The Geography of Health Disparities

Timothy Layton
University of Virginia and NBER

Graeme Peterson
Harvard University

NBER Trends and Patterns in Health Disparities
May 16, 2025

Roadmap

Background

Conceptual Framework

Empirical Strategy

Can Place-Based Policies Address Disparities?

The Importance of Place-by-Race Effects

Conclusion

Racial Disparities in US Health Care

Racial disparities pervade many aspects of the United States health care system:

- Quality of providers (Chandra et al., 2020; Jha et al., 2007; Bach et al., 2004)
- Health outcomes such as mortality (Murphy et al., 2015; Alsan et al., 2021)
- Patterns of treatment (Obermeyer et al., 2019; Pierson et al., 2022; Hoffman et al. 2016)
- Patients' experience of care (Nguyen et al., 2022)
- **Access to medical care (Wallace et al., 2021; Mahmoudi & Jensen, 2014; Buchmueller & Levy, 2020)**

Disparities Persist in Traditional Medicare, Where Insurance is Standard

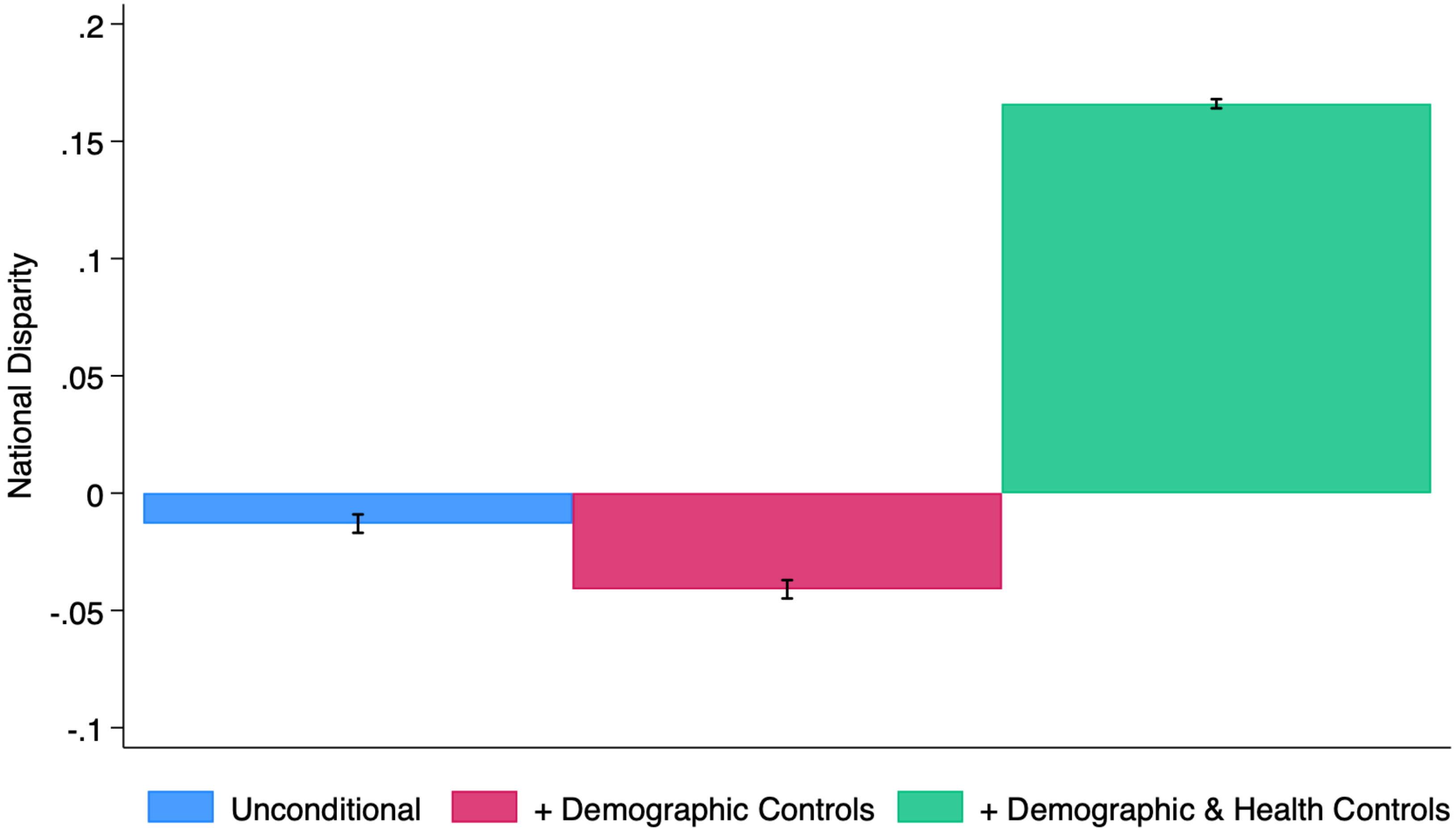


Figure. White-Black Disparity in Log Utilization

Num. E&M Visits

Col. Cancer Screen

Racial Disparities in US Health Care

The reasons for these persistent disparities 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)

Today's Focus

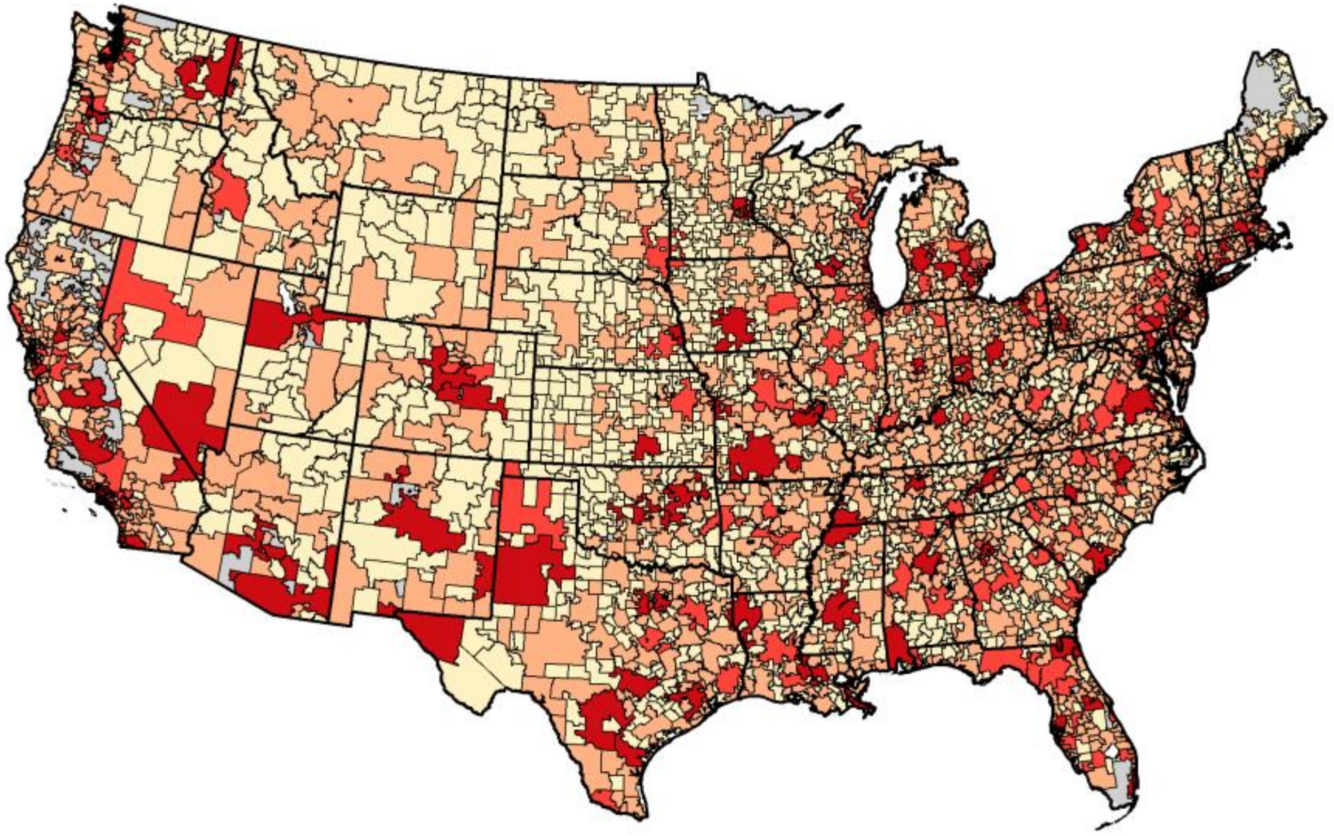
Today's focus is on the role of **geography**. Geographic variation a well-known feature of the US health care system (Wennberg, 1973; Fisher, 2003; Finkelstein et al., 2016).

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

1) Differential **geographic distribution** – access to health care varies across places, and Black individuals are more likely to live in areas where access is lower → place-based policies (invest in places with low overall access)
2) Differential **causal effects of place** on access – holding fixed where people live, places have different causal effects for Black individuals than white individuals → place-by-race-based policies (invest in access *for Black individuals* in places where access is low *for Black individuals*)

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

This Paper

- Start by developing a conceptual framework that allows us to decompose disparities into **place** and **person** components
  - Key inputs: causal place effects, geographic distribution by race, disparity estimates

- Can **place-based policies** help to close disparities?
  - With homogeneous place effects, place component generally explains little of national disparity → limited scope for place-based policy to close disparities

- Would **place-by-race-based policies** do better?
  - Decomposition with heterogeneous place effects → larger role for place
  - Place effects heterogeneity is key: Black and white place effects uncorrelated, moves up ***race-concordant*** place effects distribution have much larger effects on access

Roadmap

Conceptual Framework

We follow Finkelstein, Gentzkow, and Williams (2016). There are individuals *i*, in places *j*, at time *t*. Utilization y_{ij}^* is sum of a place component ψ_j and a person component y_i^*:

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

This allows us to write average utilization for area *j* as:

$$\bar{y}_{j,t}^r = \psi_j + \frac{1}{N_{j,t}^r} \sum_{i \in r,j} y_i^* = \psi_j + \bar{y}_{j,t}^{r*}$$

where $N_{j,t}^r$ is the number of individuals of race *r* in place *j* at time *t*.

Conceptual Framework

We use this setup to divide the national disparity between Black and white beneficiaries into place and non-place factors. We define the disparity as $\bar{y}_t^w - \bar{y}_t^b$ and write:

$$\begin{aligned}
\bar{y}_t^w - \bar{y}_t^b &= \sum_{j=1}^{J} (\sigma_{j,t}^w \, \bar{y}_{j,t}^w - \sigma_{j,t}^b \, \bar{y}_{j,t}^b) \\
&= \sum_{j=1}^{J} [\sigma_{j,t}^w (\psi_j + \bar{y}_{j,t}^{w*}) - \sigma_{j,t}^b (\psi_j + \bar{y}_{j,t}^{b*})] \\
&= \underbrace{\sum_{j=1}^{J} \psi_j (\sigma_{j,t}^w - \sigma_{j,t}^b)}_{\text{place}} + \underbrace{\sum_{j=1}^{J} (\sigma_{j,t}^w \bar{y}_{j,t}^{w*} - \sigma_{j,t}^b \bar{y}_{j,t}^{b*})}_{\text{person}}
\end{aligned}$$

where $\sigma_{j,t}^r$ is the share of the national population of race *r* that lives in area *j* at time *t*.

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:

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

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

$$\bar{y}^w_t - \bar{y}^b_t = \underbrace{\sum_{j=1}^{J} \left(\sigma^w_{j,t}\psi^w_j - \sigma^b_{j,t}\psi^b_j\right)}_{\text{place-by-race}} + \underbrace{\sum_{j=1}^{J} (\sigma^w_{j,t}\, \bar{y}^{w*}_{j,t} - \sigma^b_{j,t}\, \bar{y}^{b*}_{j,t})}_{\Gamma \equiv \text{person}}$$

which we further decompose as:

$$\bar{y}^w_t - \bar{y}^b_t = \underbrace{\sum_{j=1}^{J} \psi^w_j \left(\sigma^w_j - \sigma^b_j\right)}_{\text{diff. geo. dist.}} + \underbrace{\sum_{j=1}^{J} \sigma^b_j \left(\psi^w_j - \psi^b_j\right)}_{\text{diff. place effects}} + \Gamma$$

Roadmap

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)
- Number of evaluation and management 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

Key inputs to the decomposition:

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

We construct each of these using Medicare claims data from 2008-2018:

1. National disparity → measure using Medicare claims (IP, OP, Carrier)
2. Population shares → measure using MBSF, 2008-2018
3. Causal place effects → movers design estimated separately for Black and white movers

Identification

- To estimate causal place effects, we leverage beneficiary migration across areas (a ‘mover design’).
- Key assumption: 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, estimating FGW-style event studies:

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

where:

- y_{it} → individual *i's* access measure in year *t*
- α_i → individual fixed effect
- $\widehat{\delta_i}$ → 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
- $\lambda_{r(i,t)}$ → year relative to move fixed effect

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:

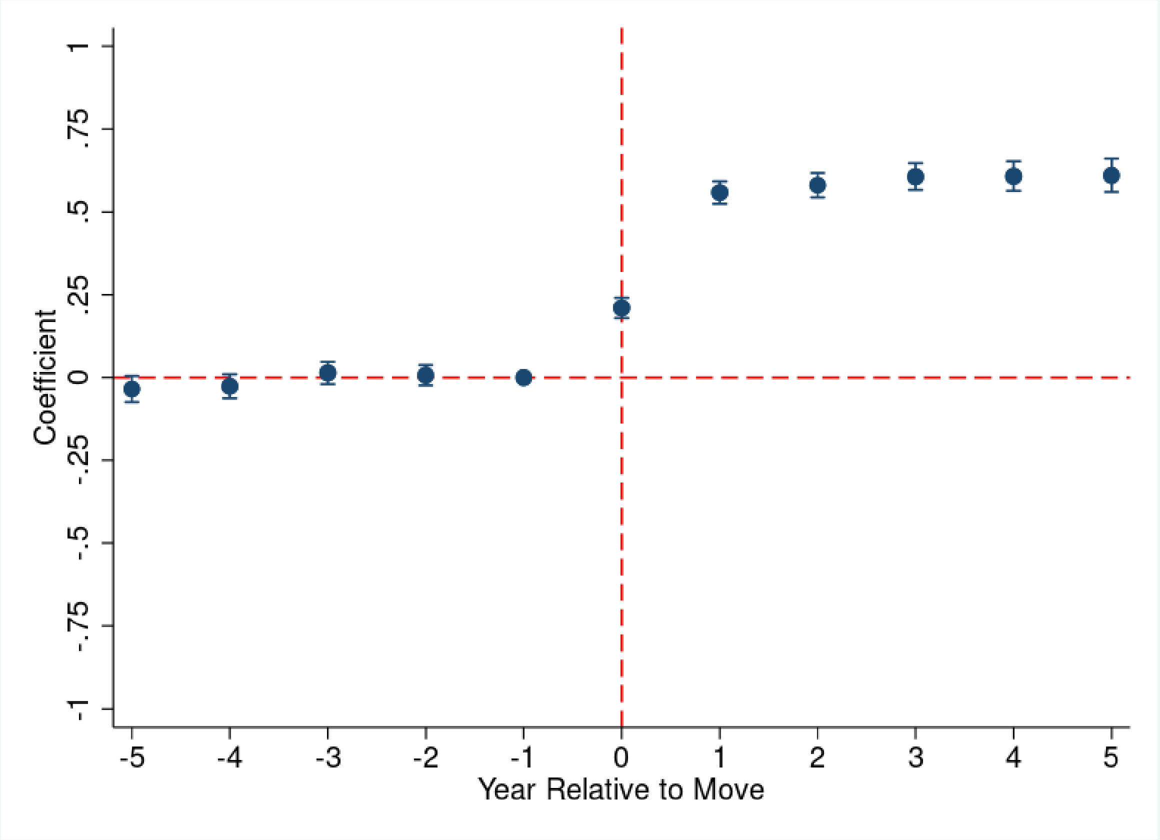
$$y_{it} = \alpha_i + \gamma_{j(i,t)} + \lambda_{r(i,t)} + \tau_t + X'_{it}\beta + \nu_{it}$$

where:

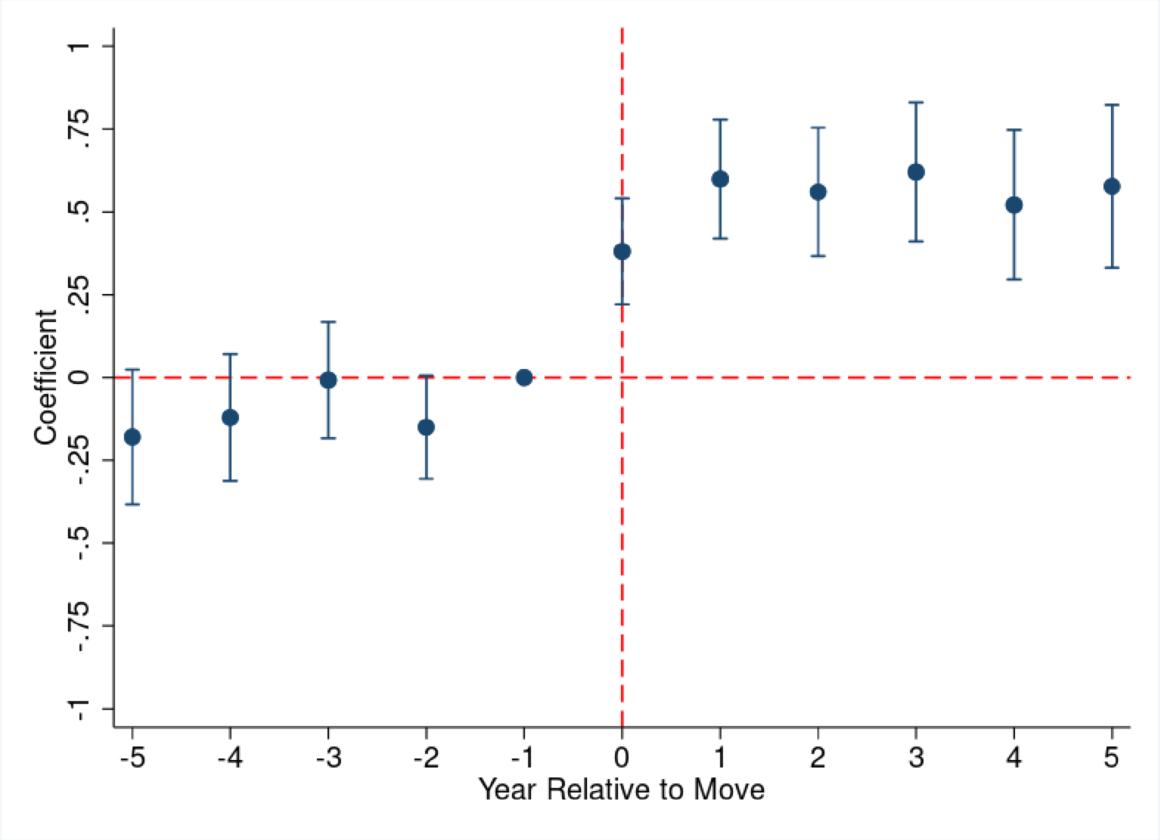
- y_{it} → individual *i's* access measure in year *t*
- α_i → individual fixed effect
- $\gamma_{j(i,t)}$ → area *j* fixed effect
- $\lambda_{r(i,t)}$ → year relative to move fixed effect
- τ_t → calendar year fixed effect
- X'_{it} → five-year age bins from ages 65-99

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.

