRR Movers	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Beneficiary Demographics								
Female	0.56	(0.50)	0.60	(0.49)	0.59	(0.49)	0.59	(0.49)
White	0.83	(0.37)	0.84	(0.37)	0.86	(0.35)	0.86	(0.34)
Black	0.07	(0.26)	0.07	(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)	0.03	(0.16)	0.02	(0.15)
AIAN	0.00	(0.07)	0.00	(0.06)	0.00	(0.06)	0.00	(0.05)
Other	0.01	(0.09)	0.01	(0.08)	0.01	(0.08)	0.01	(0.08)
Age at First Observation	72.01	(6.83)	73.26	(7.34)	73.12	(7.29)	72.93	(7.21)
Region of Residence								
Northeast	0.19	(0.39)	0.19	(0.39)	0.20	(0.40)	0.19	(0.40)
South	0.40	(0.49)	0.38	(0.49)	0.38	(0.48)	0.38	(0.49)
Midwest	0.24	(0.43)	0.22	(0.42)	0.21	(0.41)	0.21	(0.41)
West	0.17	(0.38)	0.20	(0.40)	0.21	(0.40)	0.21	(0.41)
Beneficiary Health								
Log(Utilization)	7.81	(1.47)	7.96	(1.47)	7.94	(1.46)	7.92	(1.45)
Num. Chronic Conditions	3.74	(2.74)	4.09	(2.91)	4.02	(2.88)	3.93	(2.83)
Years Observed	7.99	(3.09)	8.24	(2.86)	8.25	(2.85)	8.26	(2.86)
Died in Sample	0.24	(0.43)	0.27	(0.45)	0.26	(0.44)	0.25	(0.43)
Observations	10,383,027		10,077,330		6,538,449		4,561,262	

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. All HRR and HSA movers are also ZIP movers.

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Table. Descriptive Statistics of Movers and Non-Movers

Black and White Movers are Observably Similar

	ZIP Movers				HSA Movers				HRR Movers			
	White		Black		White		Black		White		Black	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	0.60	(0.49)	0.61	(0.49)	0.60	(0.49)	0.61	(0.49)	0.59	(0.49)	0.62	(0.49)
Age at First Observation	73.49	(7.41)	72.29	(7.20)	73.30	(7.35)	72.45	(7.19)	73.08	(7.27)	72.52	(7.17)
Region of Residence												
Northeast	0.19	(0.39)	0.17	(0.38)	0.20	(0.40)	0.20	(0.40)	0.19	(0.40)	0.20	(0.40)
South	0.38	(0.49)	0.53	(0.50)	0.38	(0.48)	0.51	(0.50)	0.39	(0.49)	0.49	(0.50)
Midwest	0.24	(0.43)	0.21	(0.41)	0.23	(0.42)	0.19	(0.39)	0.22	(0.41)	0.22	(0.41)
West	0.19	(0.39)	0.08	(0.28)	0.19	(0.39)	0.10	(0.30)	0.20	(0.40)	0.09	(0.29)
Beneficiary Health												
Log(Utilization)	7.97	(1.45)	8.03	(1.61)	7.96	(1.45)	8.00	(1.60)	7.93	(1.44)	7.97	(1.59)
Num. Chronic Conditions	4.10	(2.88)	4.38	(3.11)	4.04	(2.86)	4.32	(3.08)	3.94	(2.81)	4.26	(3.04)
Years Observed	8.37	(2.81)	7.49	(3.00)	8.36	(2.81)	7.59	(2.99)	8.37	(2.81)	7.65	(2.98)
Died in Sample	0.28	(0.45)	0.30	(0.46)	0.27	(0.44)	0.29	(0.45)	0.25	(0.43)	0.28	(0.45)
Observations	8468250		675841		5625558		344951		3945008		239181	

Notes: This table shows descriptive statistics for Black and white movers for different geographic levels of move (ZIP code moves, HSA moves, and HRR moves).

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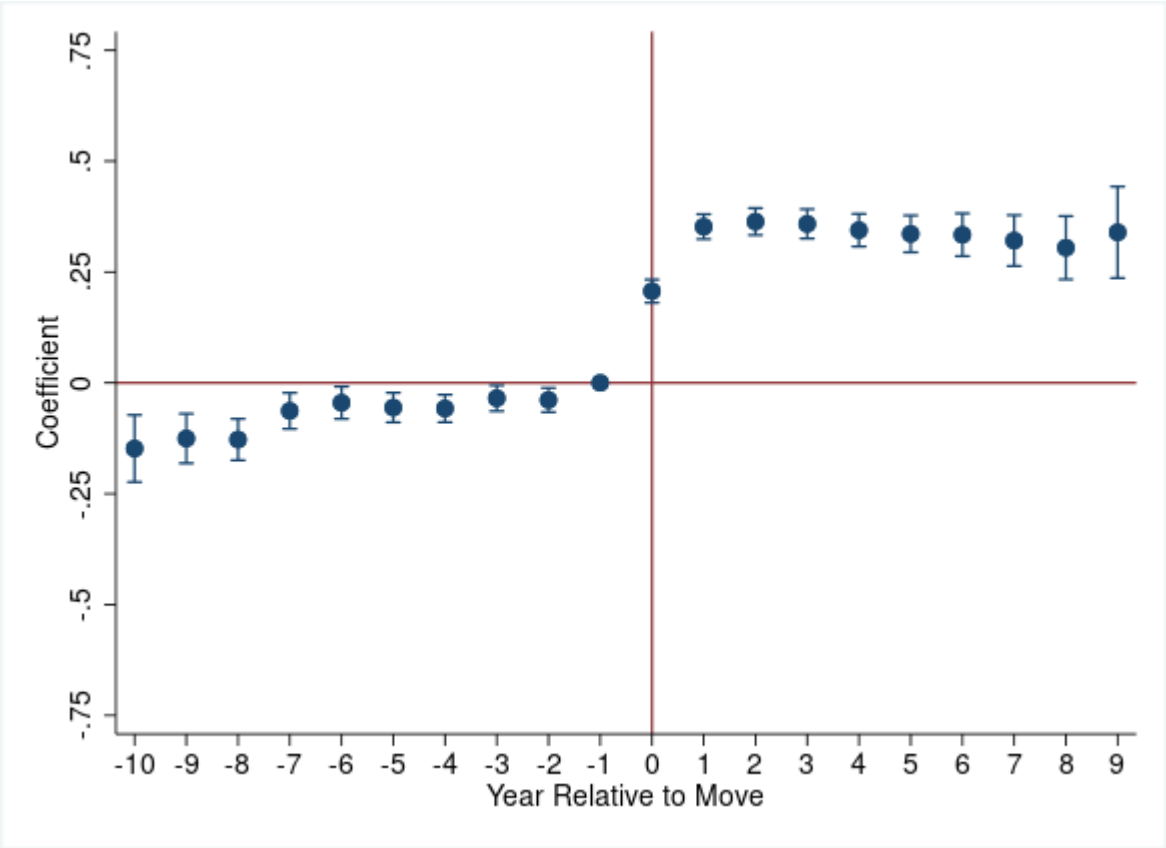
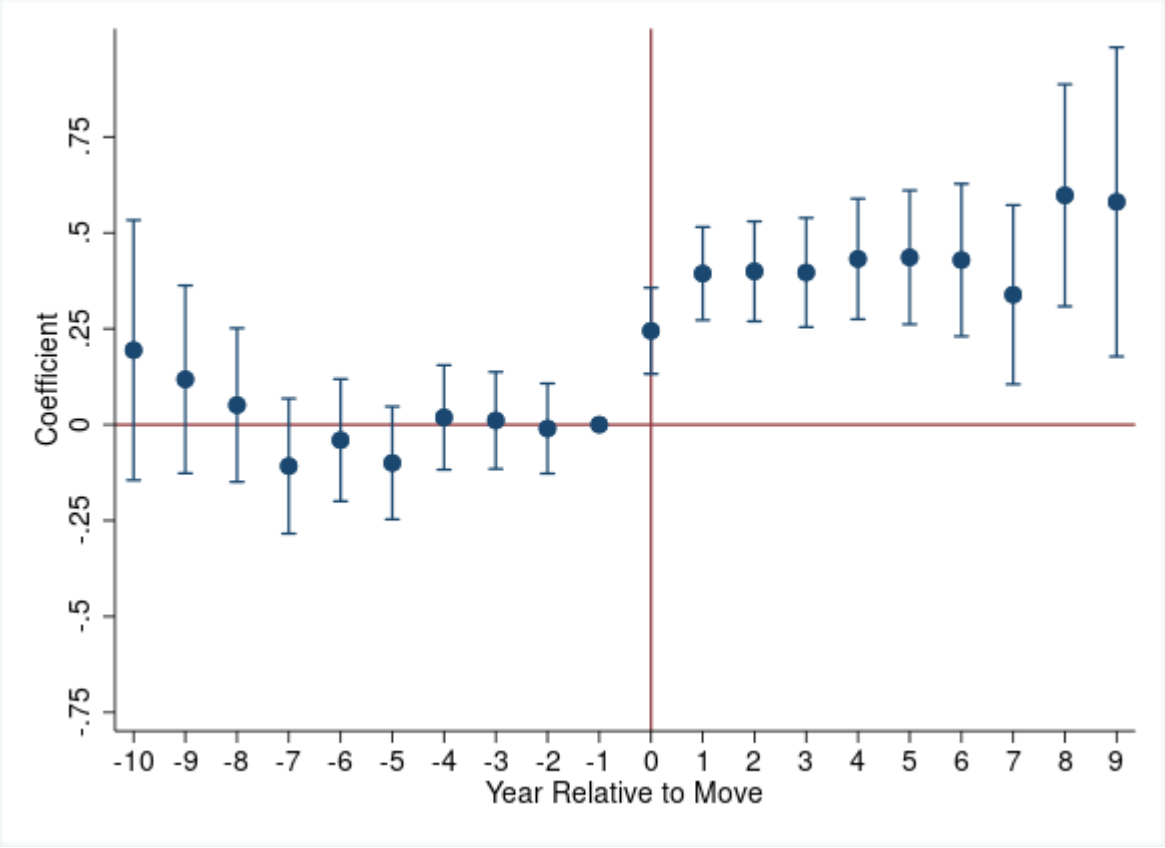
Table. Descriptive Statistics of Black and White Movers by Move Geography

Event Study: Any Primary Care (PC) Visit (0/1)