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

Num. E&M Visits

Col. Cancer Screen

Distribution of Place Effects

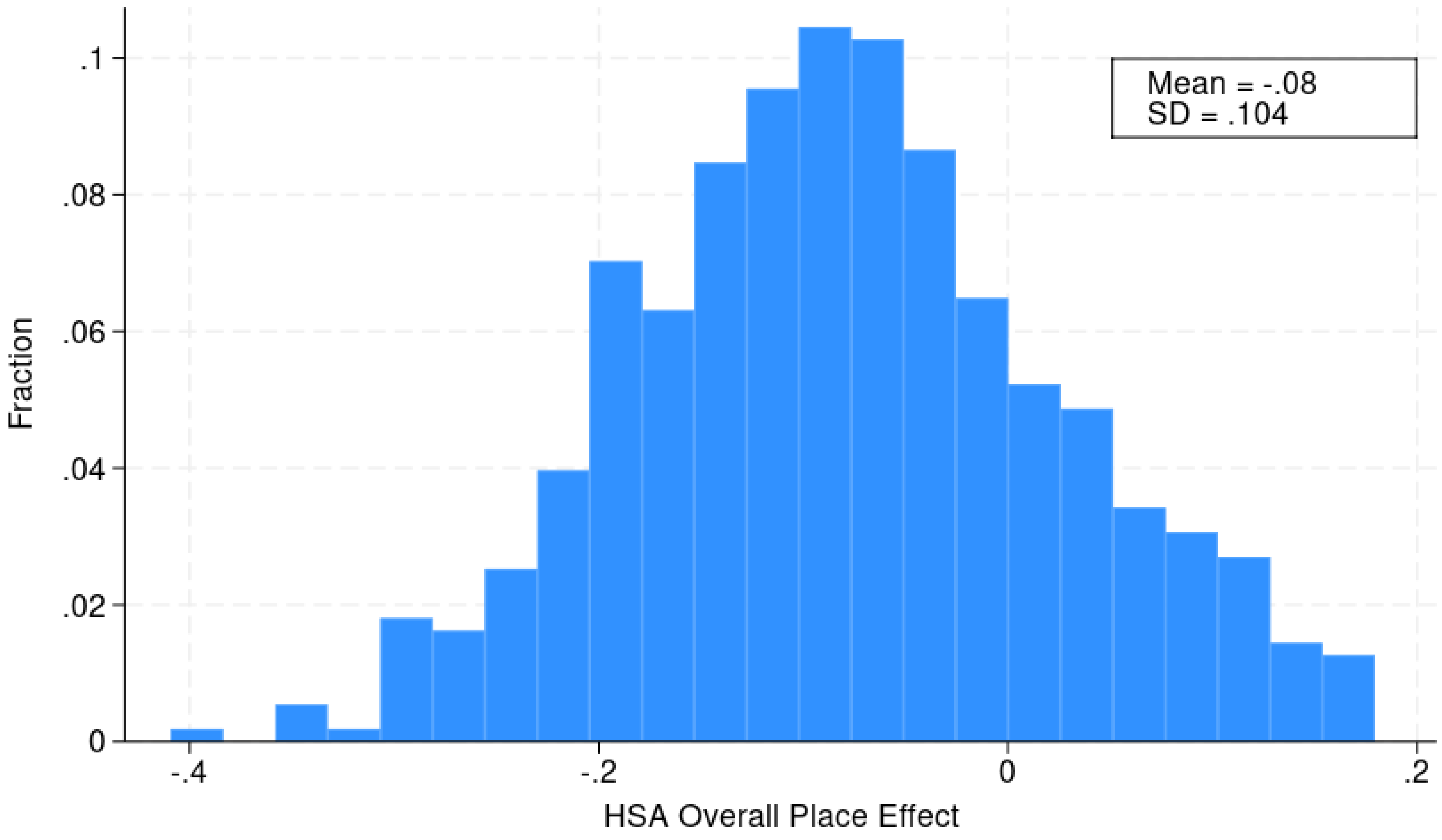
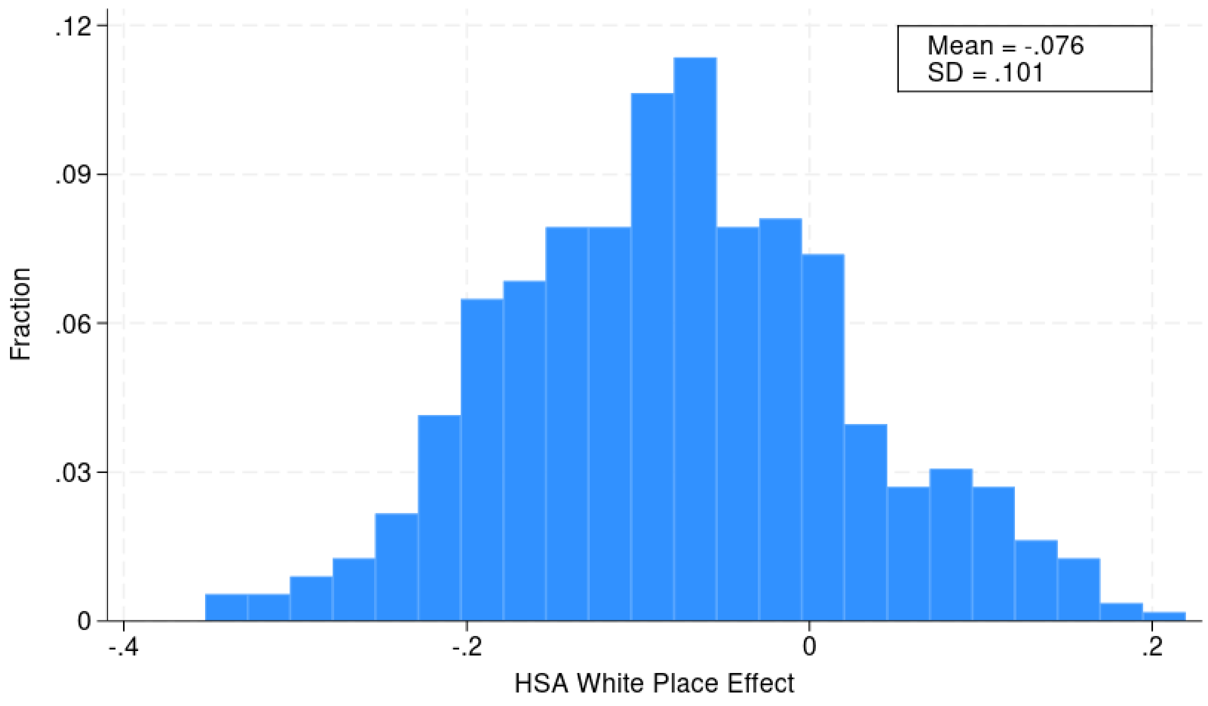
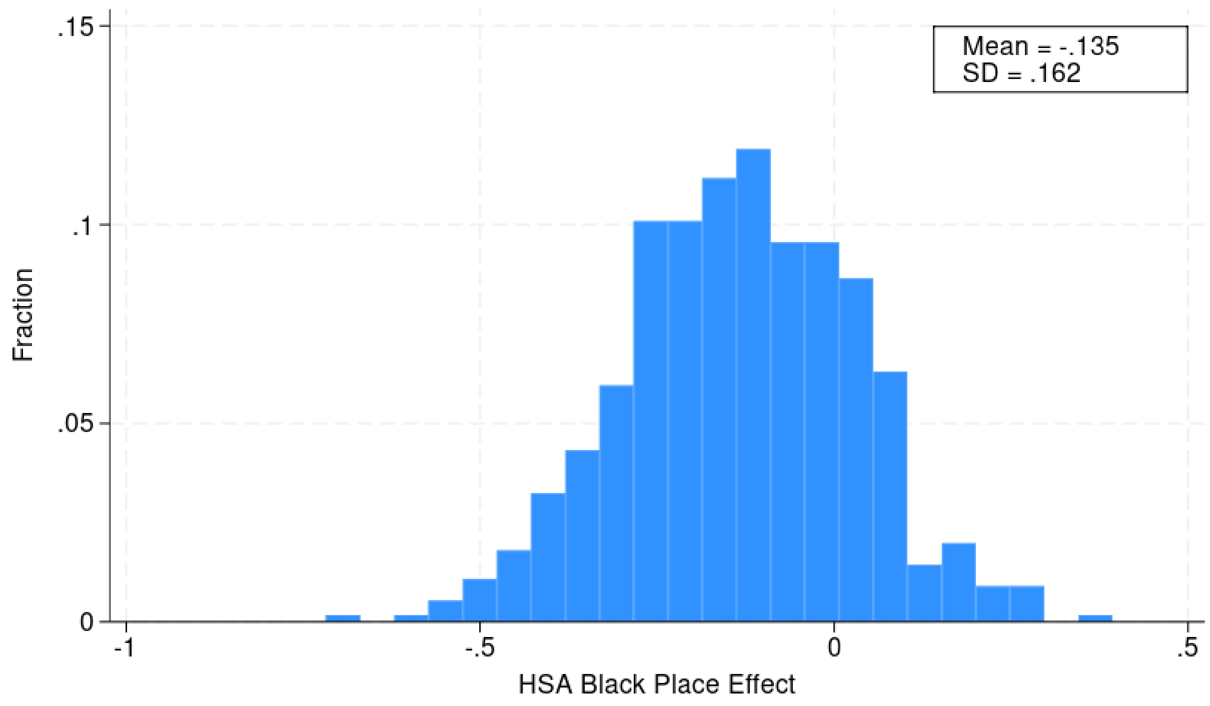


Figure. Distribution of Homogenous HSA Place Effects, Log Utilization

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

Num. E&M Visits

Col. Cancer Screen

Roadmap

Background

Conceptual Framework

Empirical Strategy

Can Place-Based Policies Address Disparities?

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

Conclusion

Homogenous Place Effects Decomposition

- Place matters very little: explains about **5%** of national disparity in log utilization

- Similar for number of E&M visits (10%); larger role for place in colorectal cancer screenings (45%)

- Suggests that place-based policies limited in their ability to resolve existing disparities

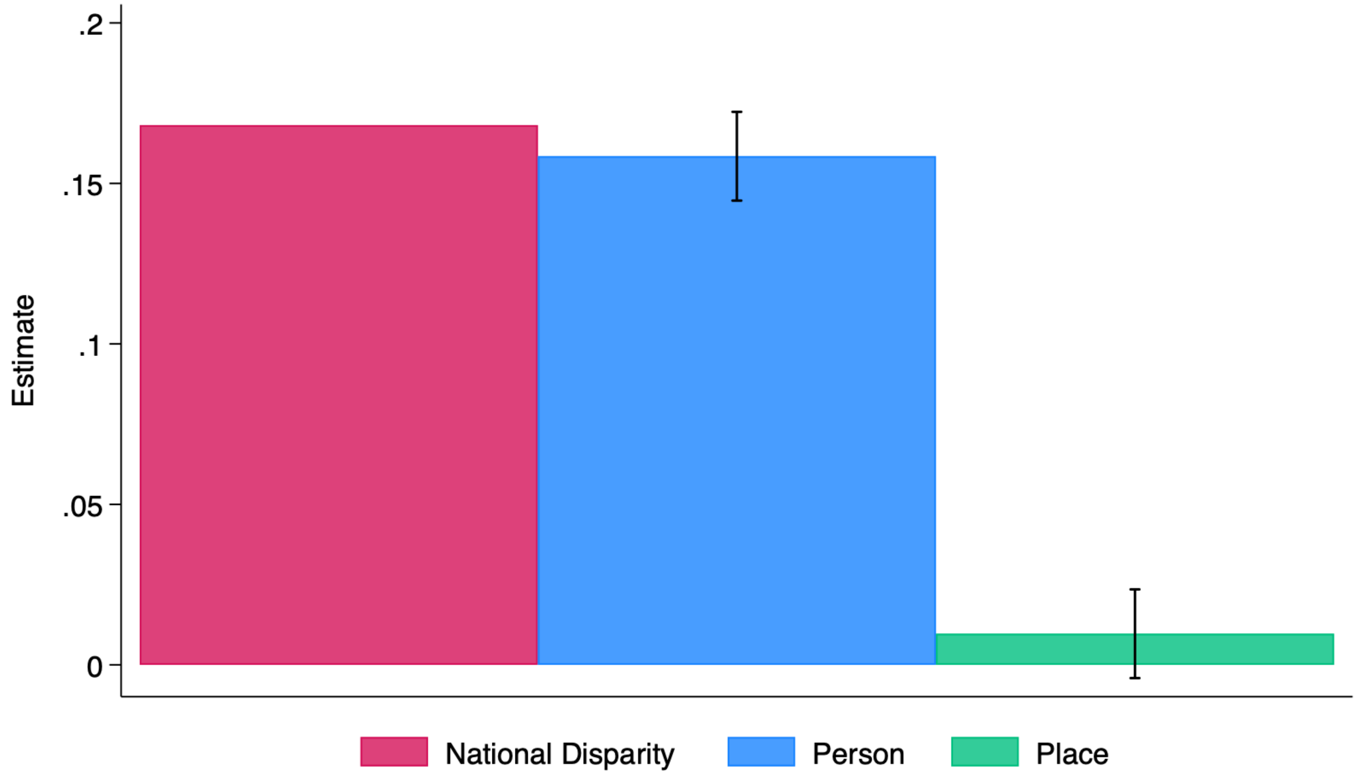


Figure. Homogenous HSA Decomposition, Log Utilization

Num. E&M Visits

Col. Cancer Screen

Homogenous Place Effects Decomposition

- We can also depict the place component graphically by plotting the homogeneous place effects $\hat{\gamma}_j$ against the differential geographic distribution $\hat{\sigma}^{w}_{j,t} - \hat{\sigma}^{b}_{j,t}$
- Correlation between these two objects is just **0.05**, consistent with the small role of place we find in the decomposition

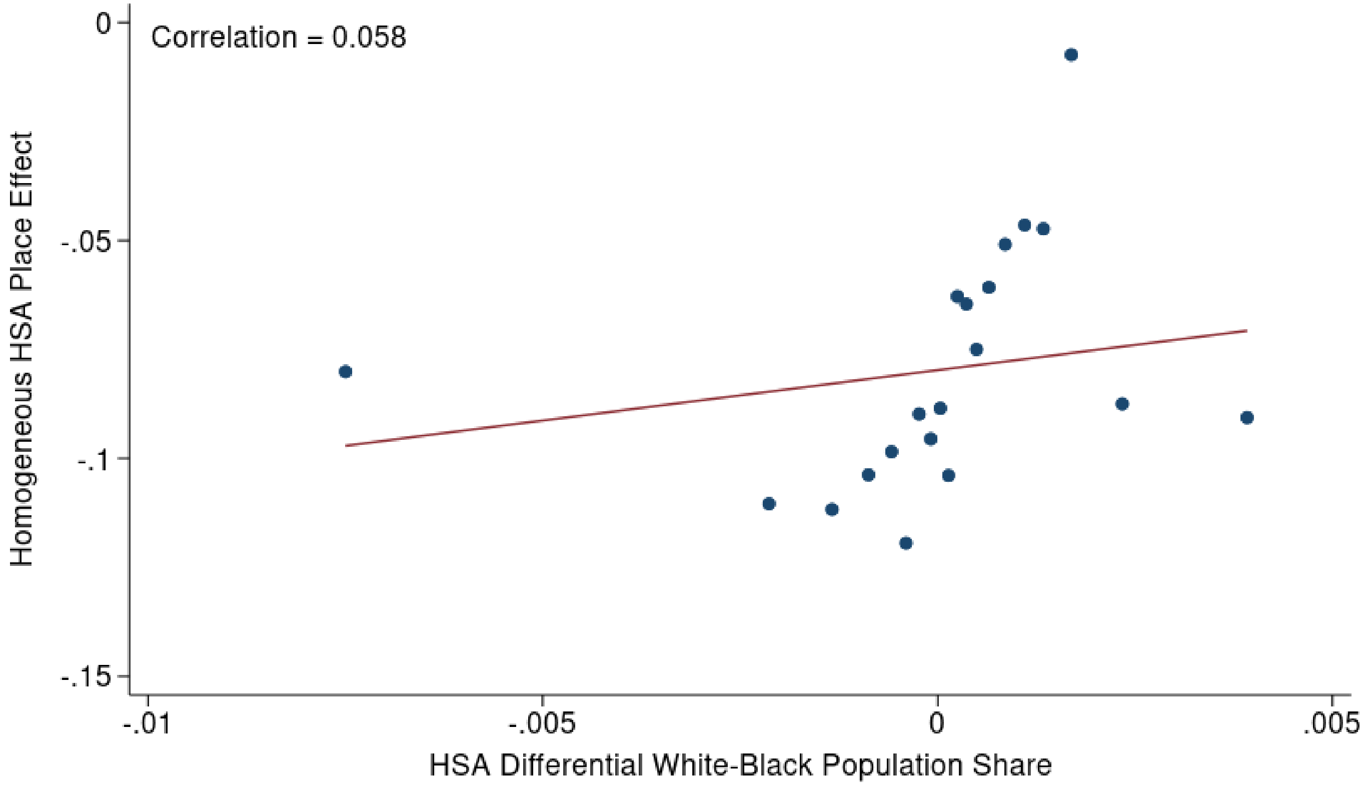


Figure. Relationship Between Homogeneous Place Effects and the Differential Geographic Distribution, Log Utilization

Num. E&M Visits

Col. Cancer Screen

Do Place-**by-Race**-Based Policies Do Better?

- Consider a decomposition where we allow place effects to vary by race
- Places account for larger fraction of national disparity in this framework:
  - 26% for log utilization
  - 109% for colorectal cancer screenings
  - Negligible role for E&M visits
- Suggests place-by-race-based policies may have more scope for closing disparities

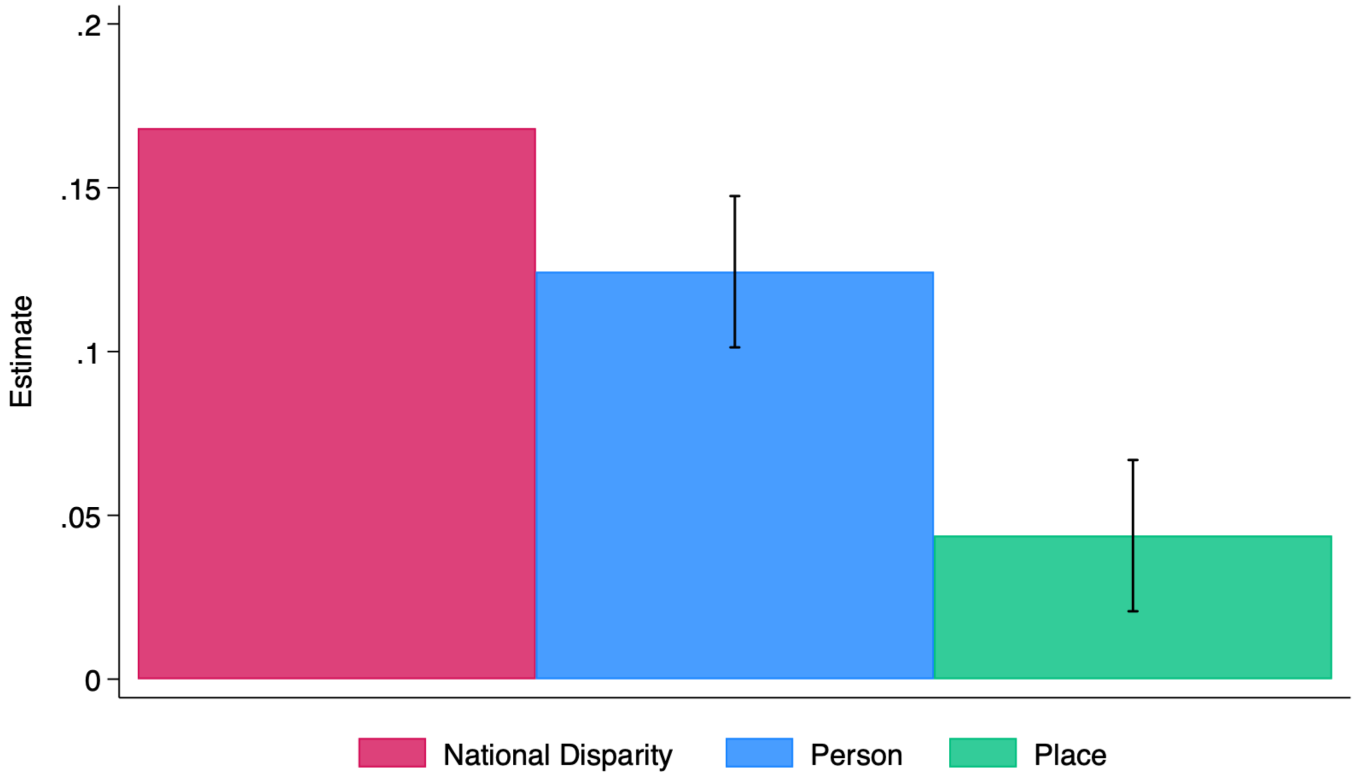


Figure. Heterogeneous Decomposition, Log Utilization

Num. E&M Visits

Col. Cancer Screen

Decomposing the Place Component

- What drives the place component?

- When we break the place component down, we find that majority of the effect of place 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.