(a) Effect of HSA Move on Any PC Visit, White Movers



(b) Effect of HSA Move on Any PC Visit, Black Movers

Figure: Effect of Moving on Any PC Visit, White and Black HSA Movers

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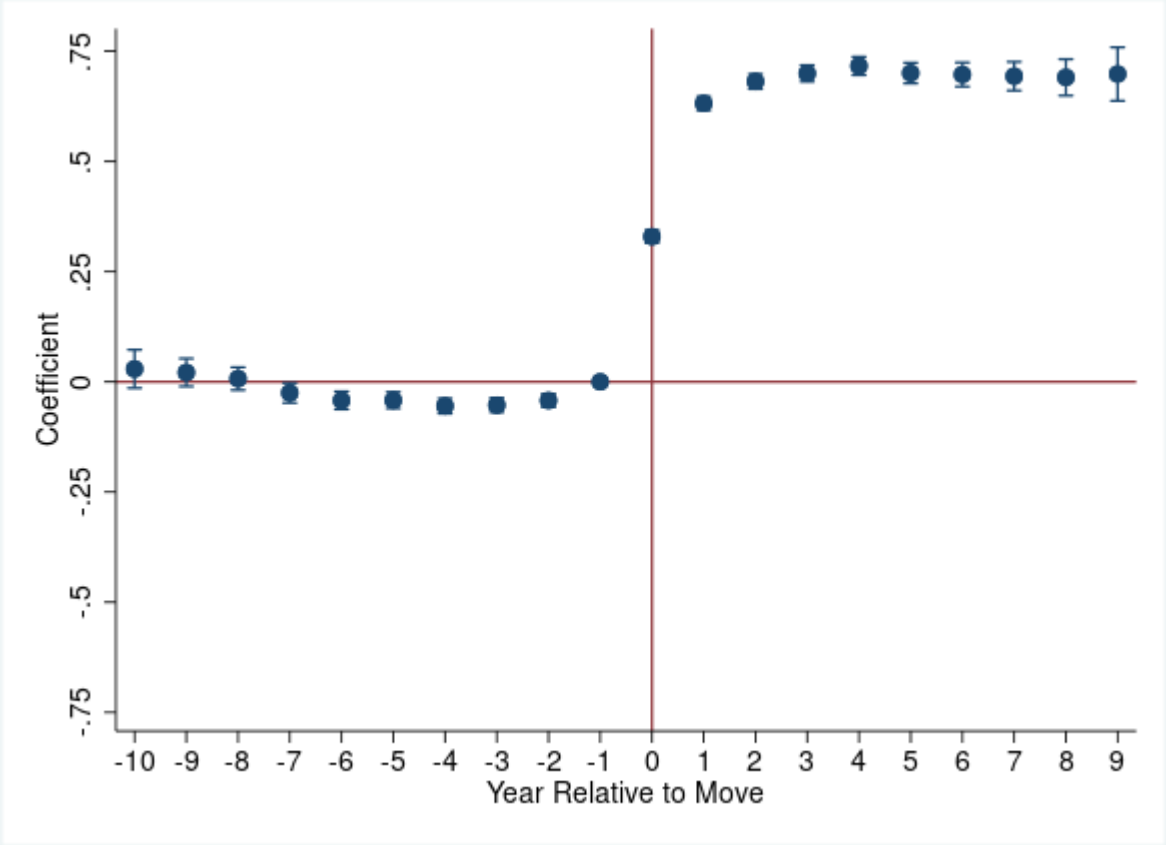
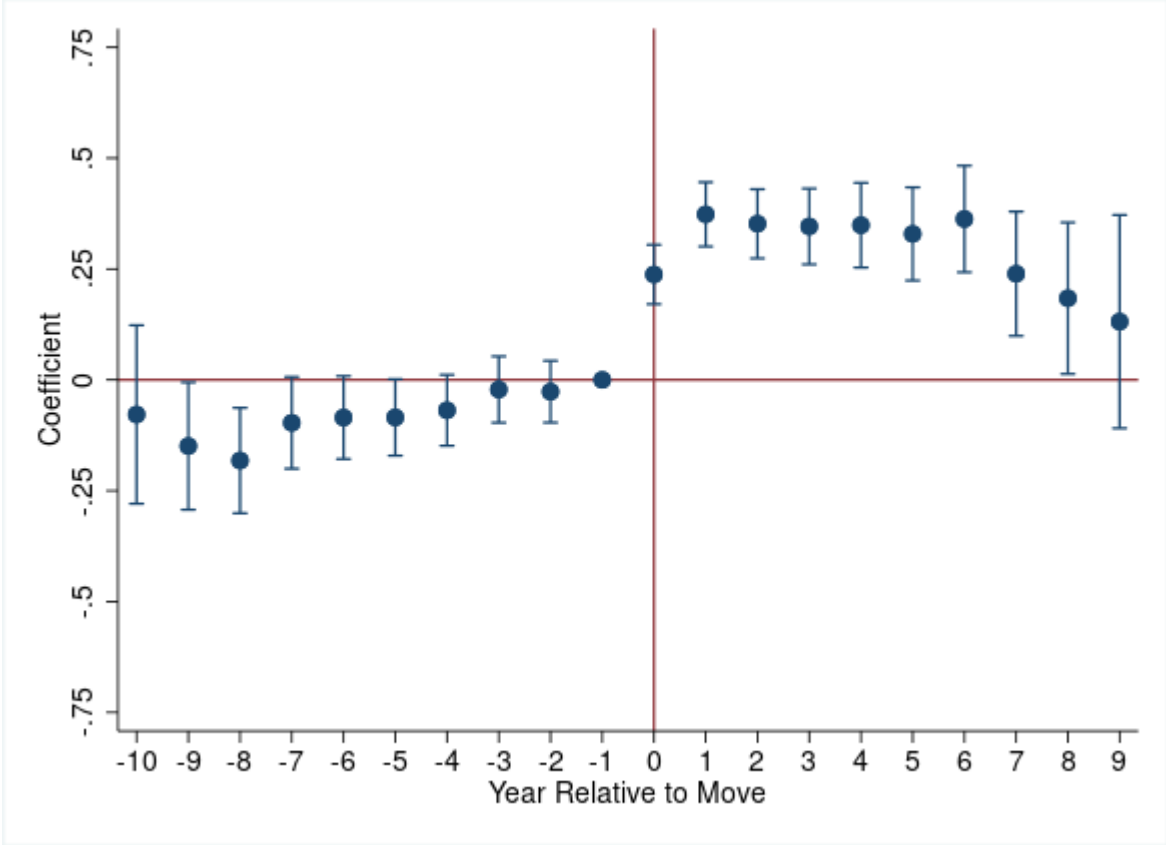
Event Study: Number of Primary Care (PC) Visits



(a) Effect of HSA Move on Number of Primary Care Visits, White Movers



(b) Effect of HSA Move on Number of Primary Care Visits, Black Movers

Figure: Effect of Moving on Number of Primary Care Visits, White and Black HSA Movers

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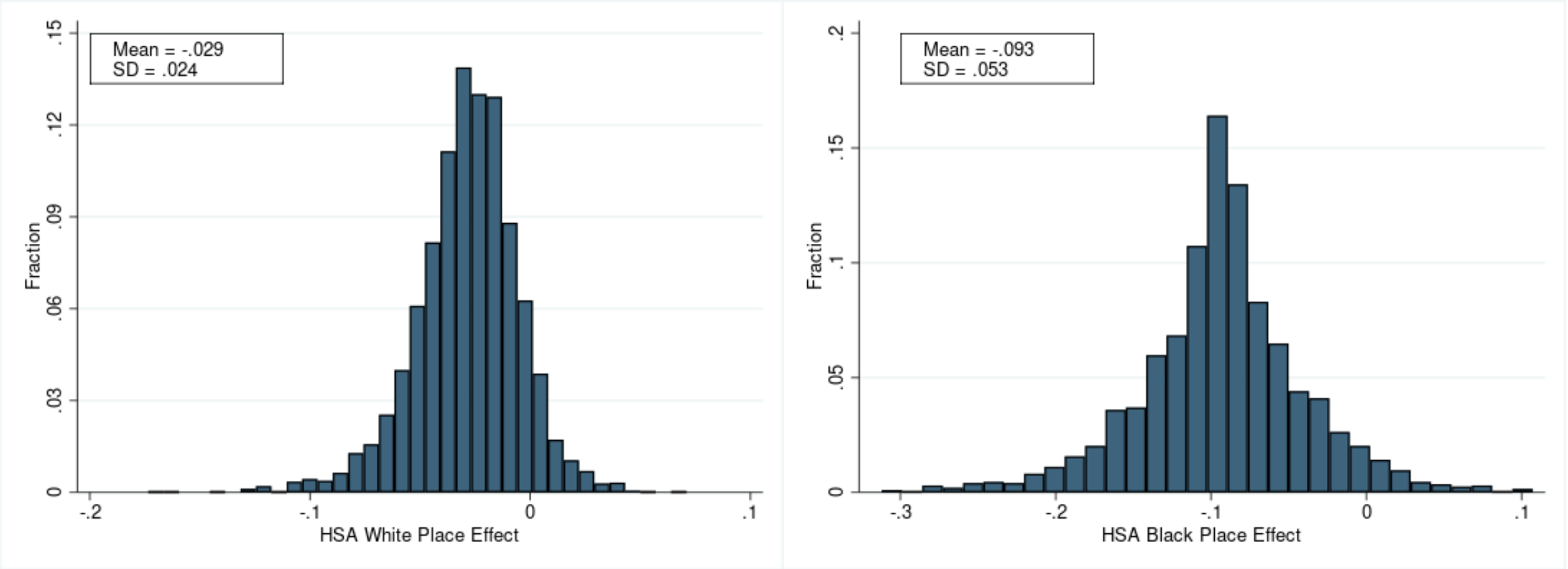
Distribution of Place Effects: Any PC Visit



(a) HSA Place Effects on Any PC Visit, White Movers

(b) HSA Place Effects on Any PC Visit, Black Movers

Figure. Distribution of Place Effects for Any PC Visit, White and Black HSA Movers

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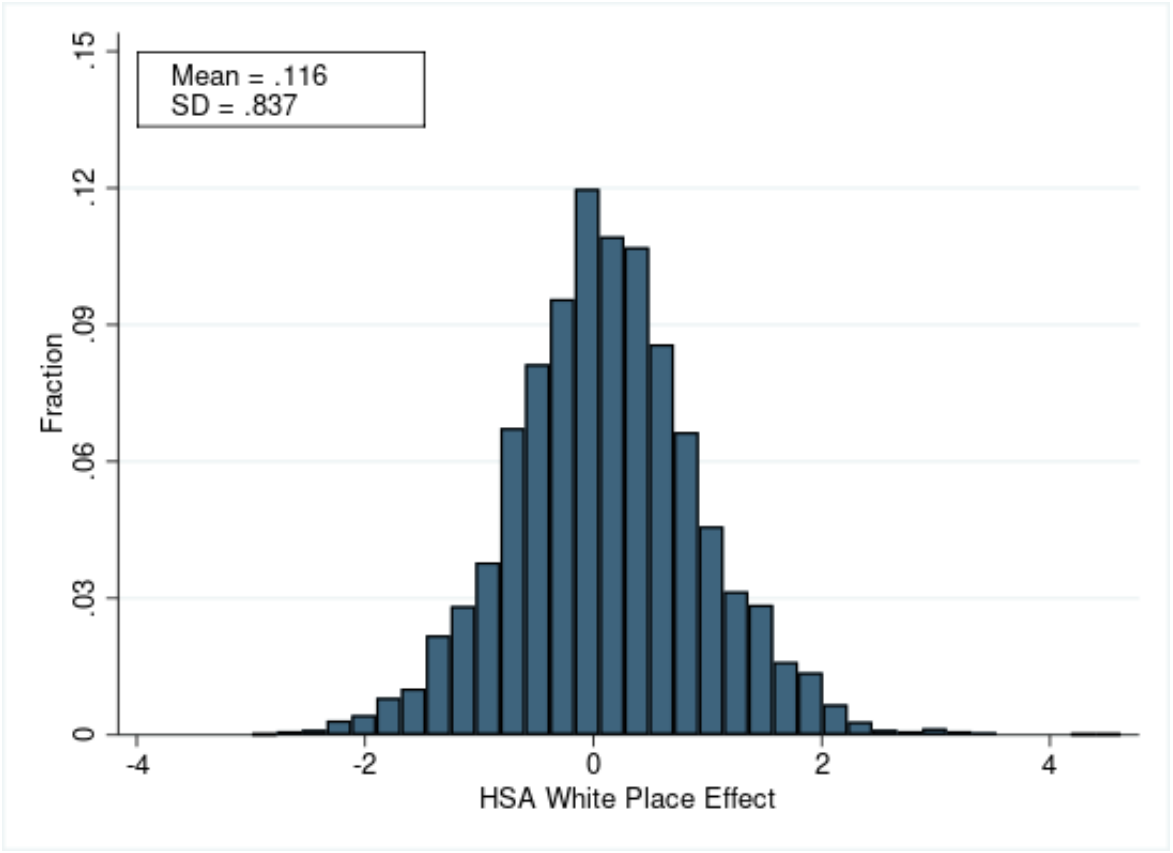
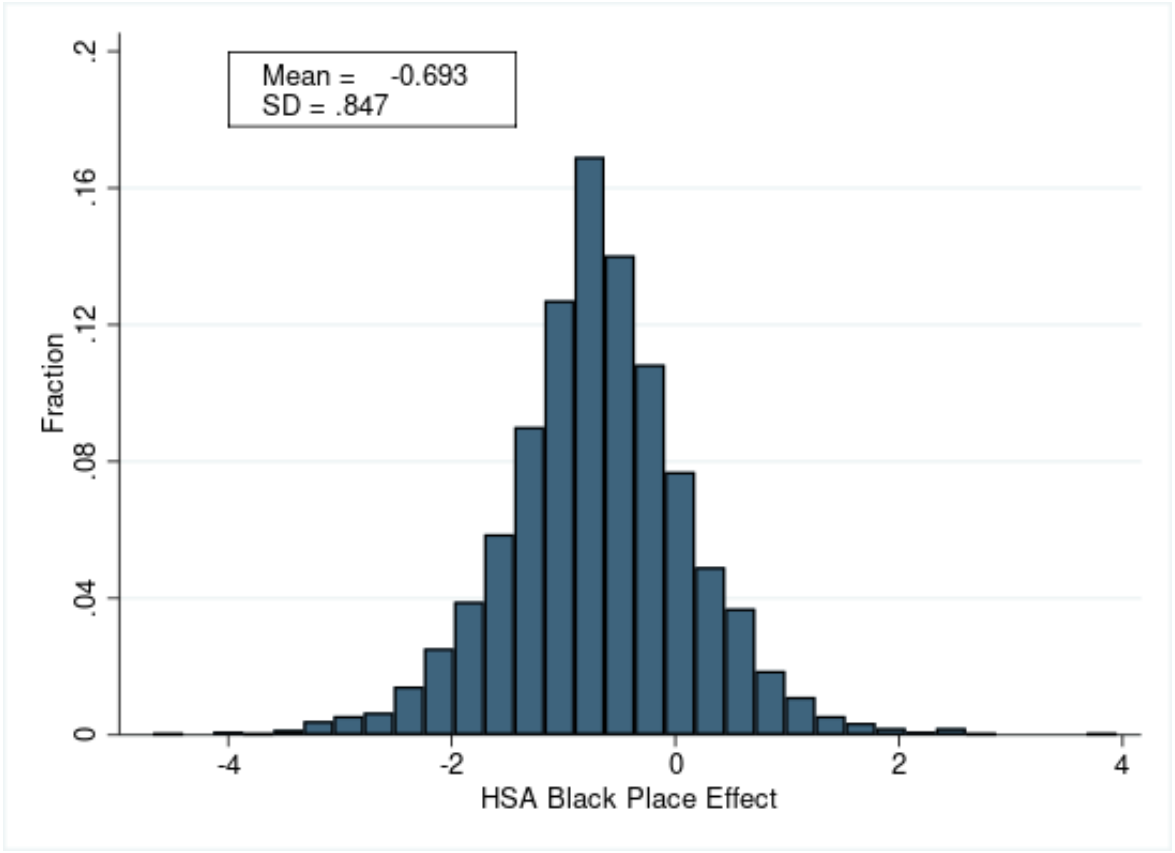
Distribution of Place Effects: Num. PC Visits