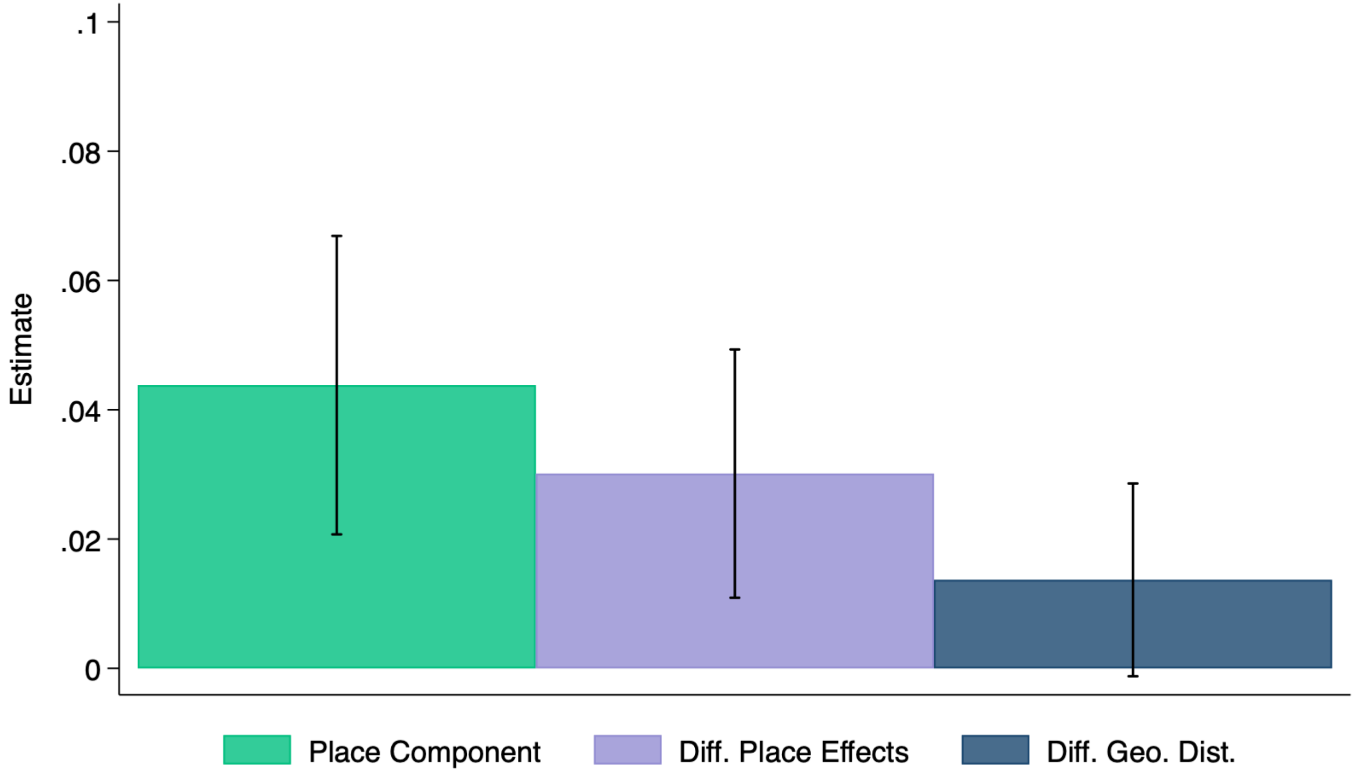


Figure. HSA Place Component Decomposition, Log Utilization

Num. E&M Visits

Col. Cancer Screen

How Would Changing Place Effects Change Disparities?

- How much would changing these differential place effects affect disparities?
- Reconduct decomposition replacing bottom quartile Black place effects with average top quartile Black place effect
- Fix person component and recompute disparity under new place effects
- Improving differential place effects reduces disparity substantially:
  - 43% decline for log utilization
  - 44% decline for number of E&M visits
  - 180% decline for colorectal cancer screening (reverses disparity)

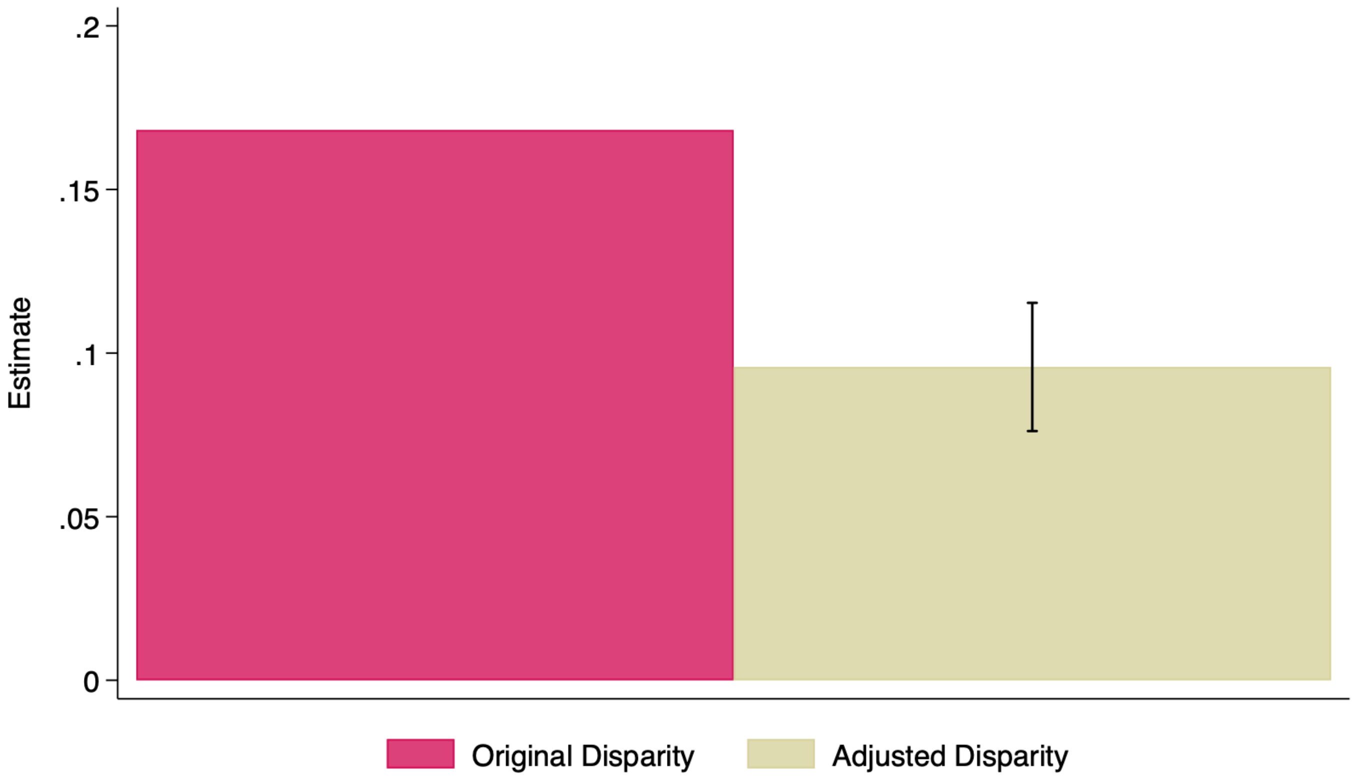


Figure: Reallocation Exercise, Log Utilization

Num. E&M Visits

Col. Cancer Screen

Roadmap

Background

Conceptual Framework

Empirical Strategy

Can Place-Based Policies Address Disparities?

The Importance of Place-by-Race Effects

Conclusion

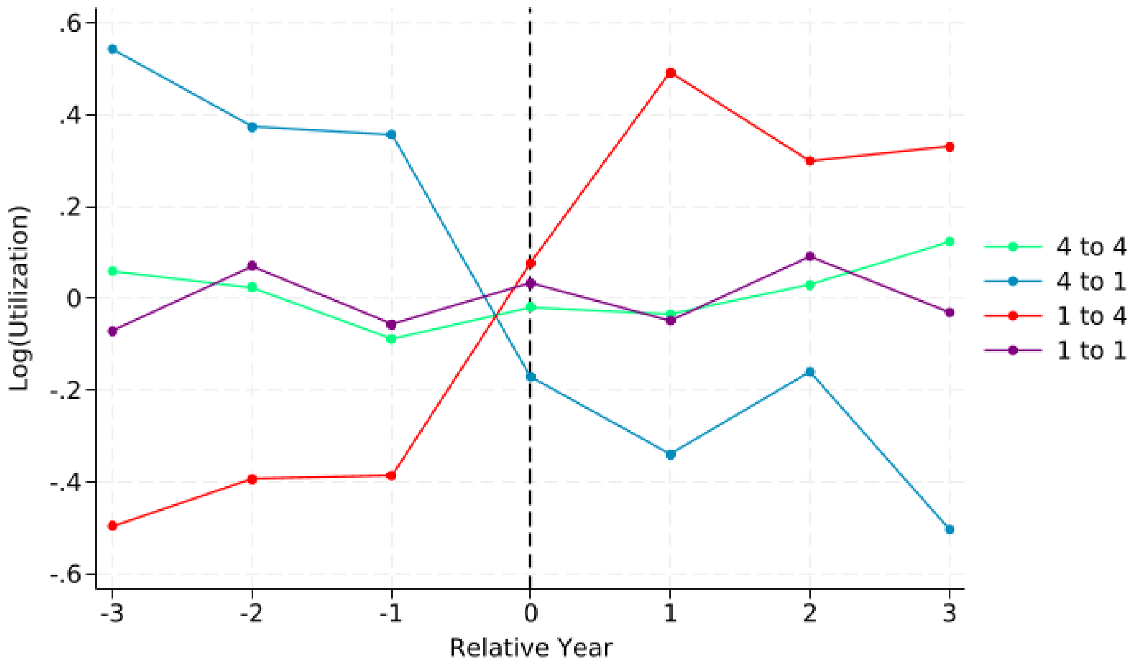
Examining the Geographic Distribution

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

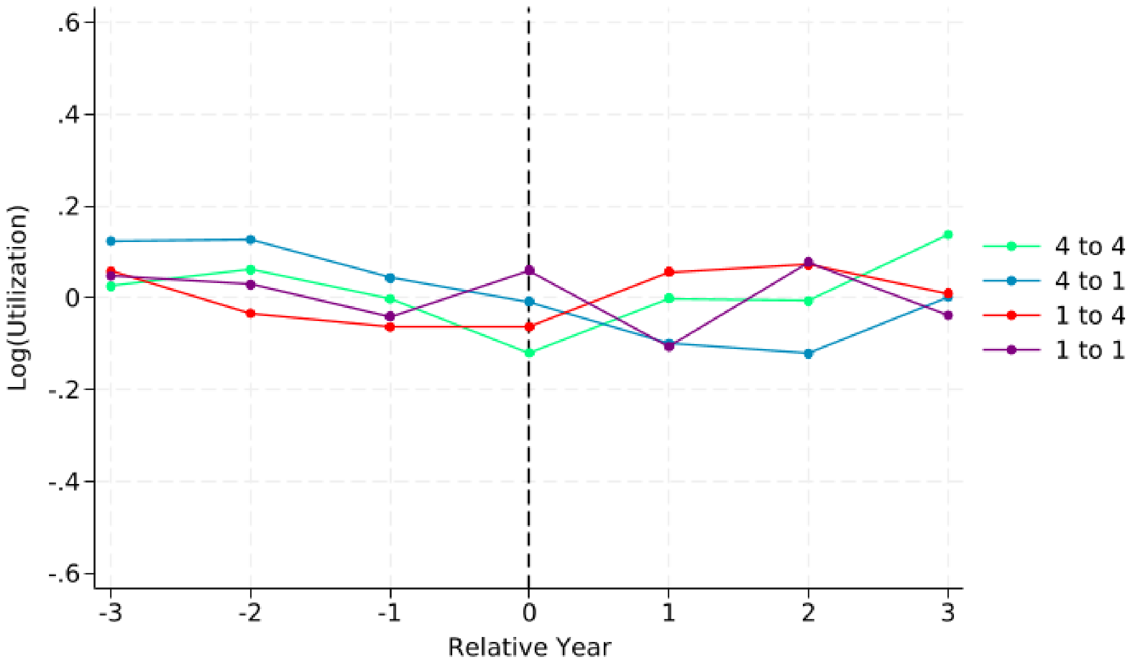
$$\bar{y}_t^w - \bar{y}_t^b = \underbrace{\sum_{j=1}^{J} \psi_j^w \left(\sigma_j^w - \sigma_j^b\right)}_{\text{diffs. due to geo. dist.}} + \underbrace{\sum_{j=1}^{J} \boxed{\sigma_j^b \left(\psi_j^w - \psi_j^b\right)}}_{\text{diffs. due to place effects}} + \Gamma$$

1. **Large differences in place effects for Black and white beneficiaries**
2. Little causal effect of moving up and down the differential geographic distribution

The Importance of Place-by-Race Effects



(a) Black Place Effect Moves, Black Movers



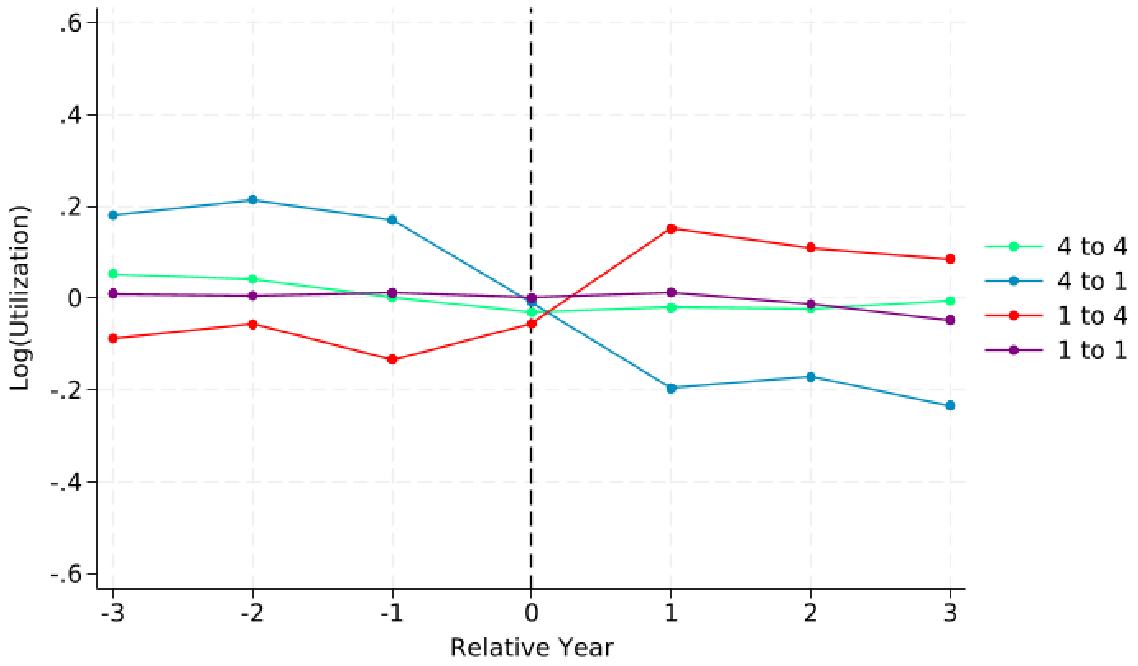
(b) White Place Effect Moves, Black Movers

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

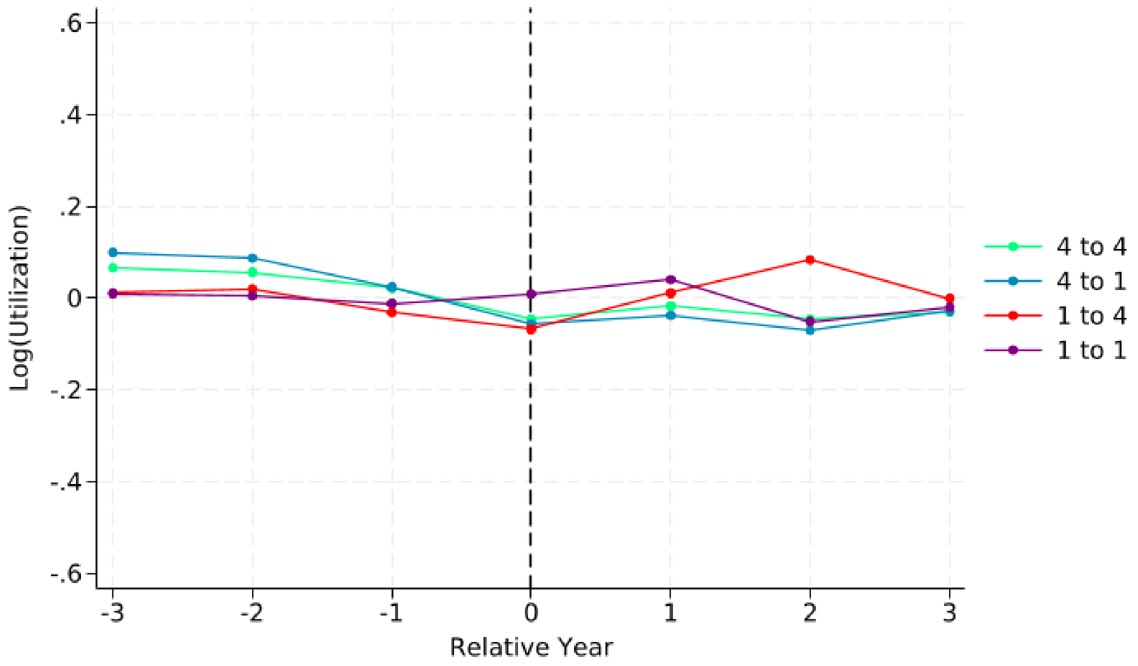
Num. E&M Visits

Col. Cancer Screen

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

Num. E&M Visits

Col. Cancer Screen

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 tests to show this is not driven by differential noise:
  - Broader geographies (HRRs)
  - Narrower geographies (HRRxZIP income quintile)
  - Randomly dropping white beneficiaries to equalize number of movers by race in an origin-destination dyad

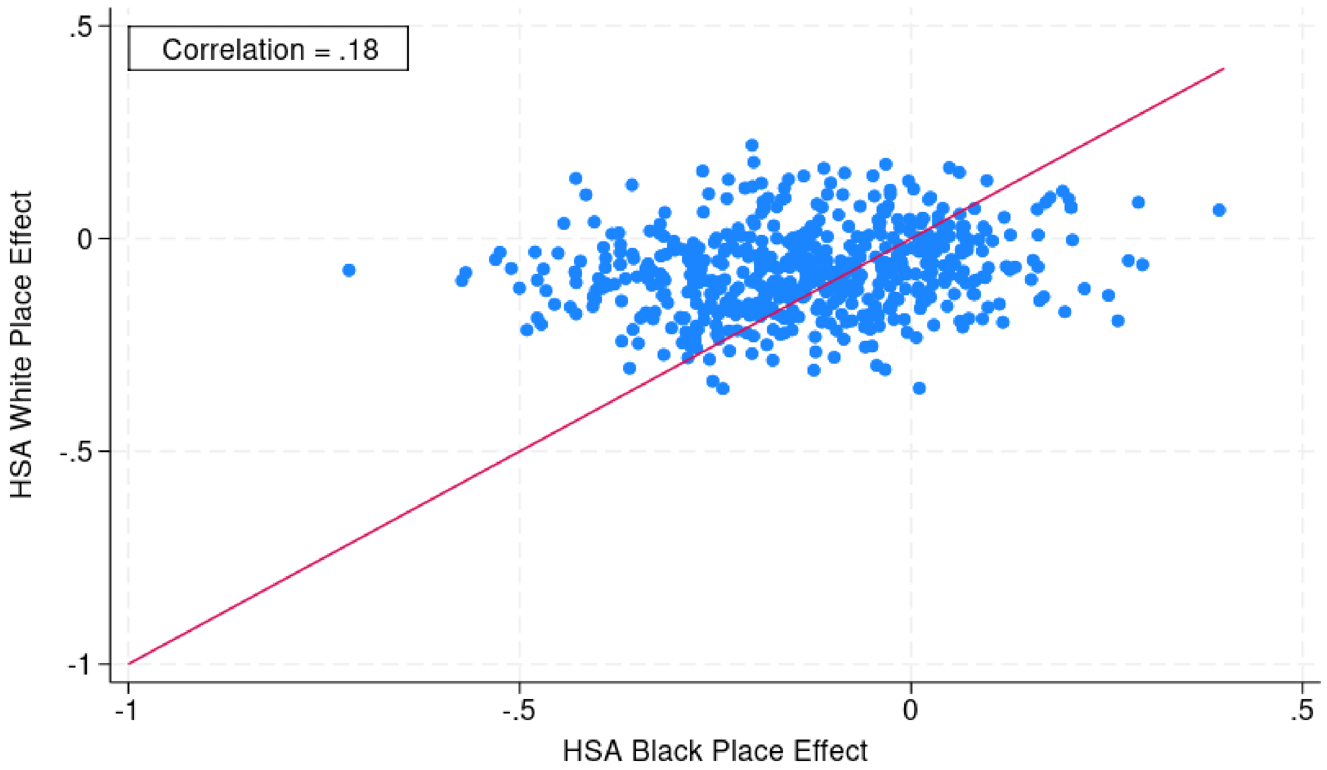


Figure. Correlation between Black and White HSA Place Effects, Log Utilization

Num. E&M Visits

Col. Cancer Screen

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:

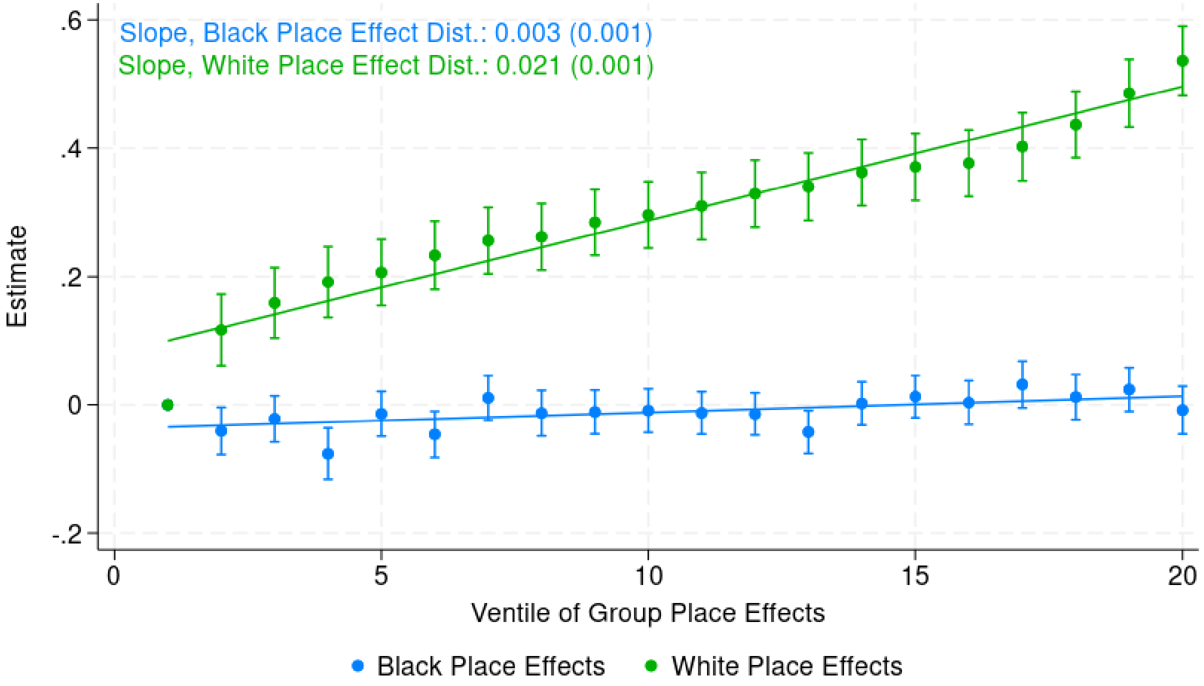
$$y_{it} = \alpha_i + \theta^{r}_{v(i,t)} + \lambda_{r(i,t)} + \tau_t + X'_{it}\beta + \nu_{it}$$

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

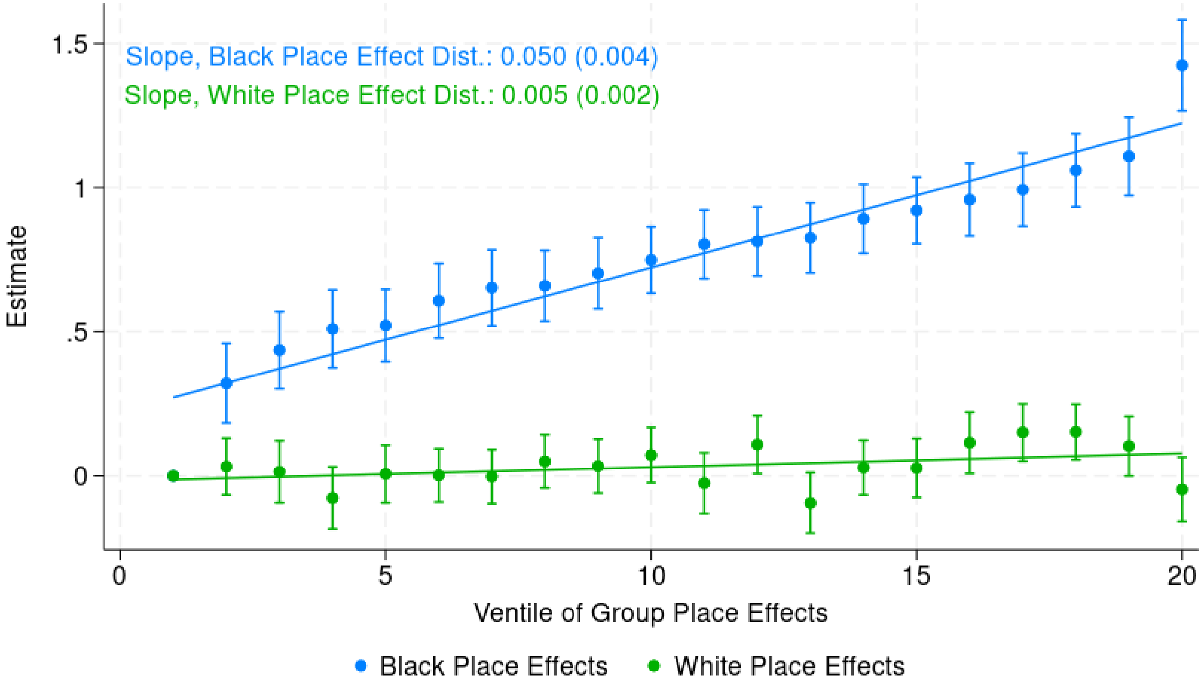
We estimate this separately for white and Black movers, testing how access changes when:

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) White Movers, Log Utilization



(b) Black Movers, Log Utilization

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

Num. E&M Visits

Col. Cancer Screen

Examining the Geographic Distribution

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

$$\bar{y}_t^w - \bar{y}_t^b = \underbrace{\sum_{j=1}^{J} \boxed{\psi_j^w\left(\sigma_j^w - \sigma_j^b\right)}}_{\text{diffs. due to geo. dist.}} + \underbrace{\sum_{j=1}^{J} \sigma_j^b\left(\psi_j^w - \psi_j^b\right)}_{\text{diffs. due to place effects}} + \Gamma$$

1. Large differences in place effects for Black and white beneficiaries
2. **Little causal effect of moving up and down the differential geographic distribution**

Examining the Geographic Distribution

We divide places based on their differential population distribution ($\hat{\sigma}_{jt}^{w} - \hat{\sigma}_{jt}^{b}$) 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 Black population to those with a larger share of the white population
2. Black beneficiaries move from areas that have a larger share of the Black population to those with a larger share of the white population

Access Unchanged by Moves Across the Geographic Distribution

- 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.

- **Reinforce earlier finding**: differential geographic distribution of individuals plays little role in driving disparities

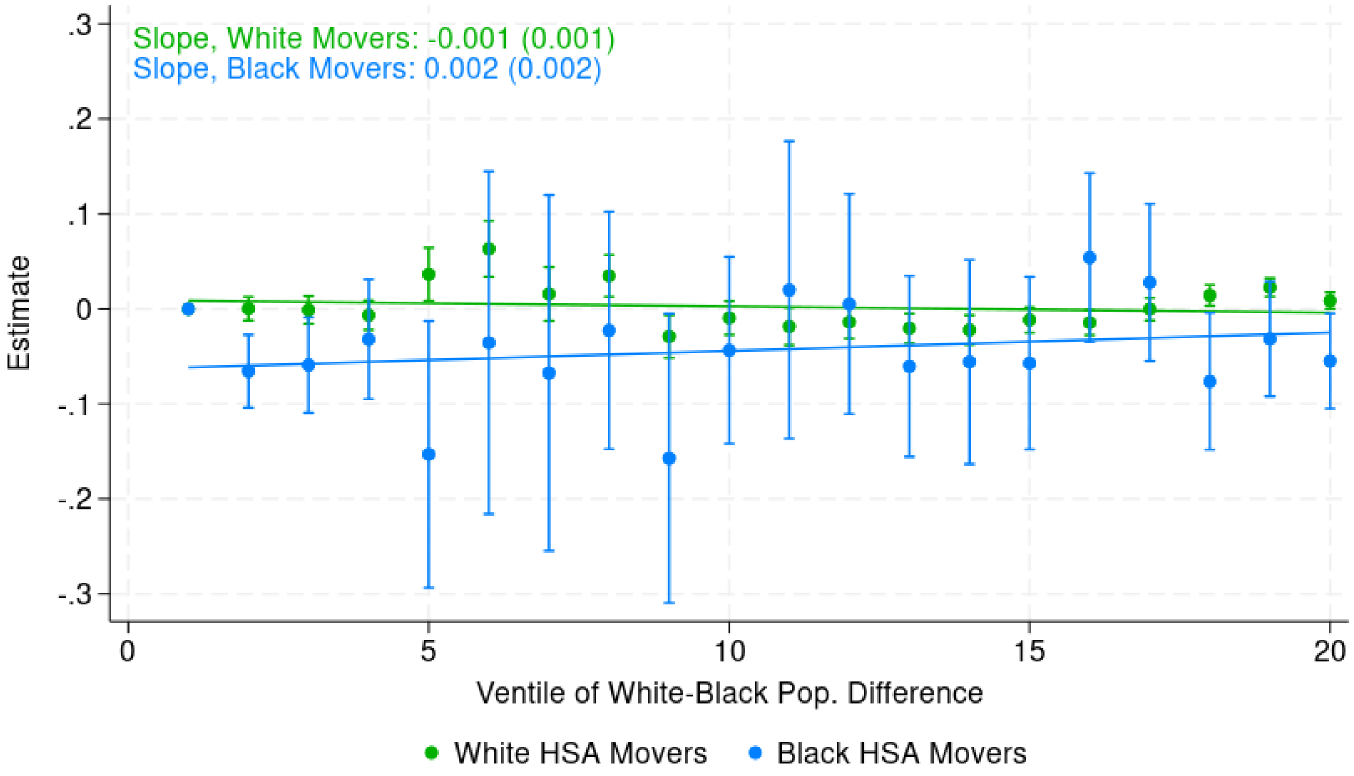


Figure: Effect of Moving to Higher Differential Population Ventile by Race, Log Utilization

Other Outcomes

What is the Right Level of Geography?

We replicate all of these analyses for both broader regions (HRRs) 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 contribute little to disparities when place effects are assumed to be homogeneous, but contribute sizably when allowing for heterogeneity
3. Differential place effects by geography drive this place component
4. The Black and white place effects for a given area are generally uncorrelated

Lack of Correlation Persists Across All Geographies

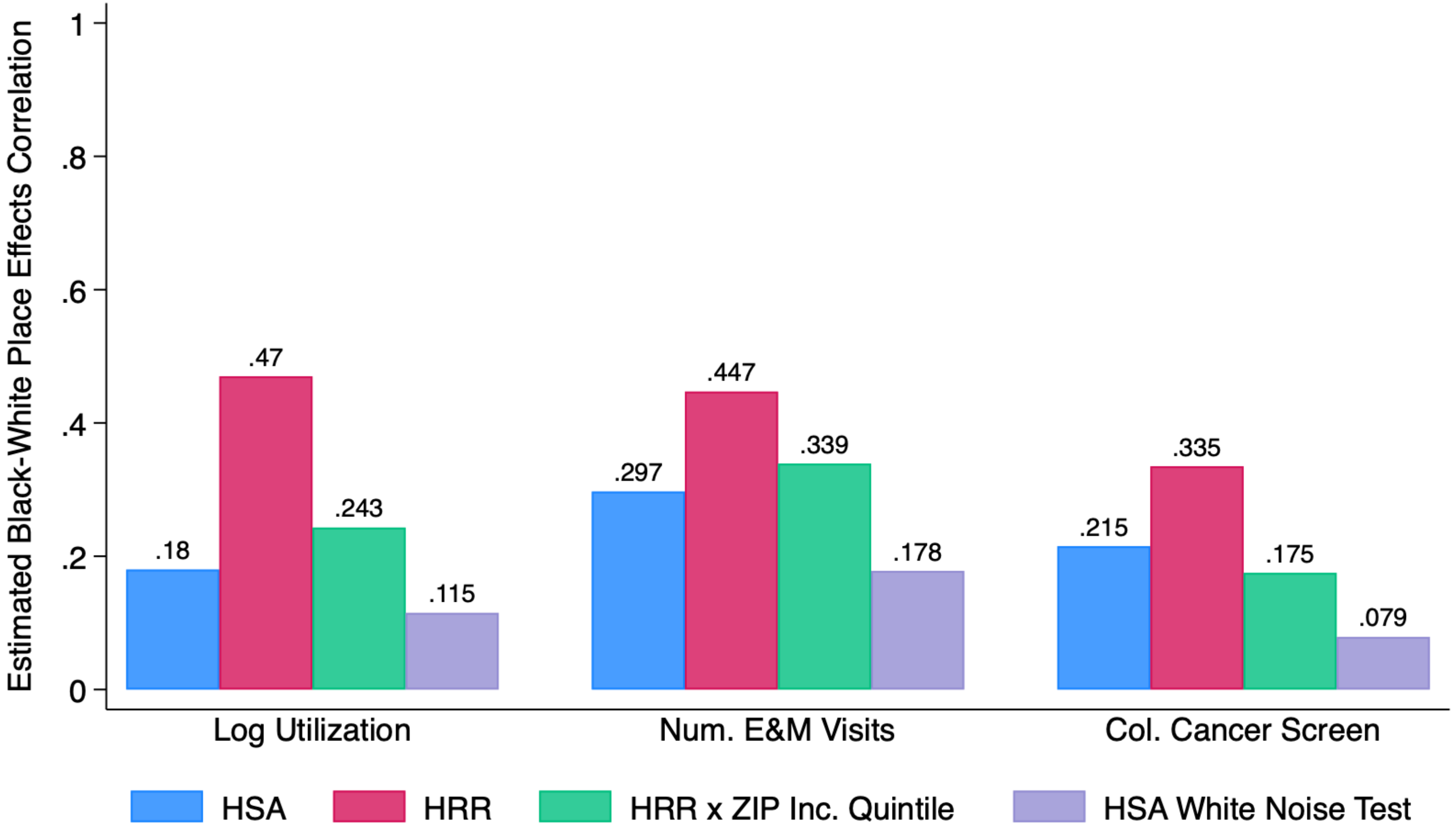


Figure. Correlation between Black and White HSA Place Effects, Varying Sample

Roadmap

Background

Conceptual Framework

Empirical Strategy

Can Place-Based Policies Address Disparities?

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. 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 at delivering access for Black beneficiaries, and vice versa.