(a) HSA Place Effects on Num. PC Visits, White Movers



(b) HSA Place Effects on Num. PC Visits, Black Movers

Figure. Distribution of Place Effects for Num. PC Visits, White and Black HSA Movers

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Homogenous Decomposition: Any PC Visit

Figure. Homogenous HSA Decomposition, Any PC Visit

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Homogenous Decomposition: Any PC Visit

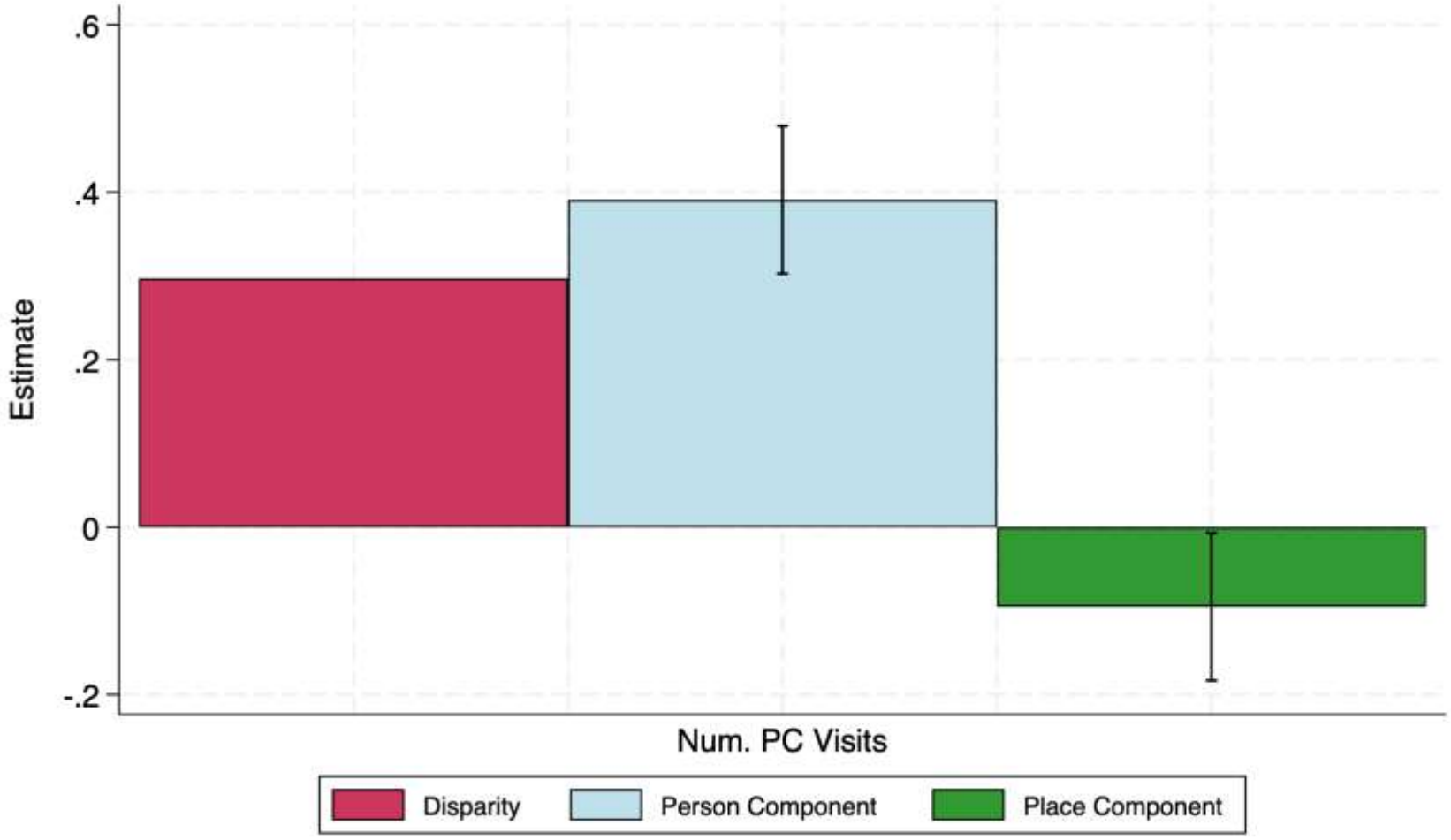

Figure. Homogenous HSA Decomposition, Num. PC Visits

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Heterogeneous Decomposition: Any PC Visit

Figure. Heterogeneous HSA Decomposition, Any PC Visit

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Heterogeneous Decomposition: Num. PC Visits

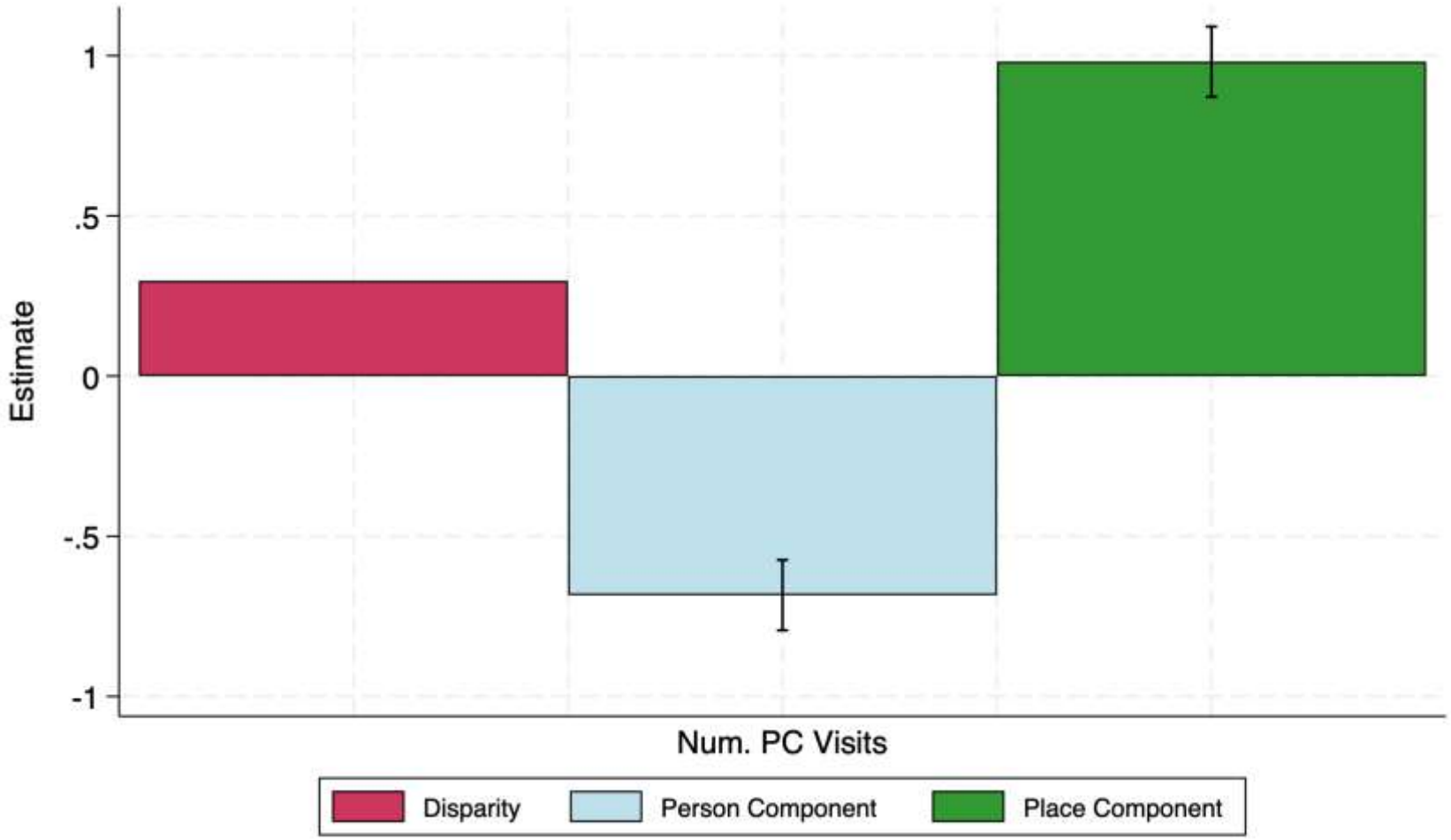

Figure. Heterogeneous HSA Decomposition, Num. PC Visits

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Place Component Decomposition: Any PC Visit