What does this mean for 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

White-Black Disparities, Number of E&M Visits

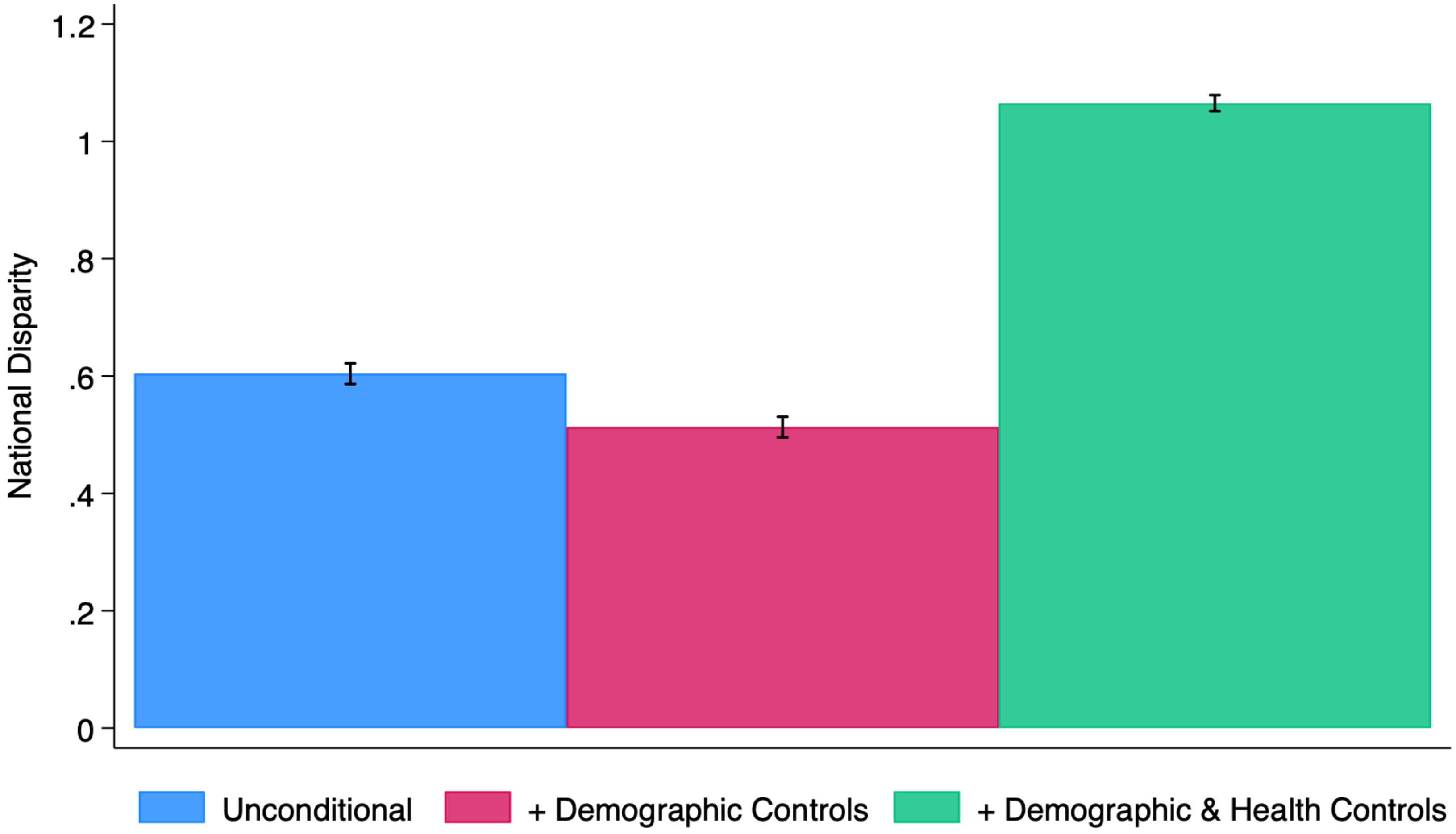


Figure. White-Black Disparity in Number of E&M Visits

Back

White-Black Disparities, Colorectal Cancer Screening

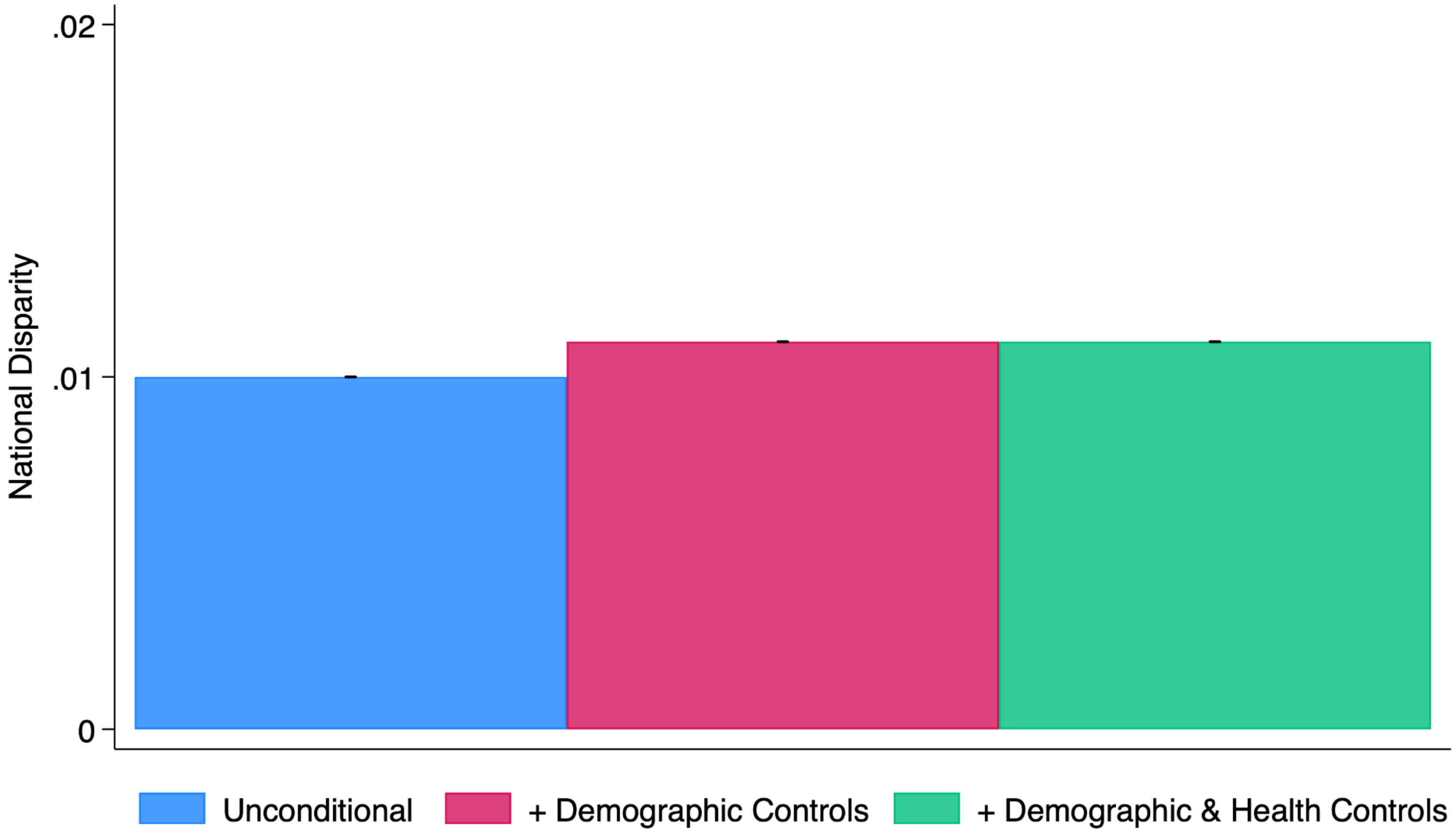


Figure. White-Black Disparity in Colorectal Cancer Screenings

Back

Considerable Geographic Variation in Access Across and Within Groups

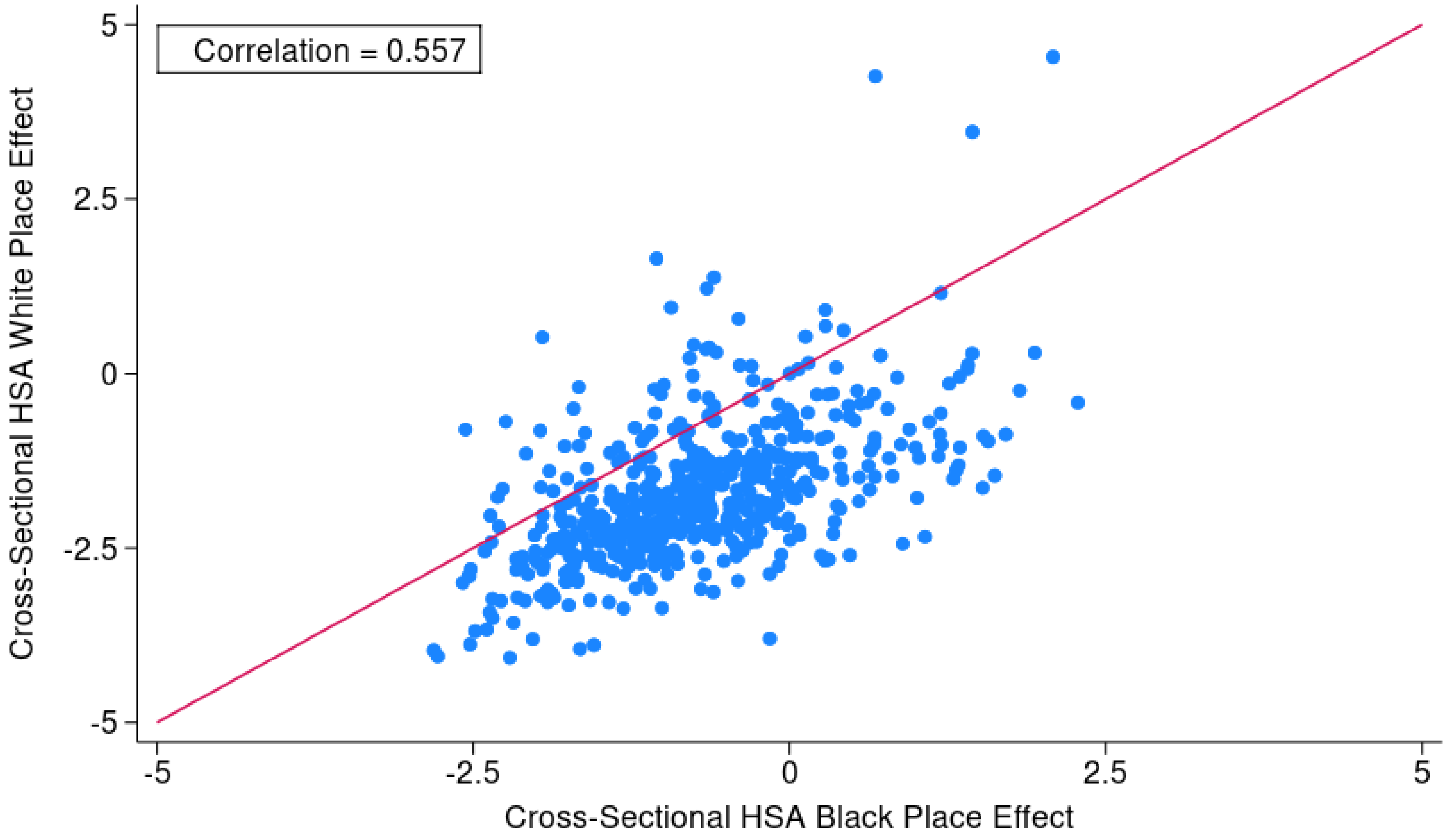


Figure. Cross-Sectional White-Black HSA “Place Effects”, Number of E&M Visits

Back

Considerable Geographic Variation in Access Across and Within Groups

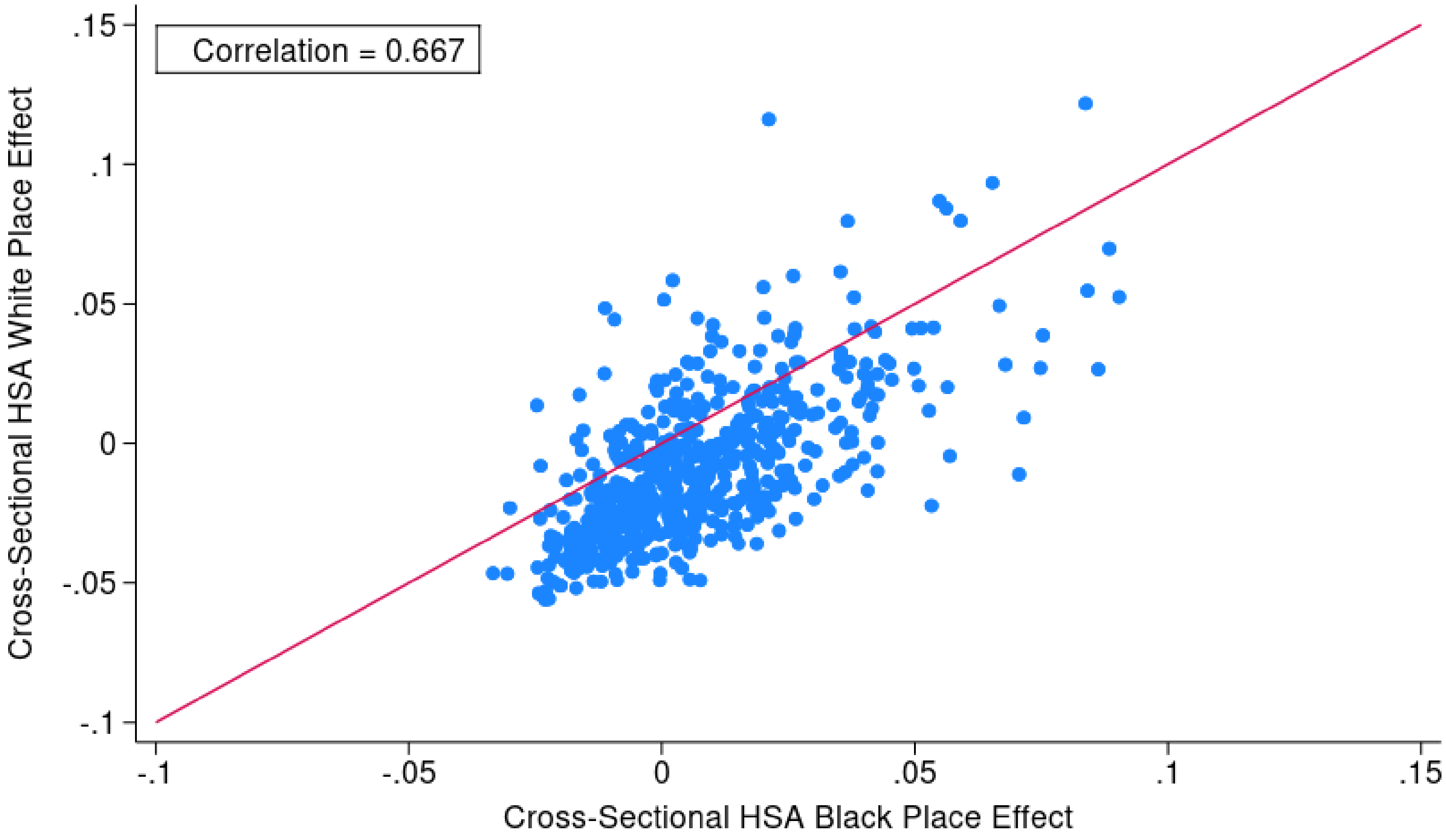


Figure. Cross-Sectional White-Black HSA “Place Effects”, Colorectal Cancer Screening

Back

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.

Back

Table. Descriptive Statistics of Movers and Non-Movers

Black and White Movers are Observably Similar

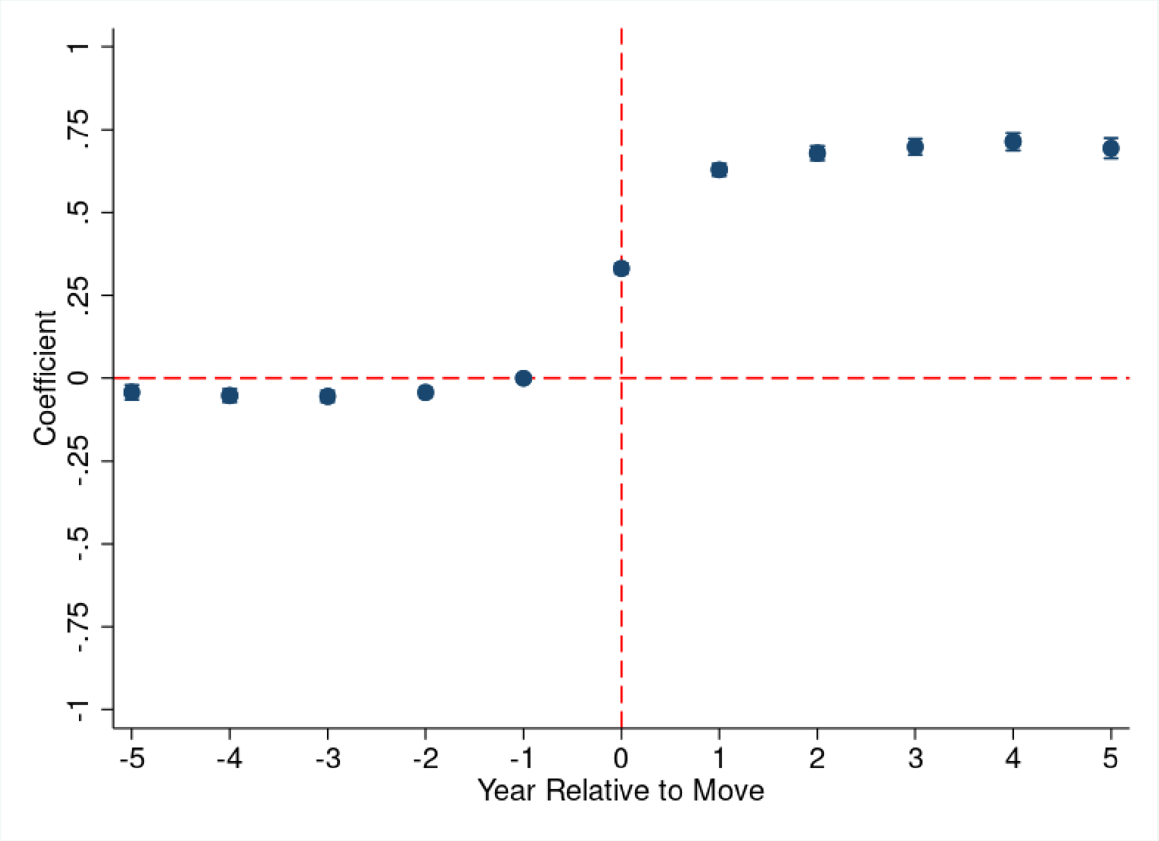
	ZIP Movers				HSA Movers				HRR Movers			
	White		Black		White		Black		White		Black	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Female	0.60	(0.49)	0.61	(0.49)	0.60	(0.49)	0.61	(0.49)	0.59	(0.49)	0.62	(0.49)
Age at First Observation	73.49	(7.41)	72.29	(7.20)	73.30	(7.35)	72.45	(7.19)	73.08	(7.27)	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).

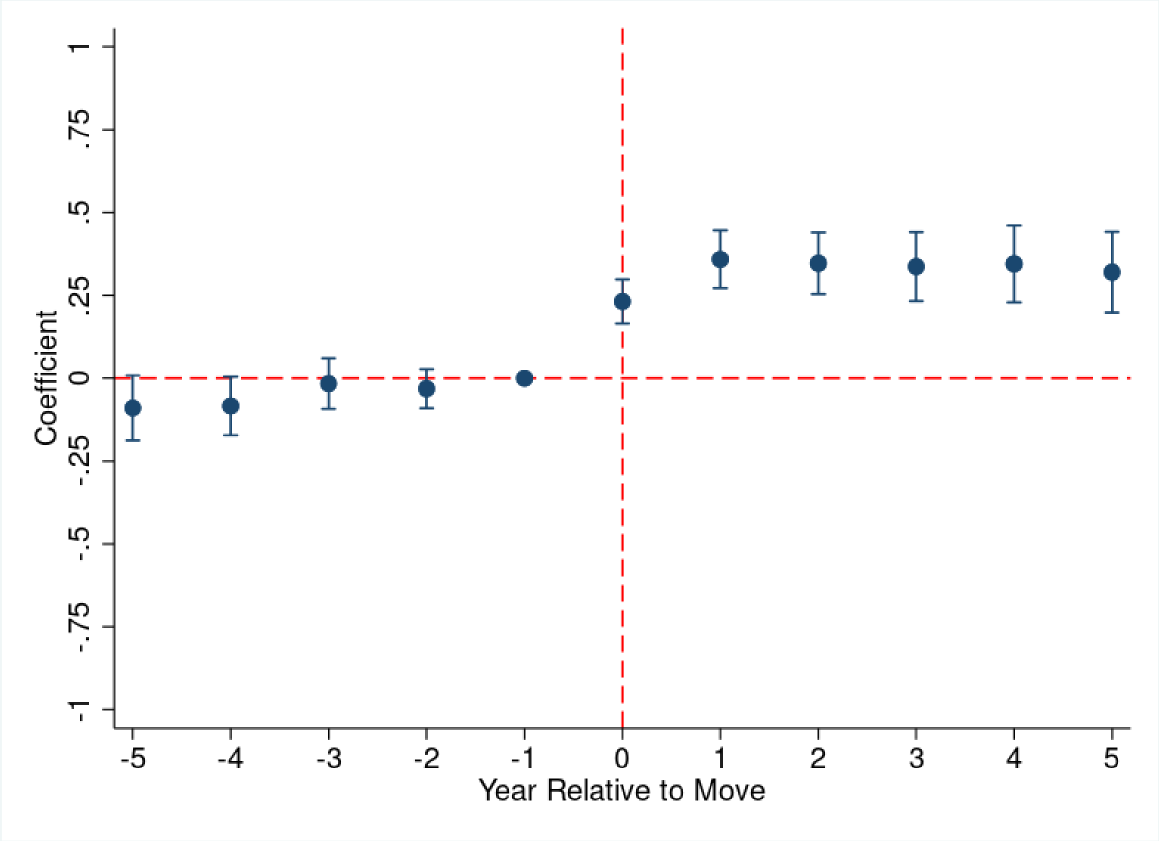
Back

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

Event Study: Number of Primary Care (PC) Visits



(a) Effect of HSA Move on Number of E&M Visits, White Movers

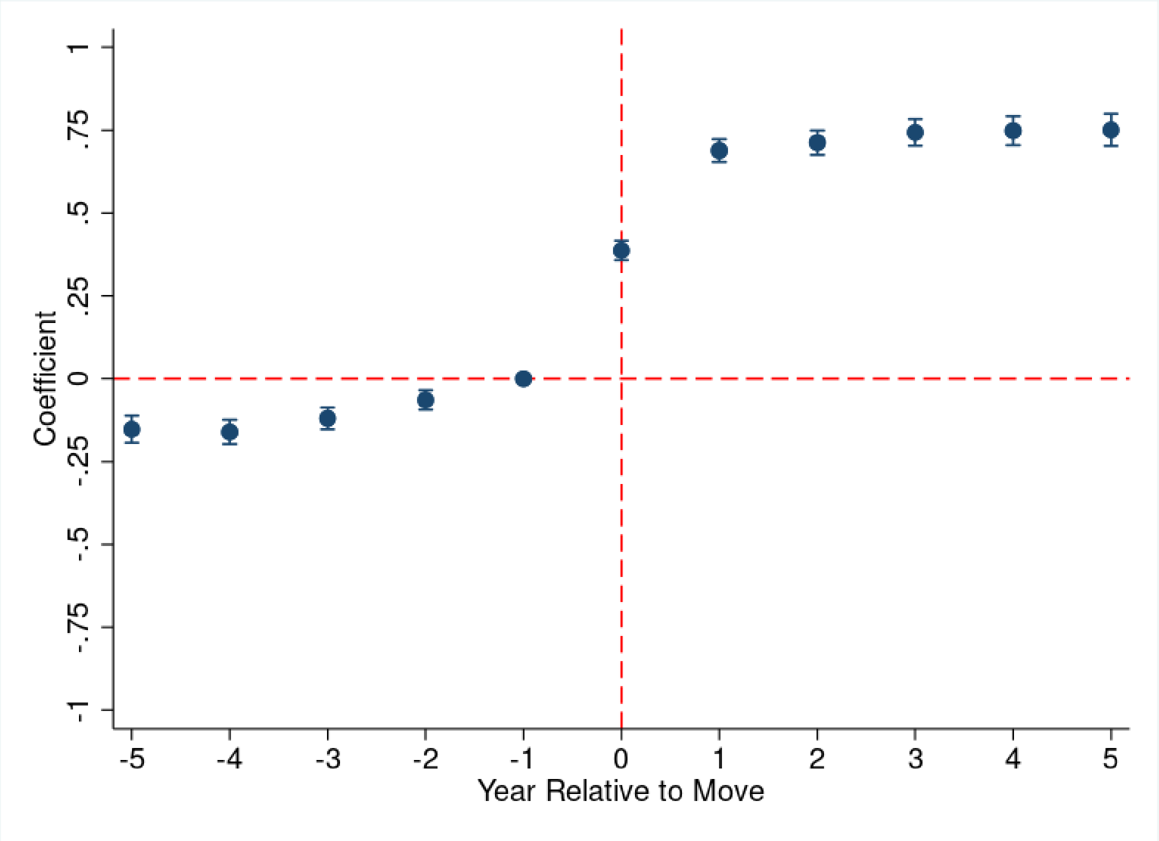


(b) Effect of HSA Move on Number of E&M Visits, Black Movers

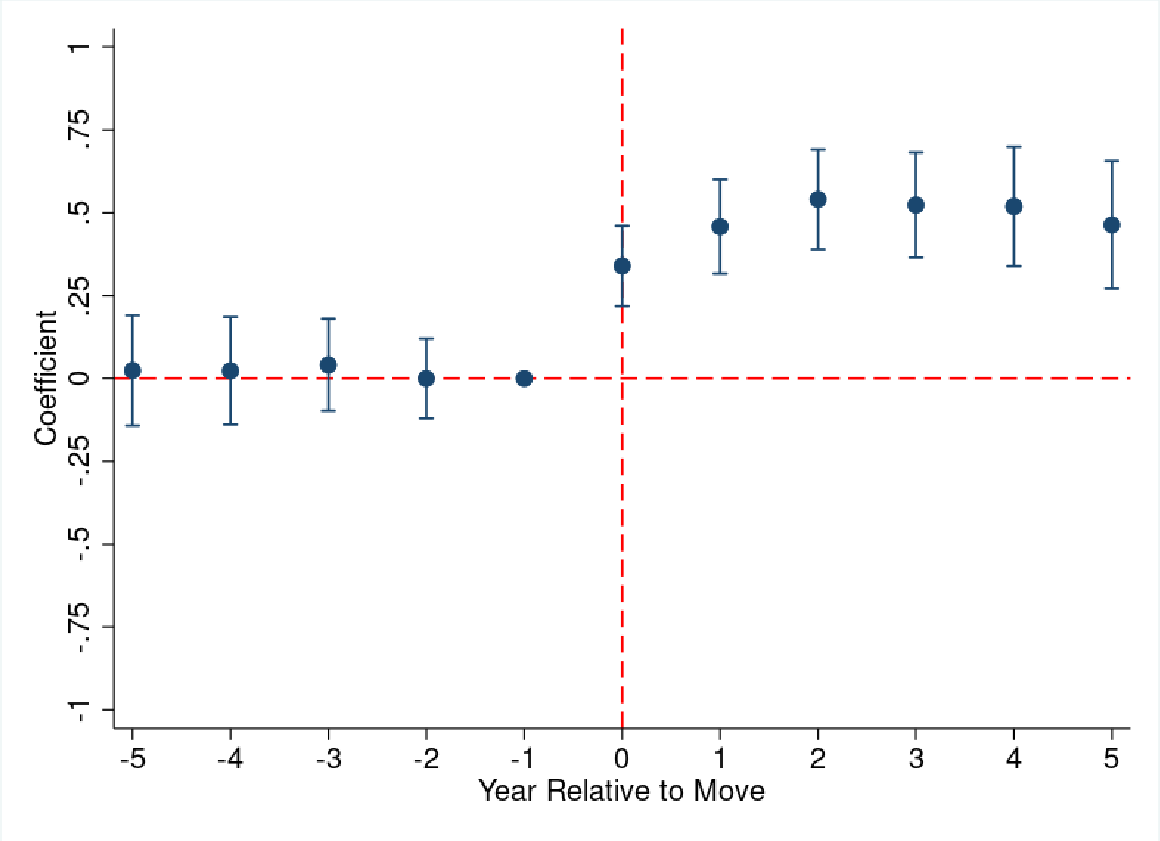
Figure: Effect of Moving on Number of E&M Visits, White and Black HSA Movers

Back

Event Study: Colorectal Cancer Screenings



(a) Effect of HSA Move on Colorectal Cancer Screening, White Movers

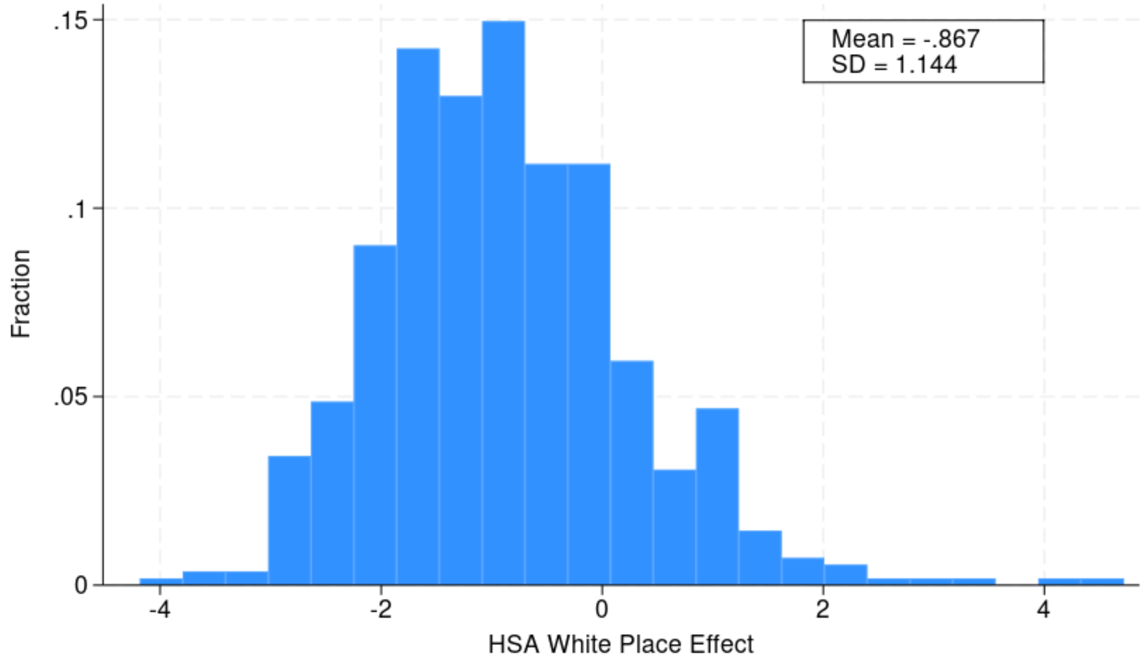


(b) Effect of HSA Move on Colorectal Cancer Screening, Black Movers

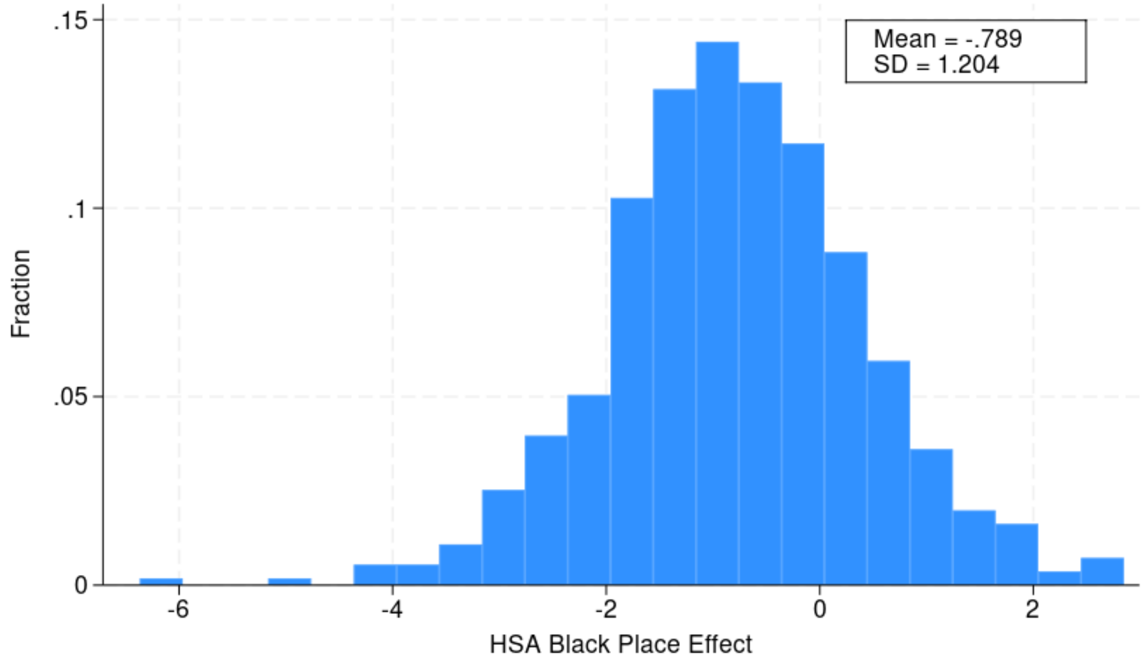
Figure: Effect of Moving on Colorectal Cancer Screening, White and Black HSA Movers

Back

Distribution of Place Effects: Number of E&M Visits



(a) HSA Place Effects on Num. E&M Visits, White Movers

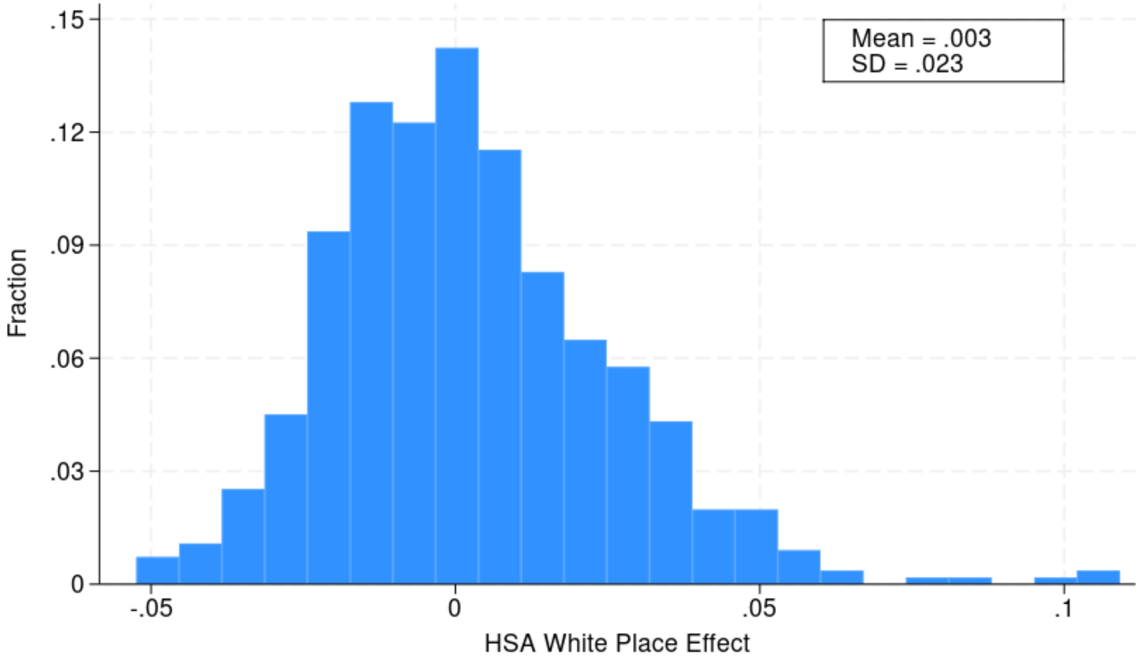


(b) HSA Place Effects on Num. E&M Visits, Black Movers

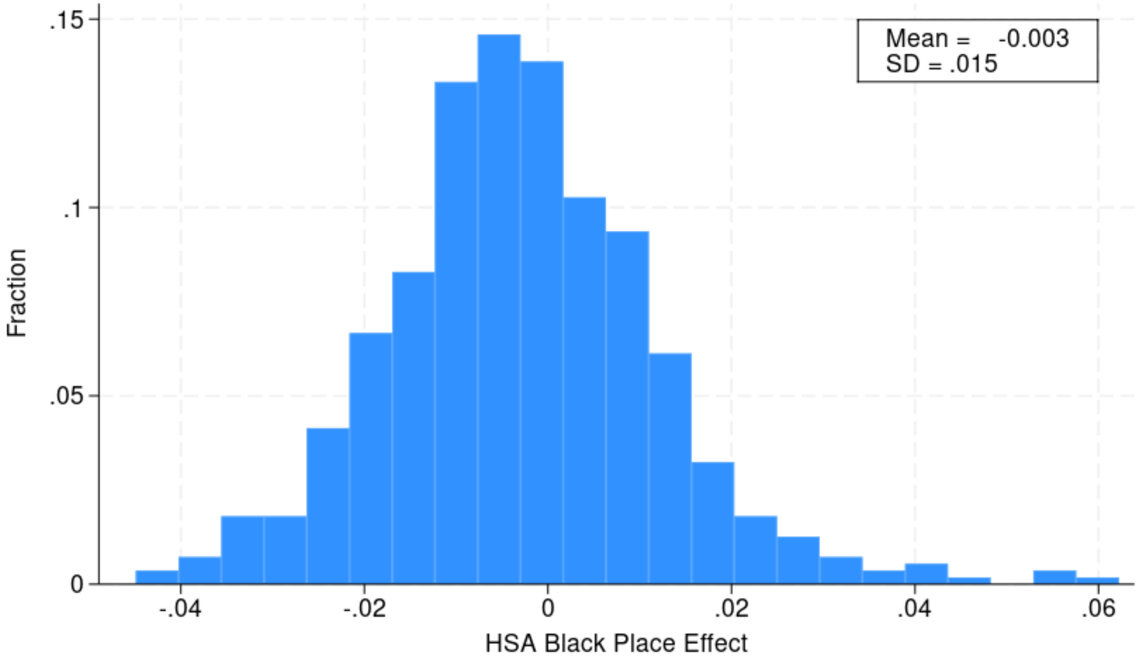
Figure. Distribution of Place Effects for Num. E&M Visits, White and Black HSA Movers

Back

Distribution of Place Effects: Colorectal Cancer Screening



(a) HSA Place Effects on Colorectal Cancer Screening, White Movers



(b) HSA Place Effects on Colorectal Cancer Screening, Black Movers

Figure. Distribution of Place Effects for Colorectal Cancer Screening, White and Black HSA Movers