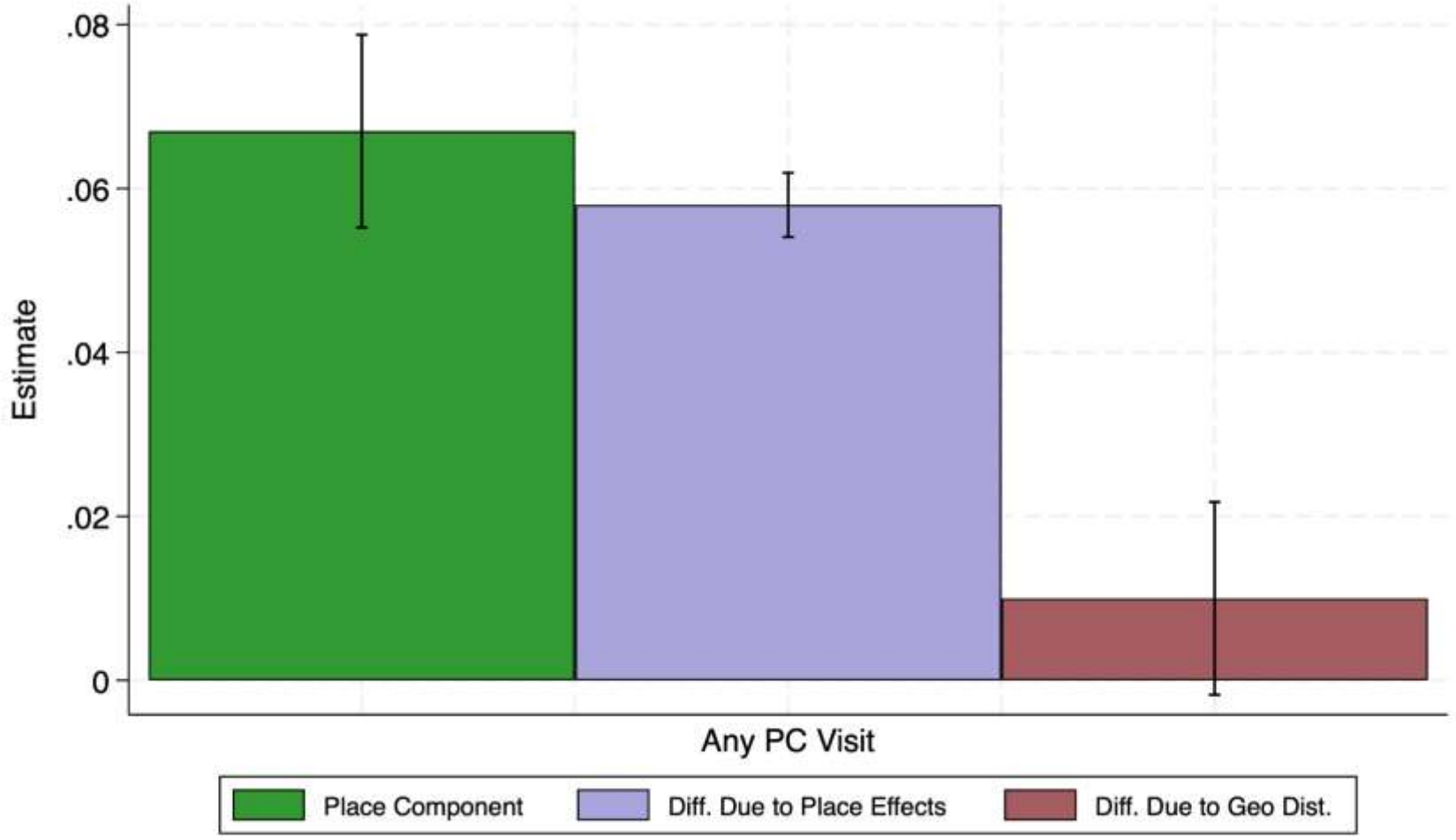

Figure. HSA Place Component Decomposition, Any PC Visit

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Place Component Decomposition: Num. PC Visits

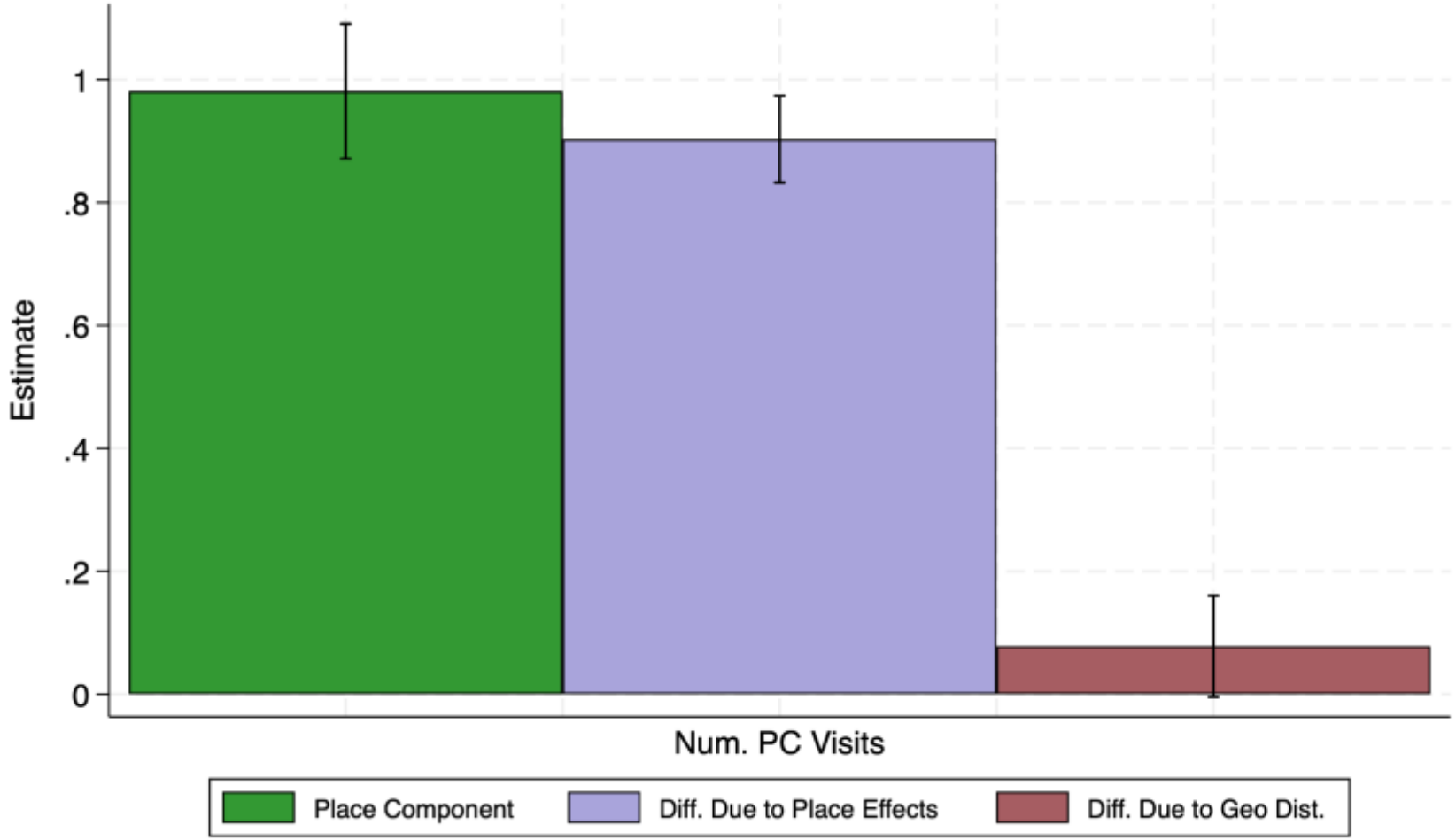

Figure. HSA Place Component Decomposition, Num. PC Visits

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Reallocation Exercise: Log(Utilization)

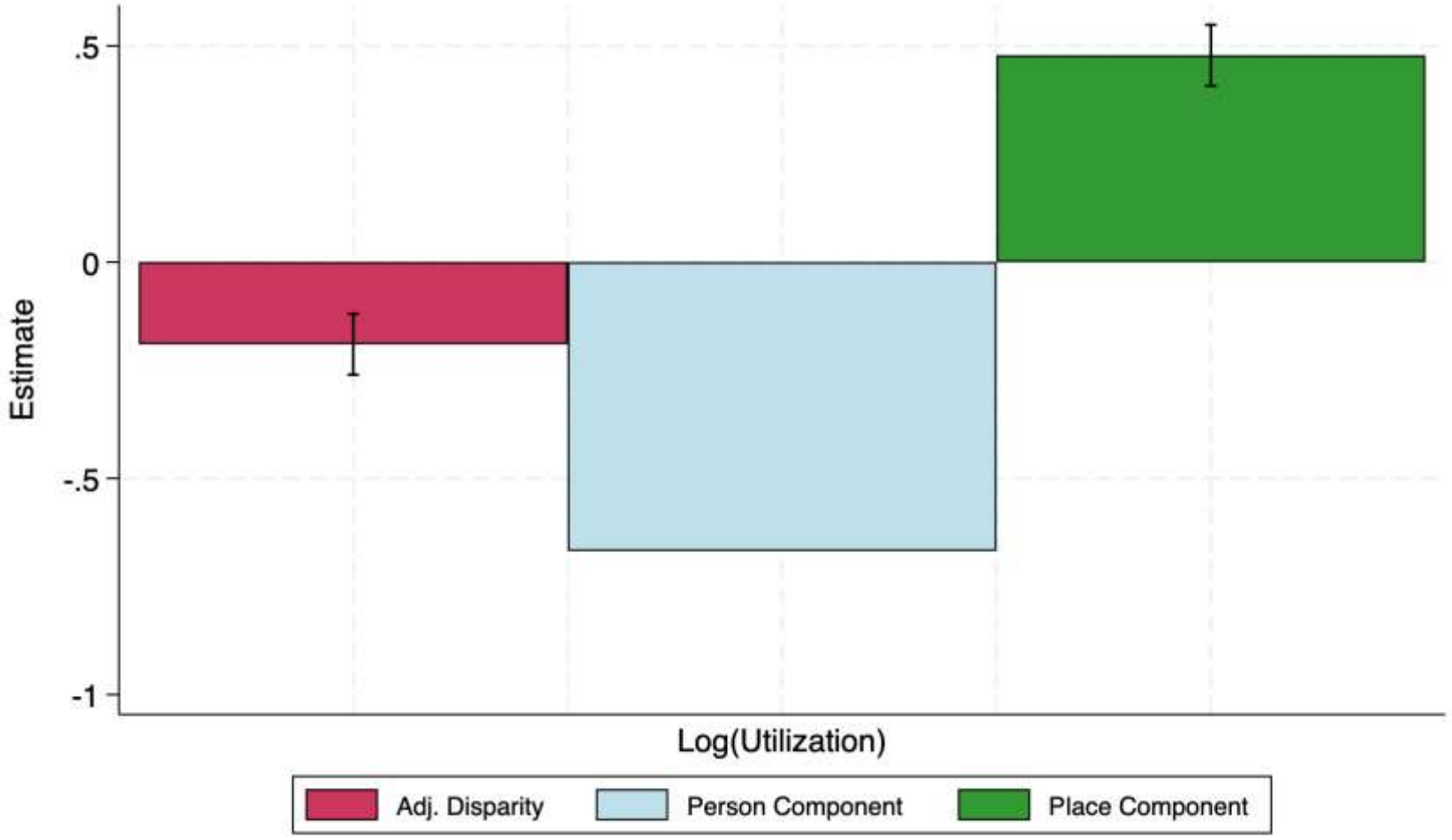

Figure. HSA Reallocation Exercise, Log(Utilization)

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Reallocation Exercise: Any PC Visit

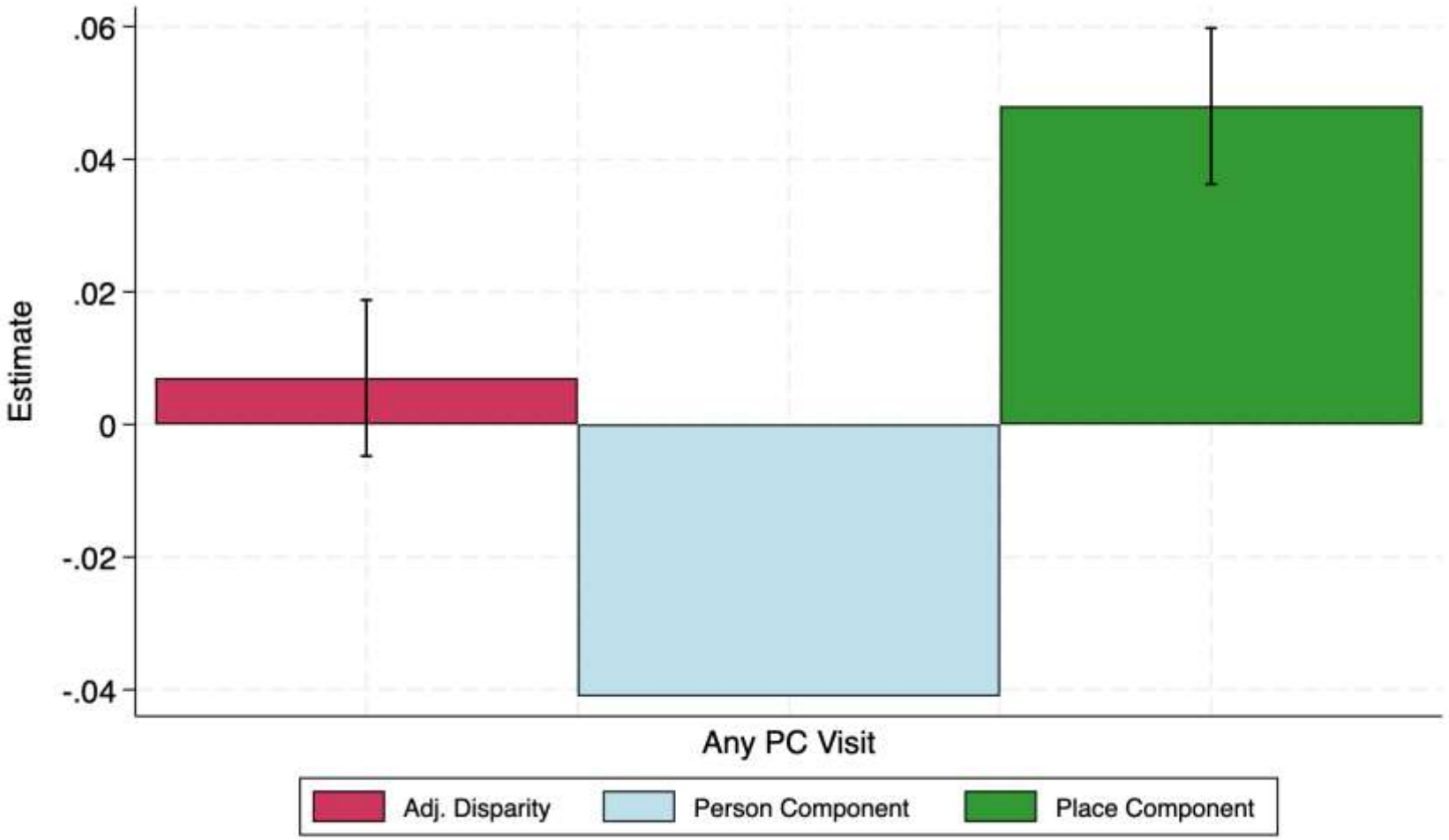

Figure. HSA Reallocation Exercise, Any PC Visit

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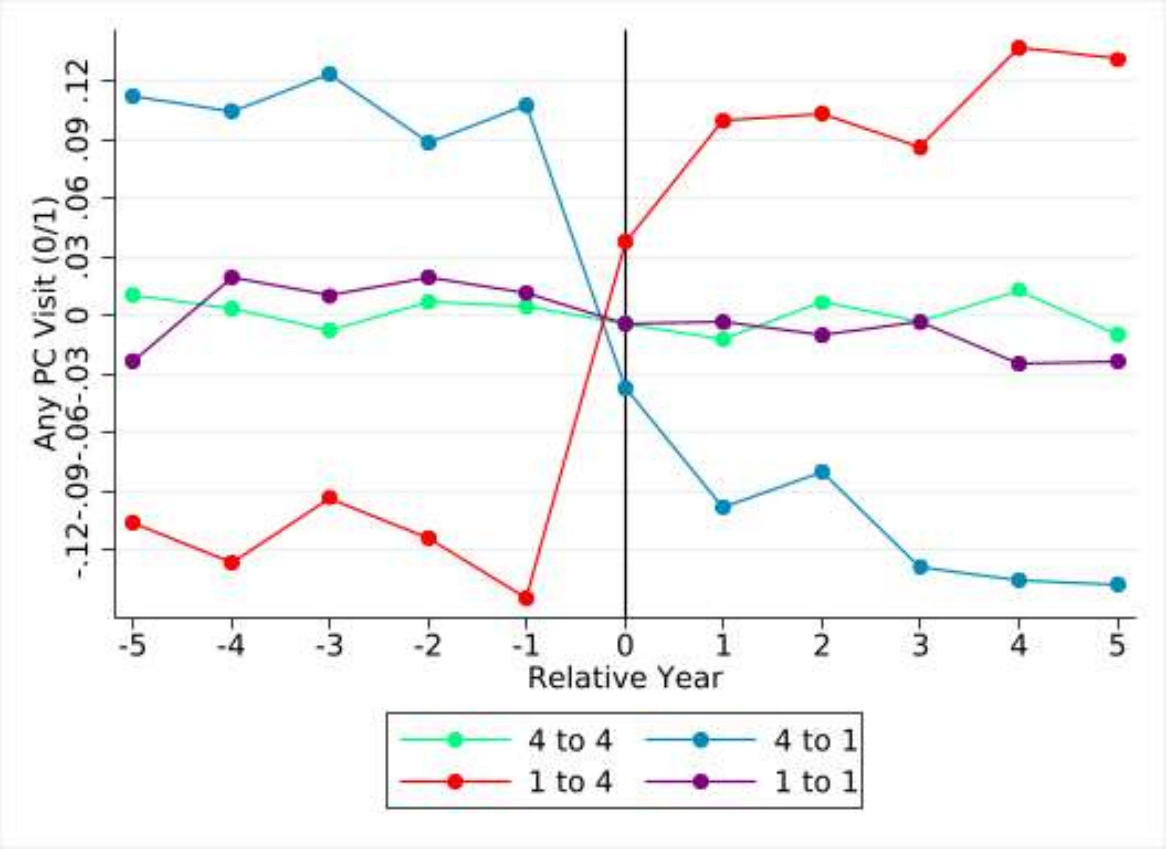
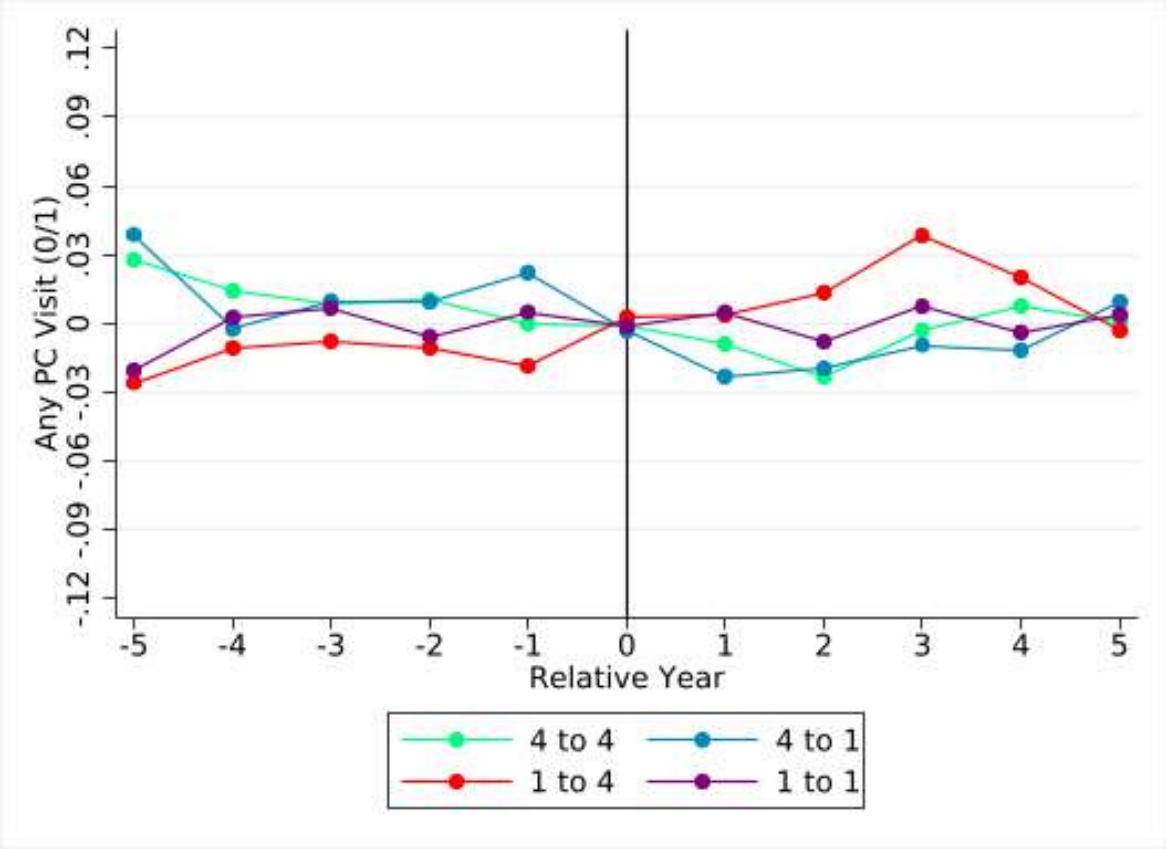
The Importance of Place-by-Race Effects: Any PC Visit



(a) Black Place Effect Moves, Black Movers



(b) White Place Effect Moves, Black Movers

Figure. Changes in Any PC Visit by Move Type, Black Movers

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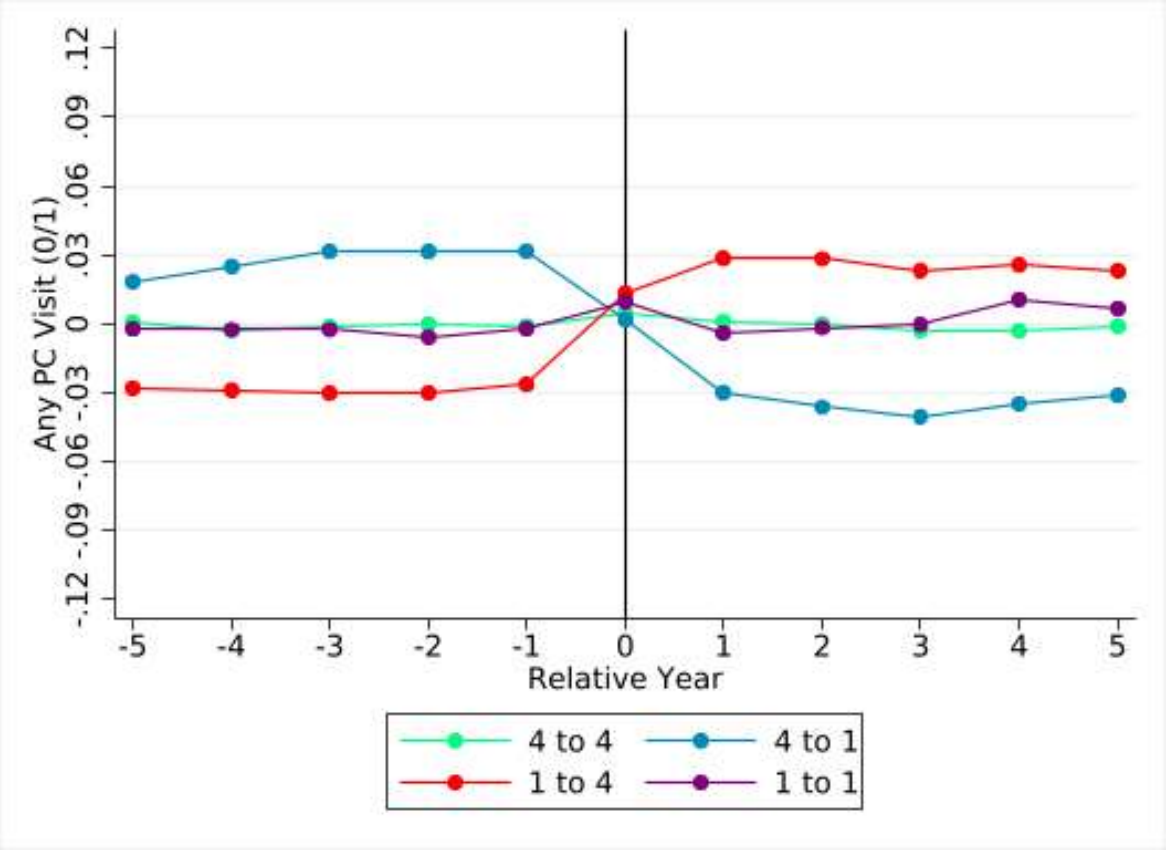
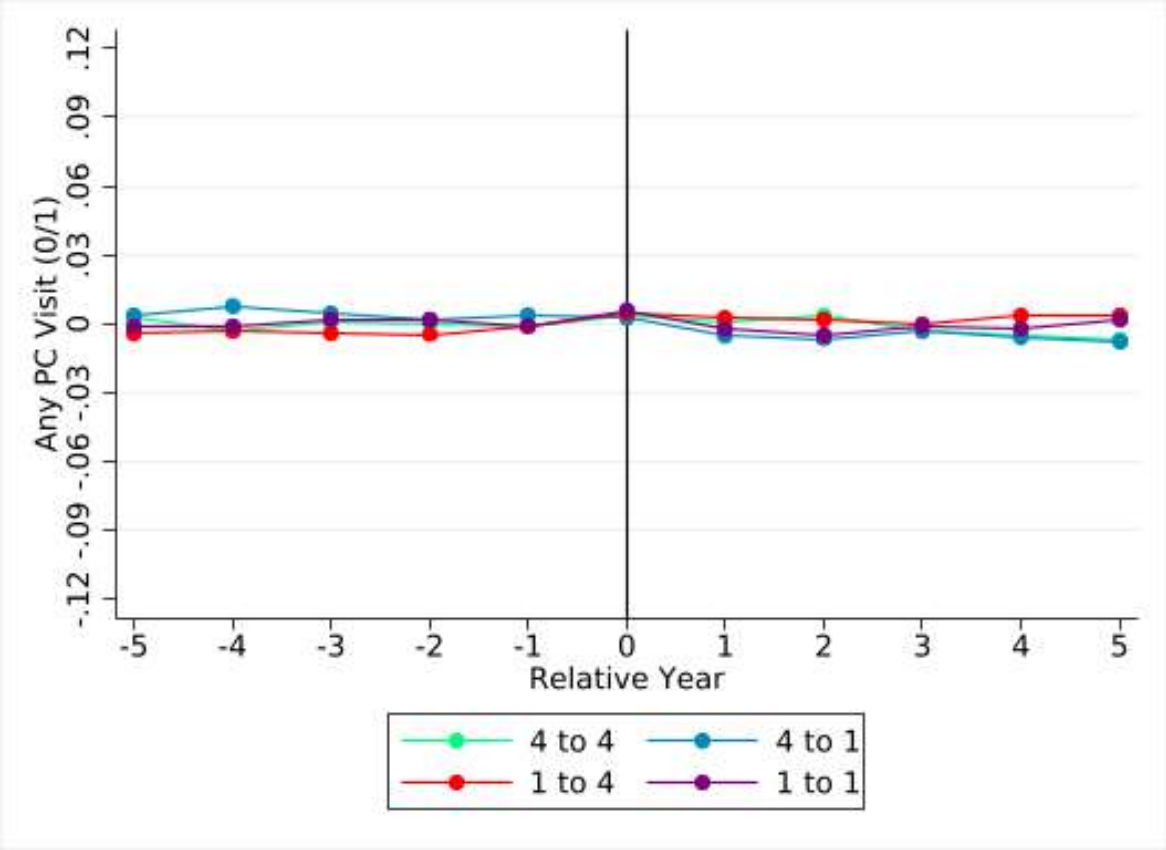
The Importance of Place-by-Race Effects: Any PC Visit