Back

Homogenous Decomposition: Number of E&M Visits

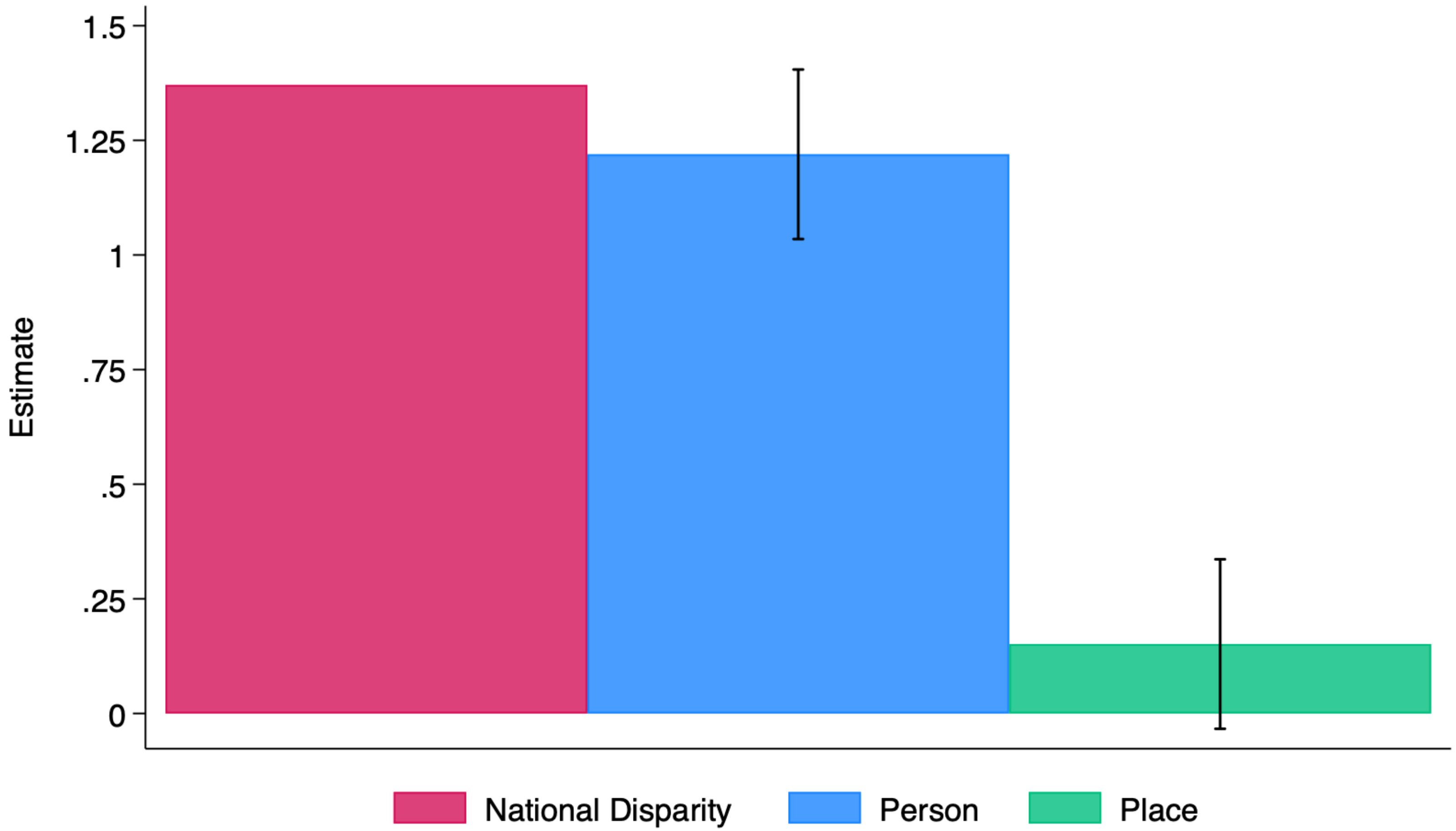


Figure. Homogenous HSA Decomposition, Number of E&M Visits

Back

Homogenous Decomposition: Colorectal Cancer Screening

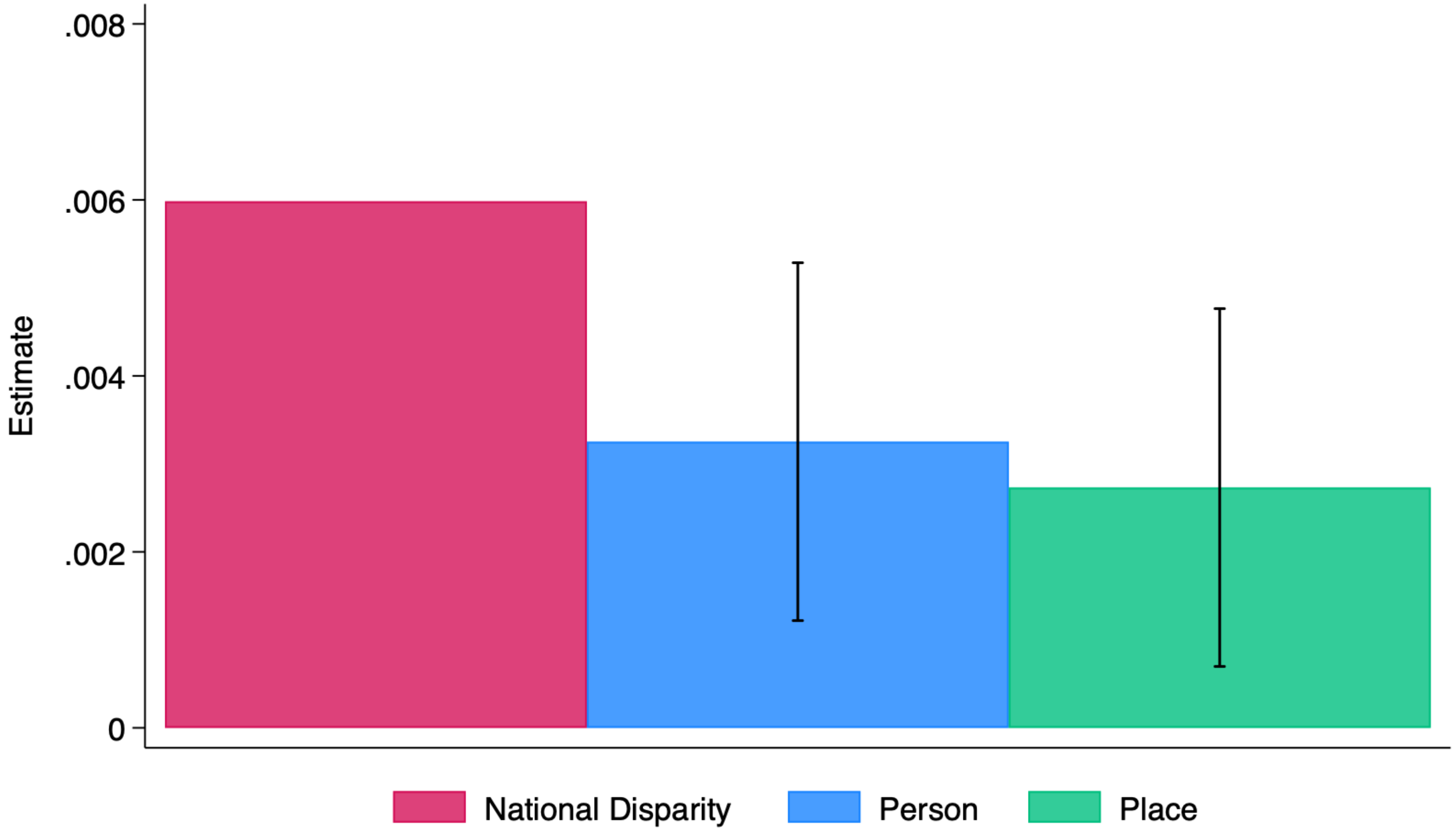


Figure. Homogenous HSA Decomposition, Colorectal Cancer Screening

Back

Place Effects vs. Geographic Distribution, Number of E&M Visits

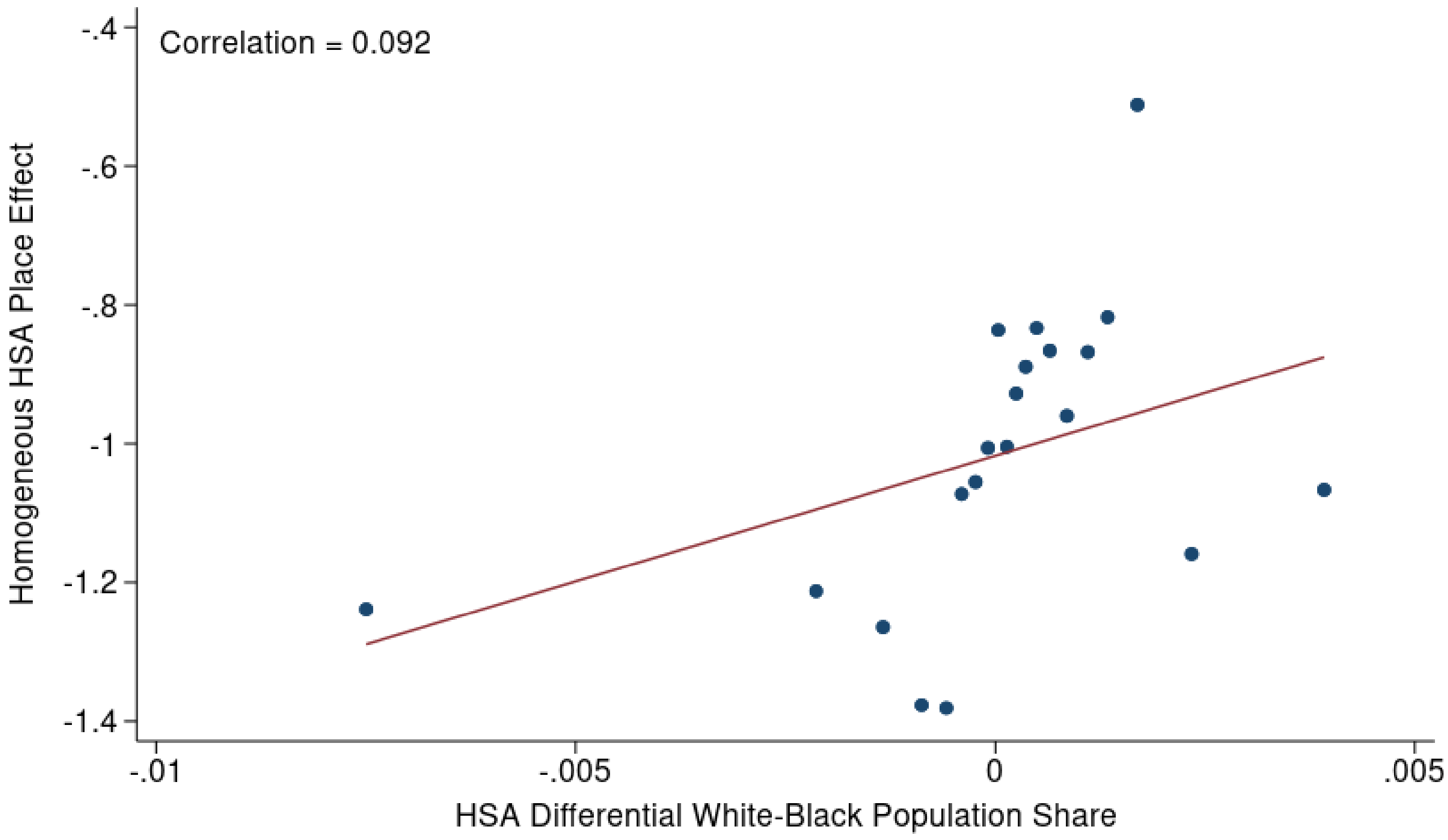


Figure. Relationship Between Homogeneous Place Effects and the Differential Geographic Distribution, Number of E&M Visits

Back

Place Effects vs. Geographic Distribution, Col. Cancer Screening

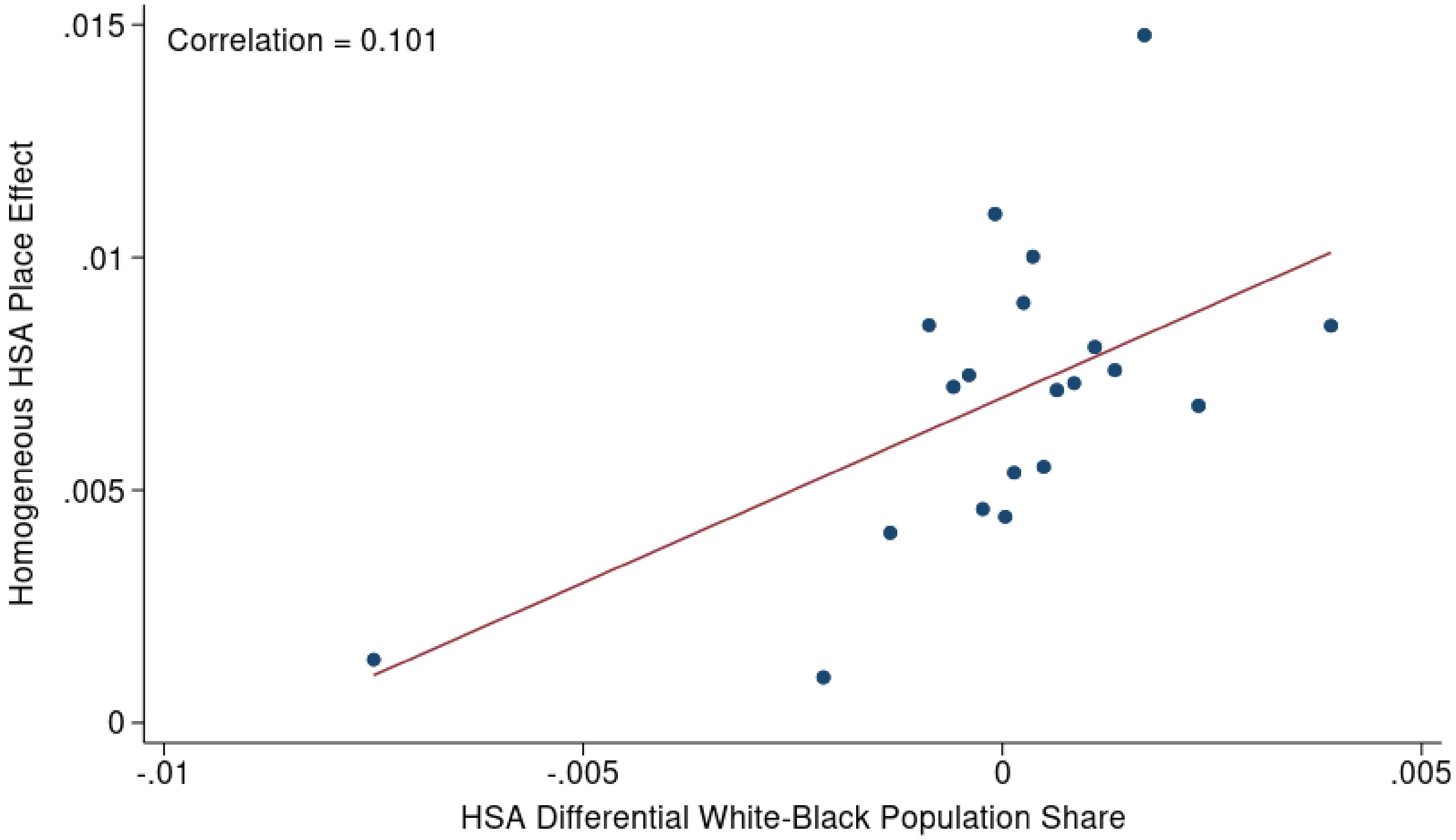


Figure. Relationship Between Homogeneous Place Effects and the Differential Geographic Distribution, Colorectal Cancer Screening