(a) White Place Effect Moves, White Movers



(b) Black Place Effect Moves, White Movers

Figure. Changes in Any PC Visit by Move Type, White Movers

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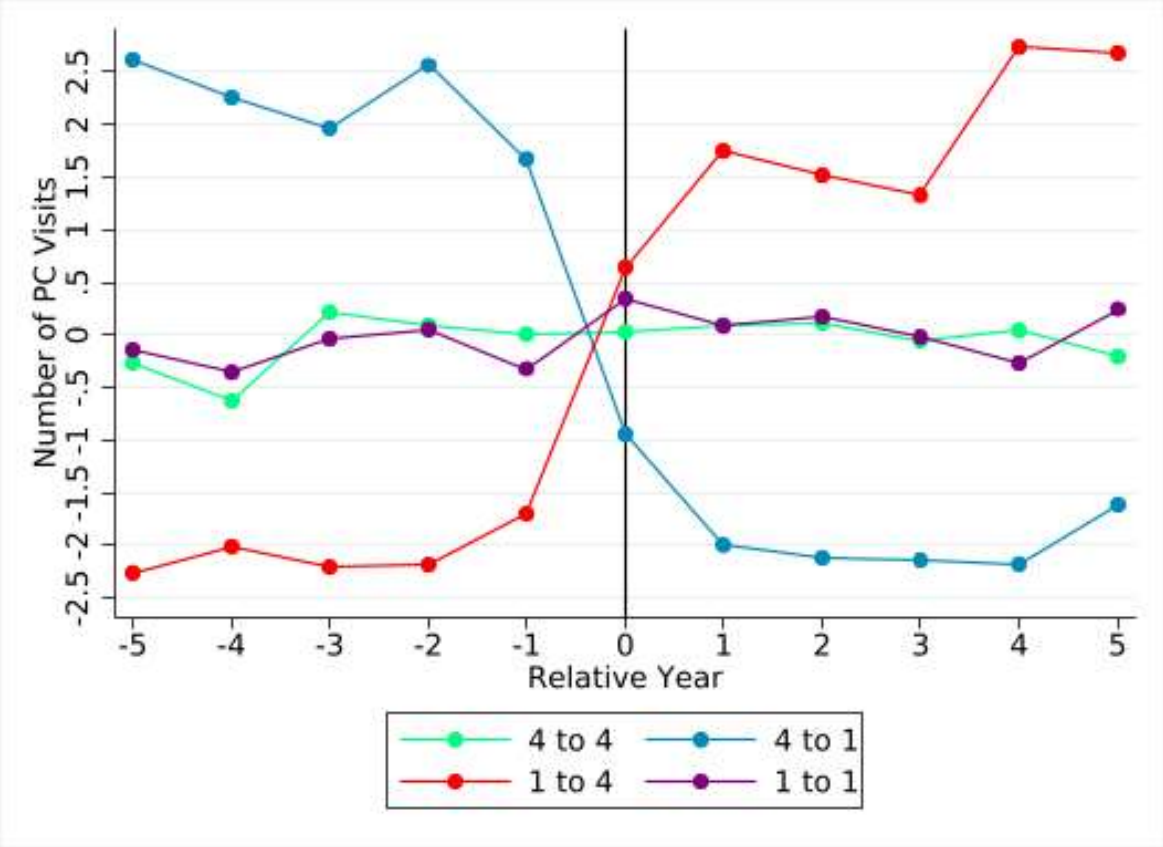
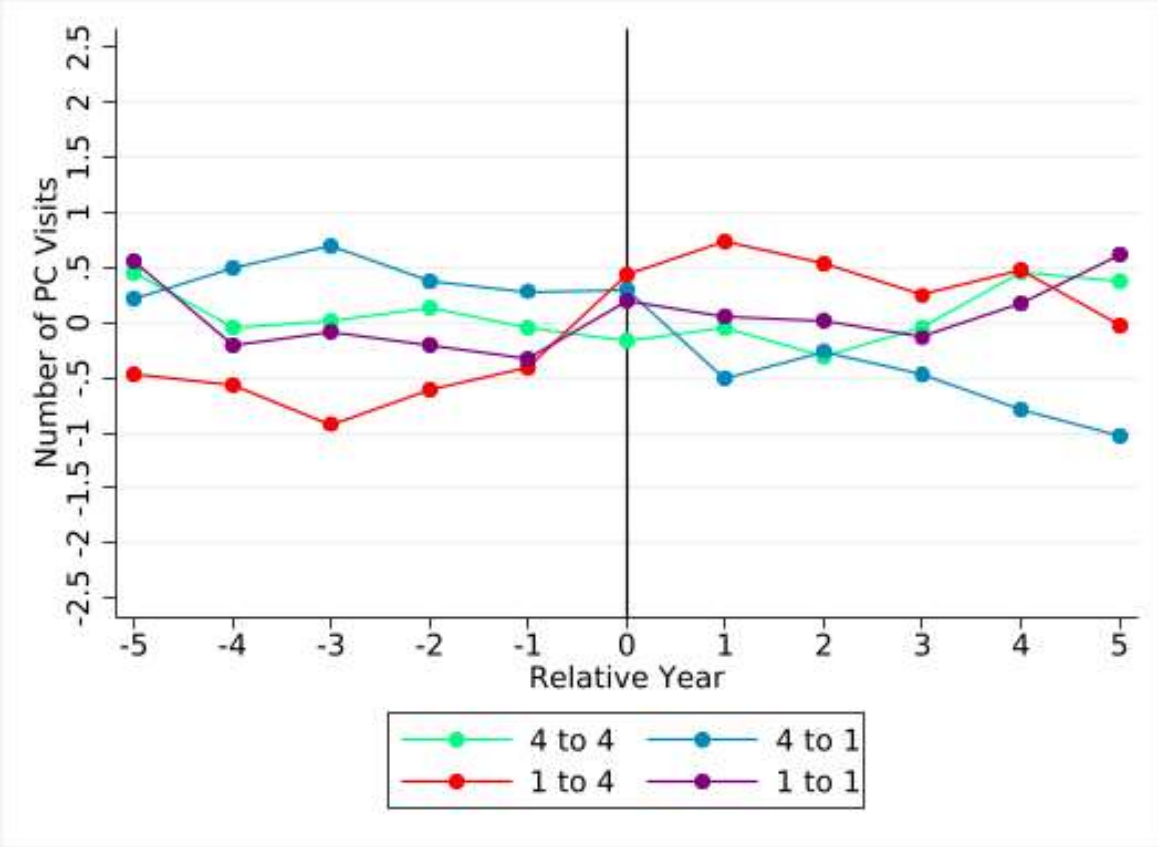
The Importance of Place-by-Race Effects: Num. PC Visits



(a) Black Place Effect Moves, Black Movers



(b) White Place Effect Moves, Black Movers

Figure. Changes in Num. PC Visits by Move Type, Black Movers

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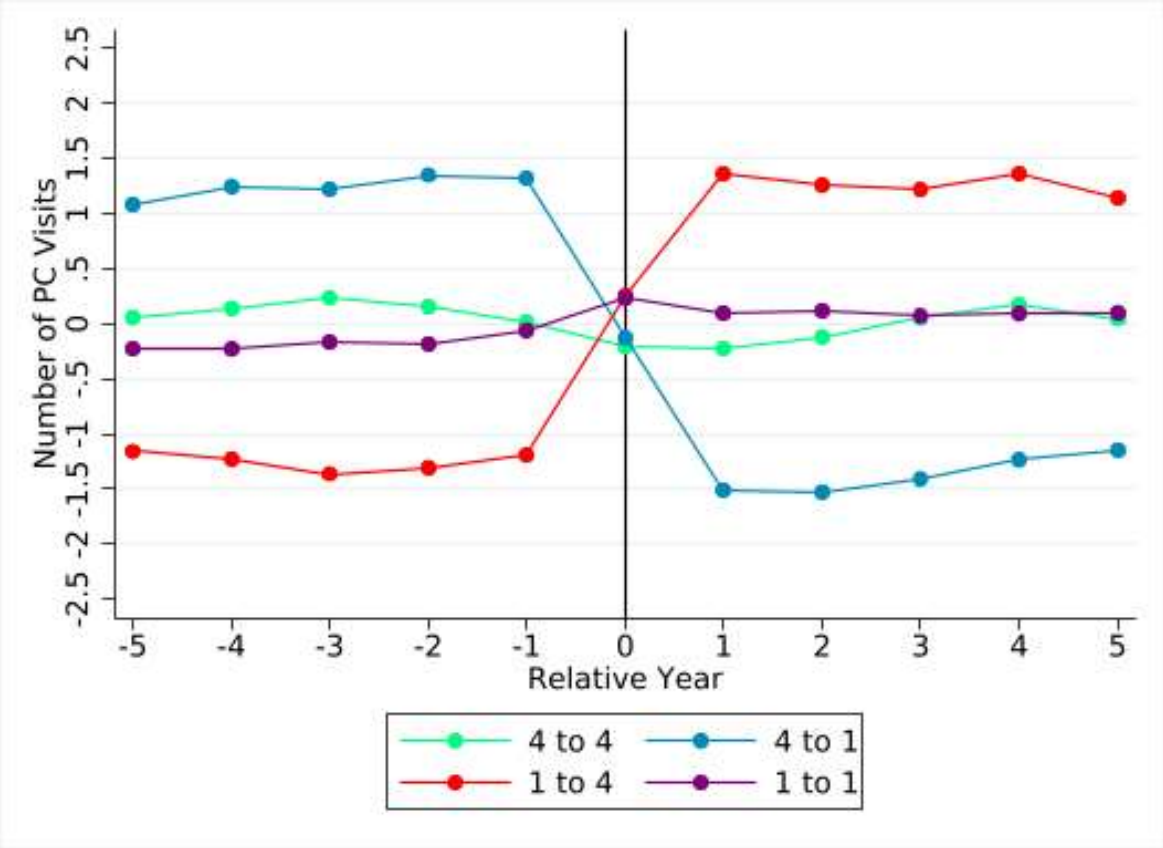
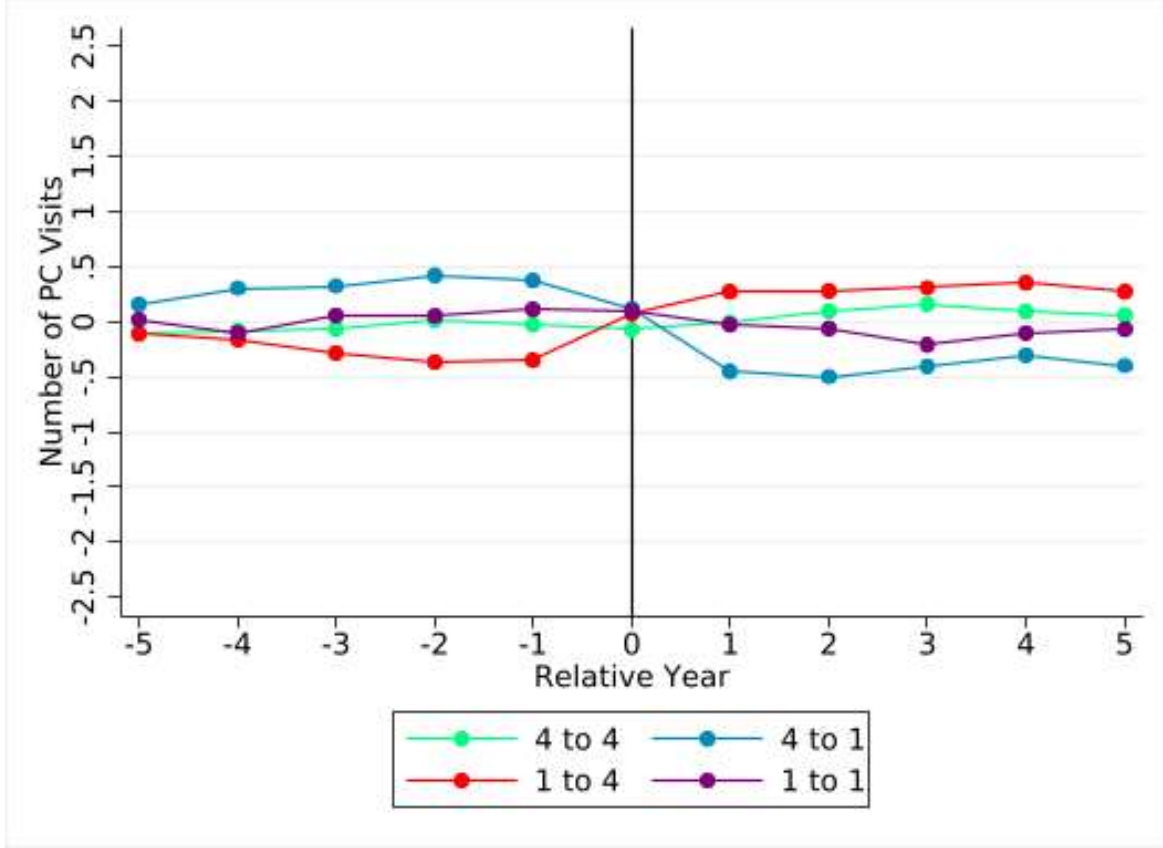
The Importance of Place-by-Race Effects: Num. PC Visits



(a) White Place Effect Moves, White Movers



(b) Black Place Effect Moves, White Movers

Figure. Changes in Num. PC Visits by Move Type, White Movers

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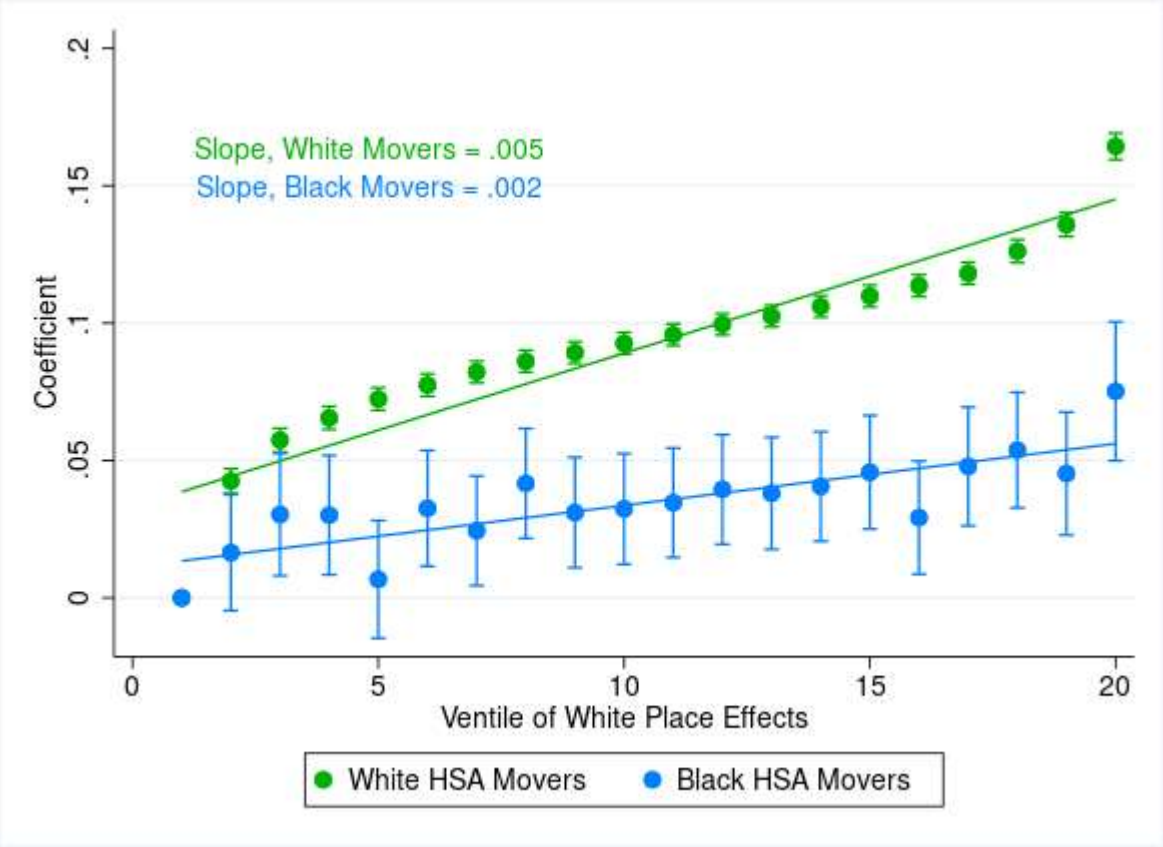
How Correlated are Place Effects?



(a) Effect of White Place Effects Ventile on Any PC Visit

(b) Effect of Black Place Effects Ventile on Any PC Visit

Figure. Causal Effect of Moving Up Place Effects Distribution by Race, Any PC Visit

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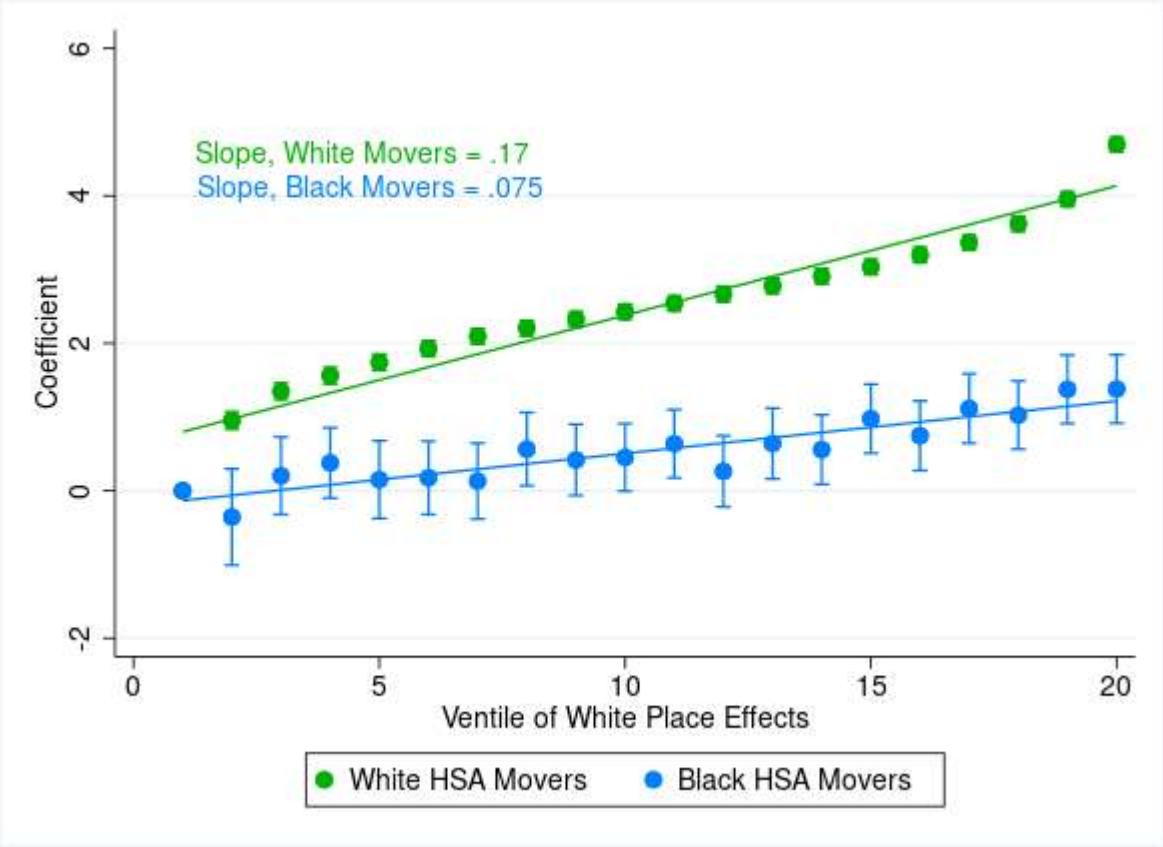
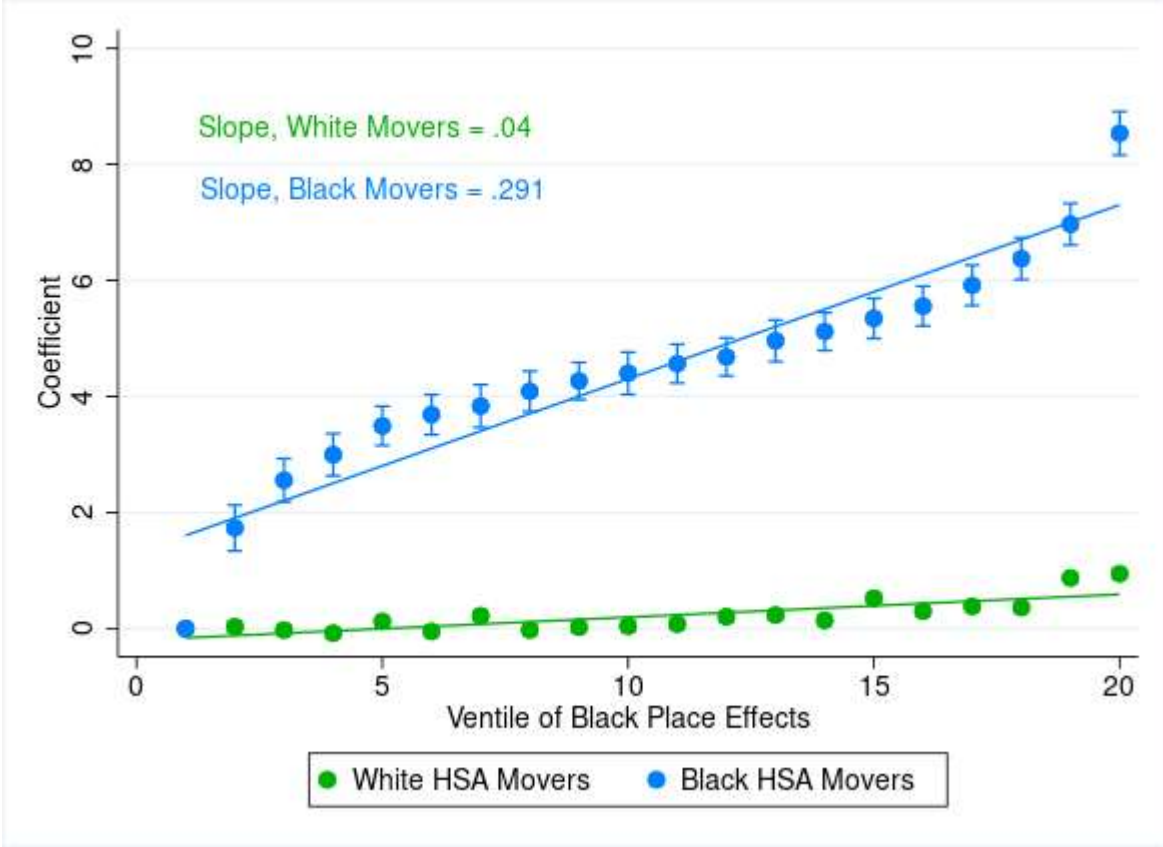
How Correlated are Place Effects?



(a) Effect of White Place Effects Ventile on Num. PC Visits



(b) Effect of Black Place Effects Ventile on Num. PC Visits

Figure. Causal Effect of Moving Up Place Effects Distribution by Race, Num. PC Visits

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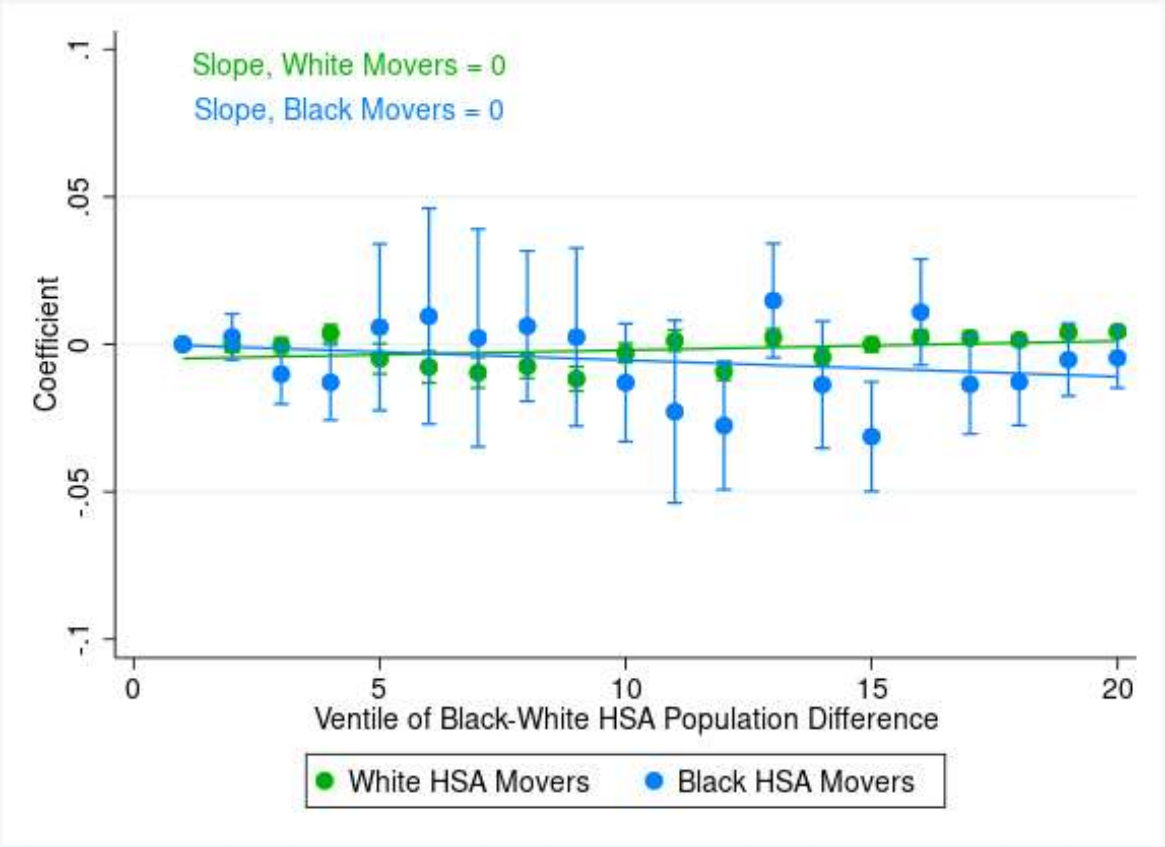
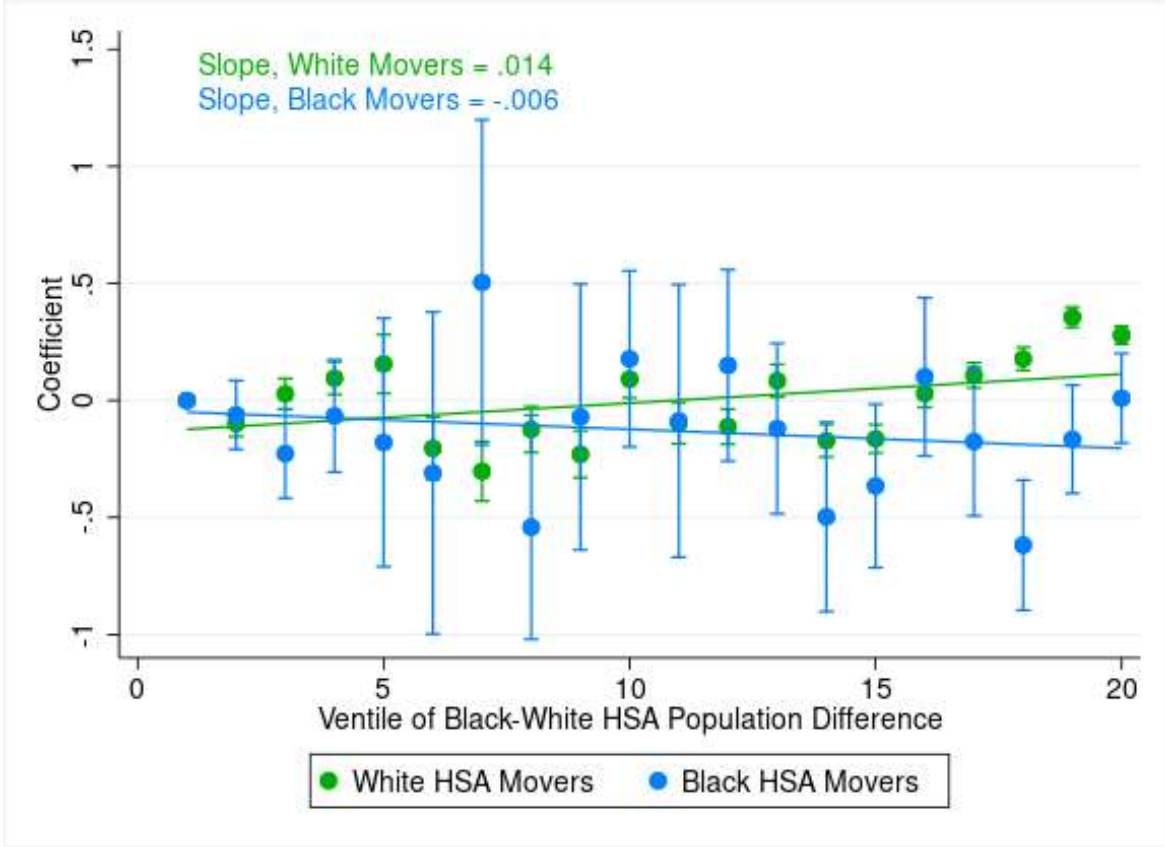
Access Unchanged by Moves Across the Geographic Distribution



(a) Any PC Visit



(b) Number of PC Visits

Figure. Causal Effect of Moving Up the Differential Geographic Distribution

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Observational Decomposition Estimates

Figure. Observational HSA Decomposition, Log(Utilization)

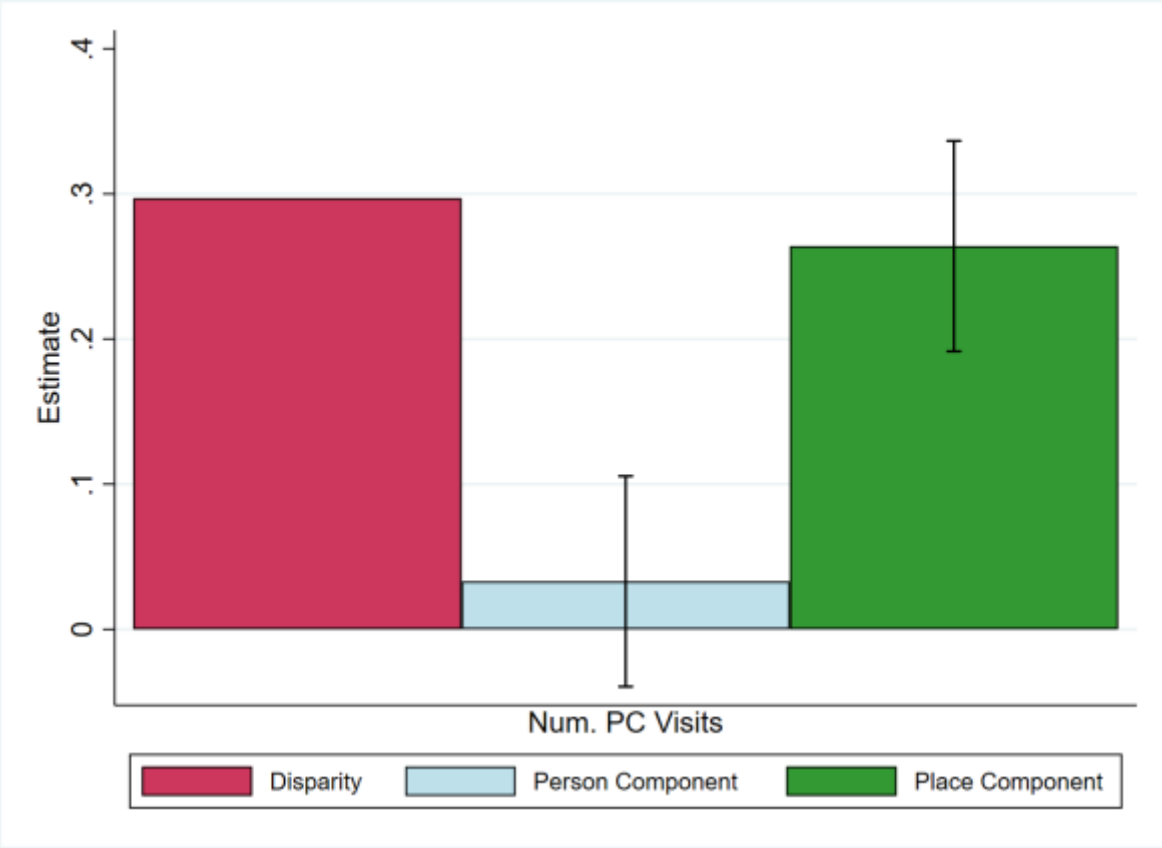

Figure. Observational HSA Decomposition, Num. PC Visits

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