Back

Heterogeneous Decomposition: Number of E&M Visits

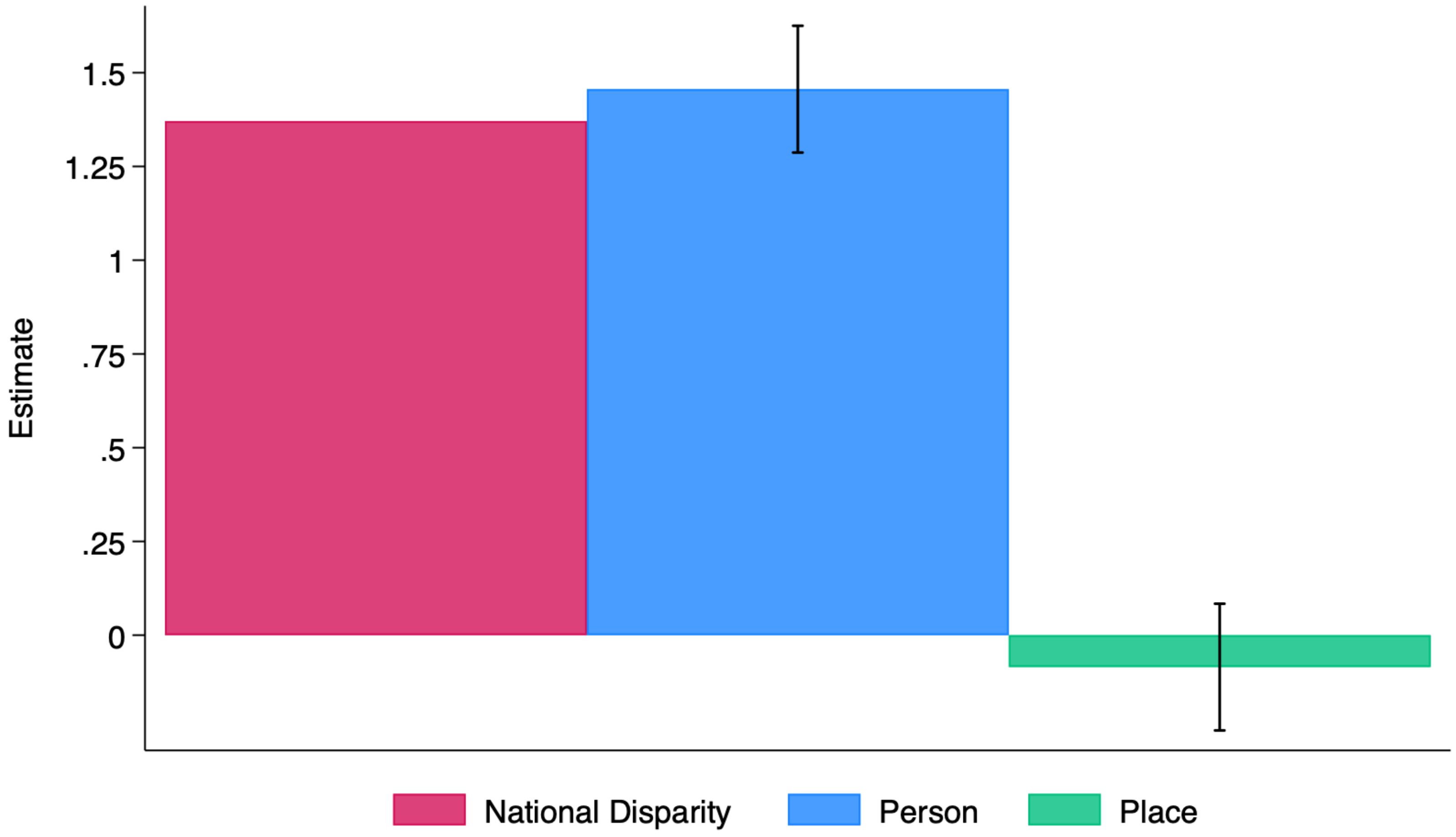


Figure. HSA Place Component Decomposition, Number of E&M Visits

Back

Heterogeneous Decomposition: Colorectal Cancer Screening

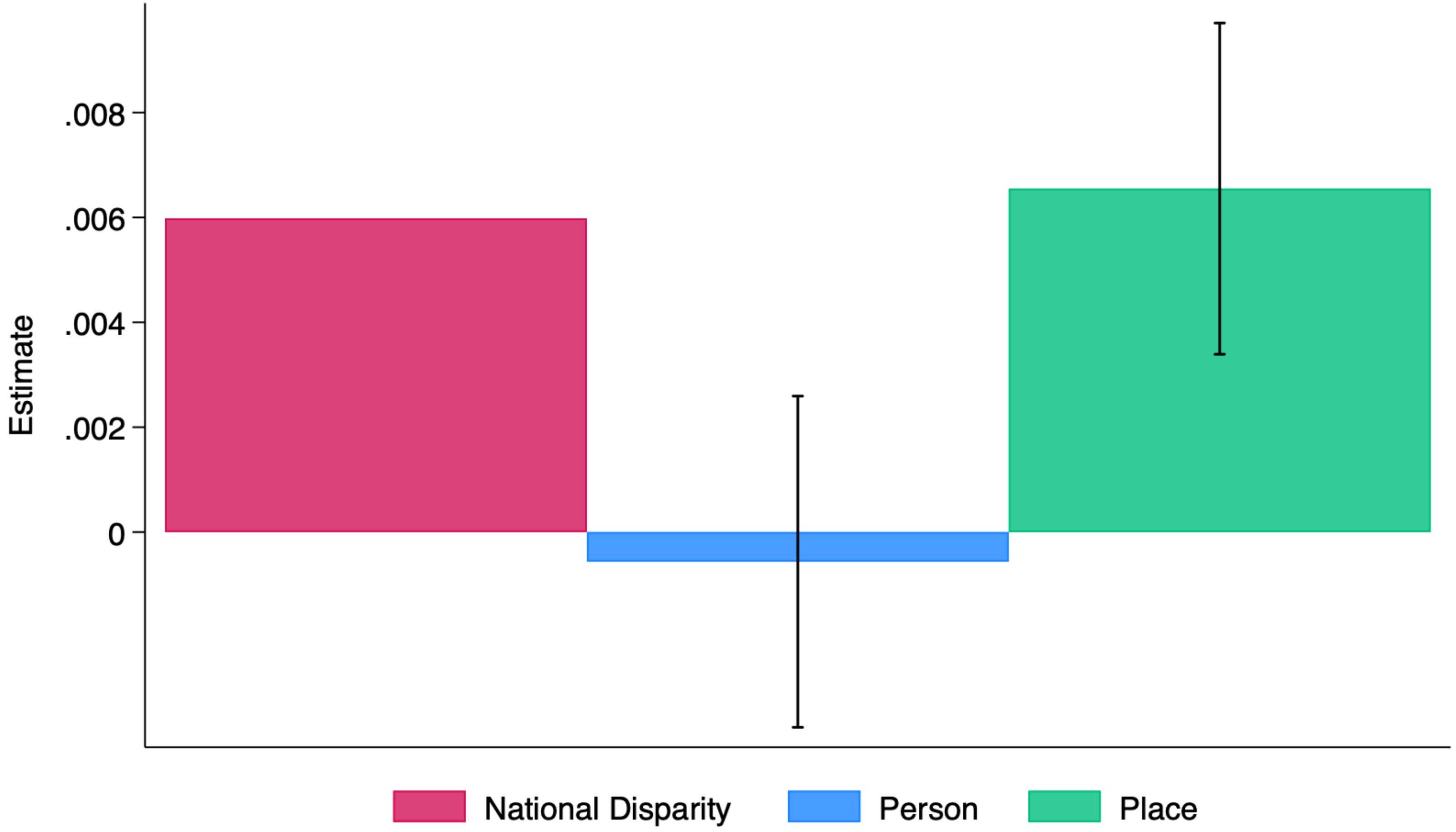


Figure. HSA Place Component Decomposition, Colorectal Cancer Screening

Back

Place Component Decomposition: Number of E&M Visits

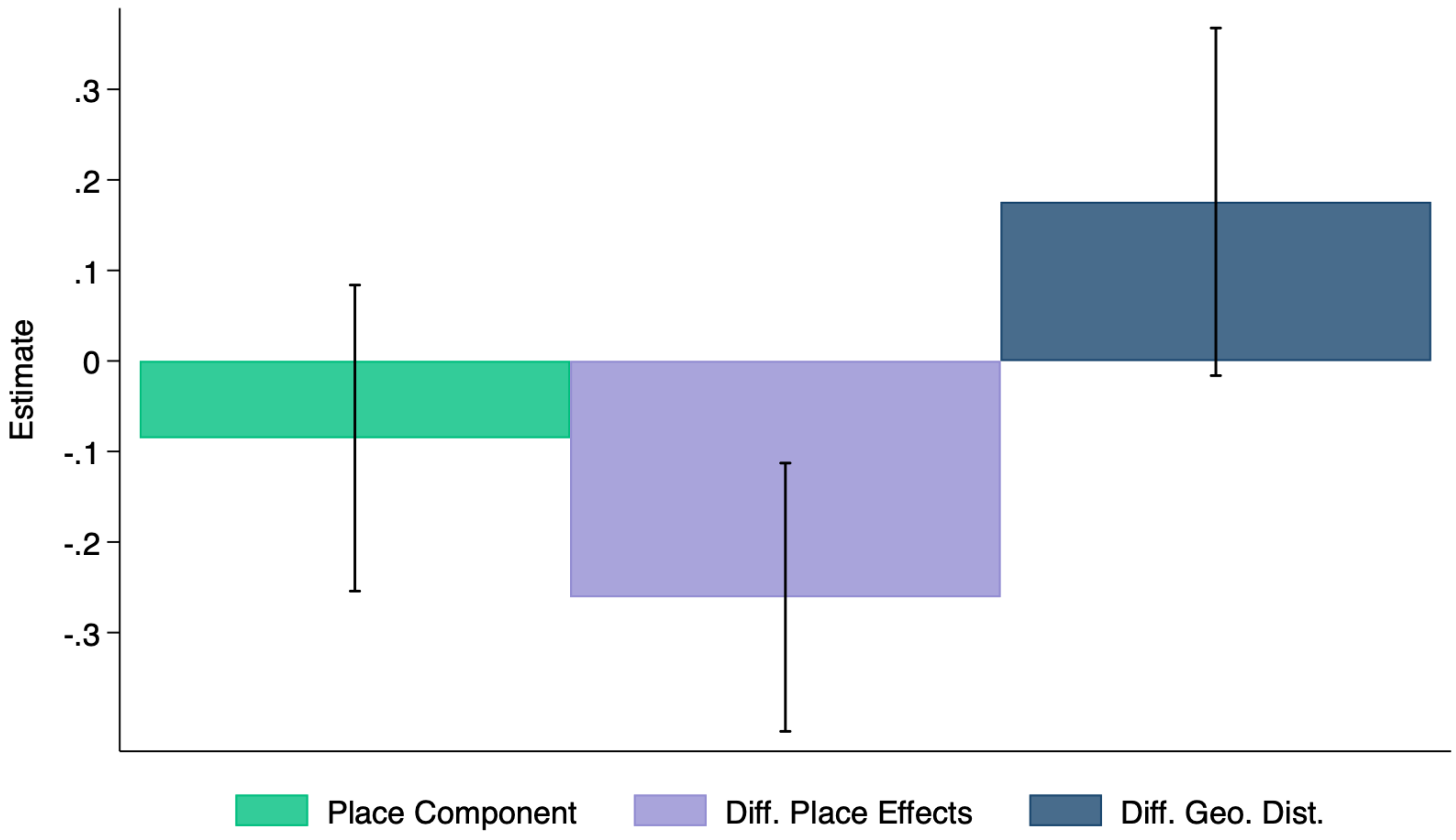


Figure. HSA Place Component Decomposition, Number of E&M Visits

Back

Place Component Decomposition: Colorectal Cancer Screening

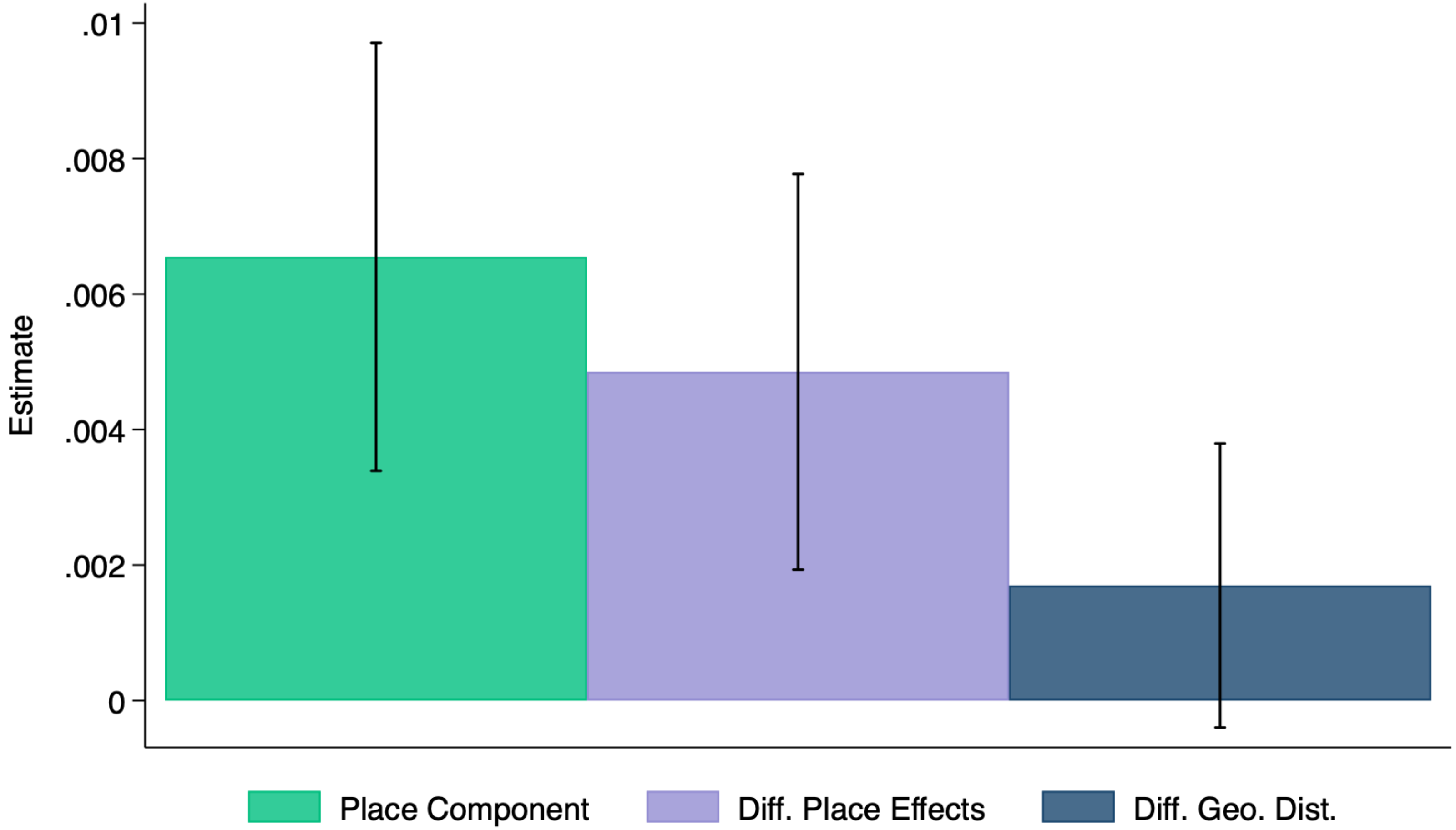


Figure. HSA Place Component Decomposition, Colorectal Cancer Screening

Back

Reallocation Exercise: Number of E&M Visits

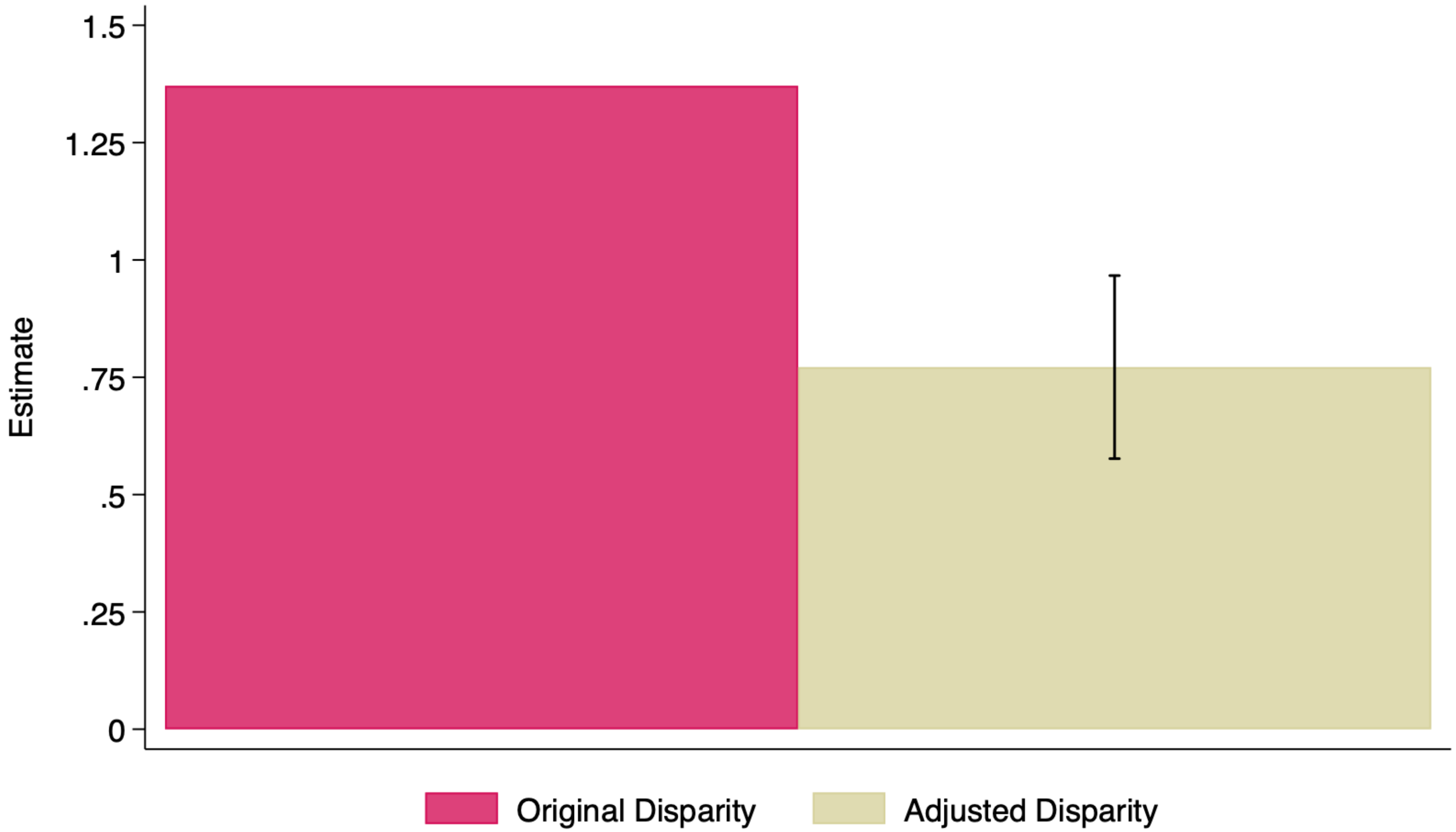


Figure. HSA Reallocation Exercise, Number of E&M Visits

Back

Reallocation Exercise: Colorectal Cancer Screening

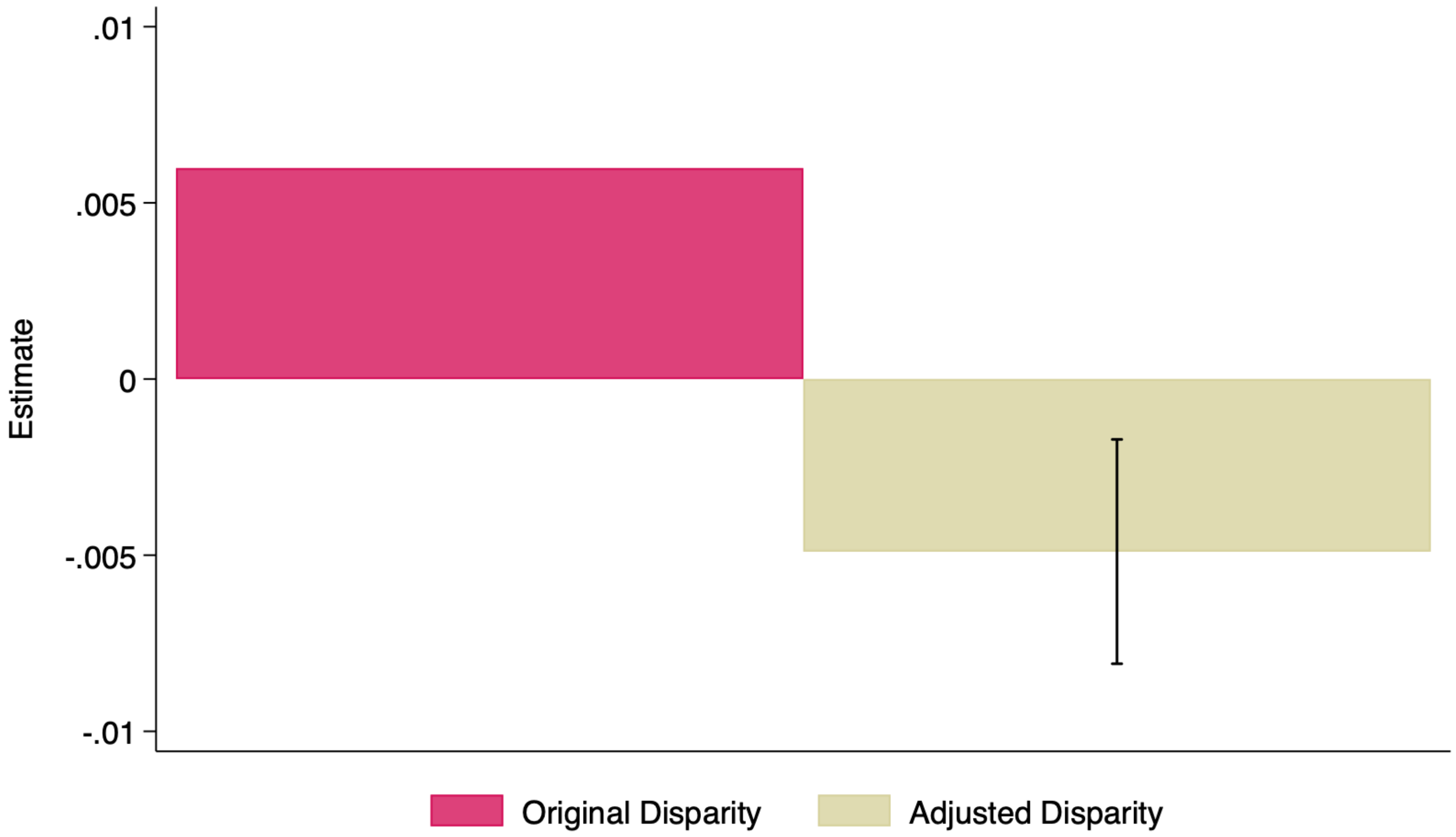
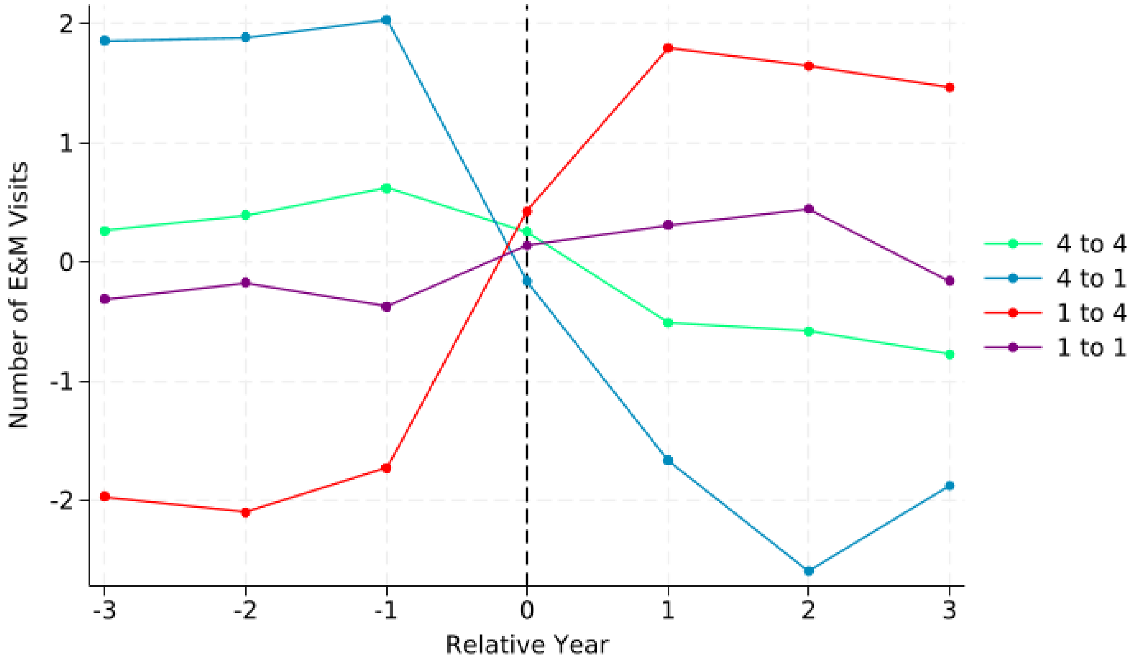


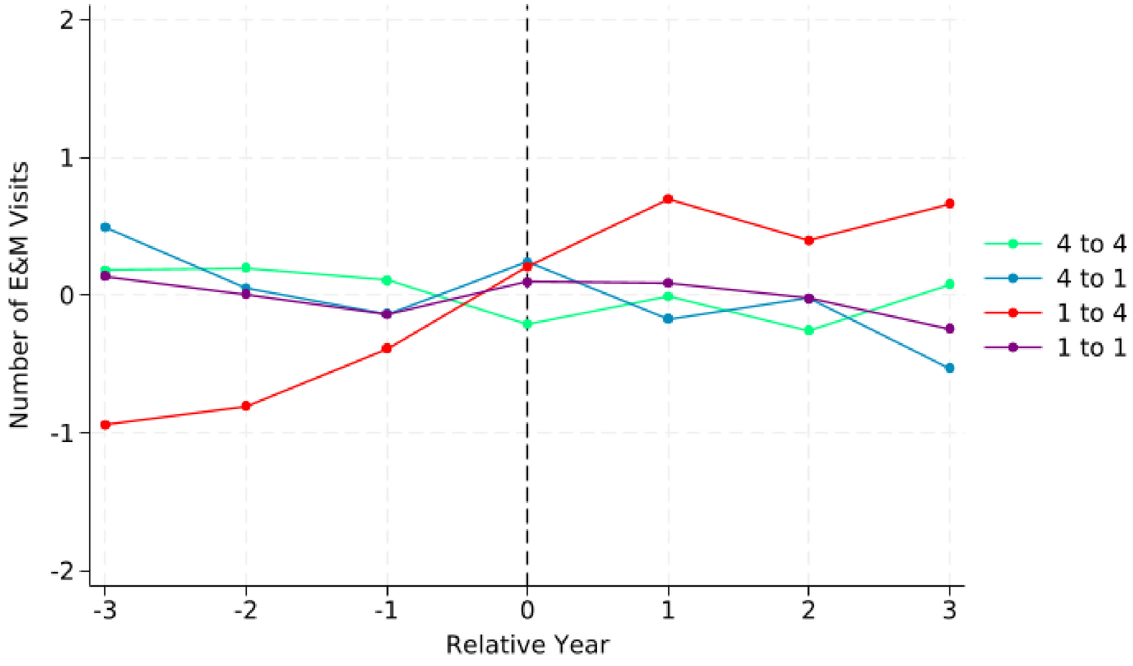
Figure. HSA Reallocation Exercise, Colorectal Cancer Screening

Back

The Importance of Place-by-Race Effects: Num. E&M Visits



(a) Black Place Effect Moves, Black Movers

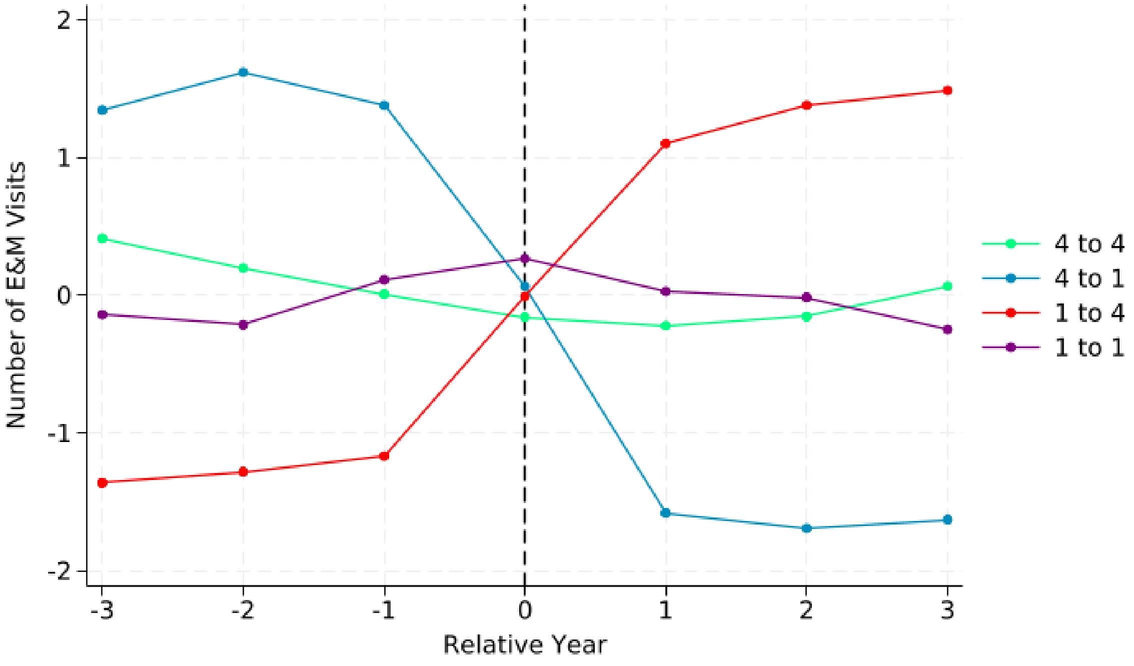


(b) White Place Effect Moves, Black Movers

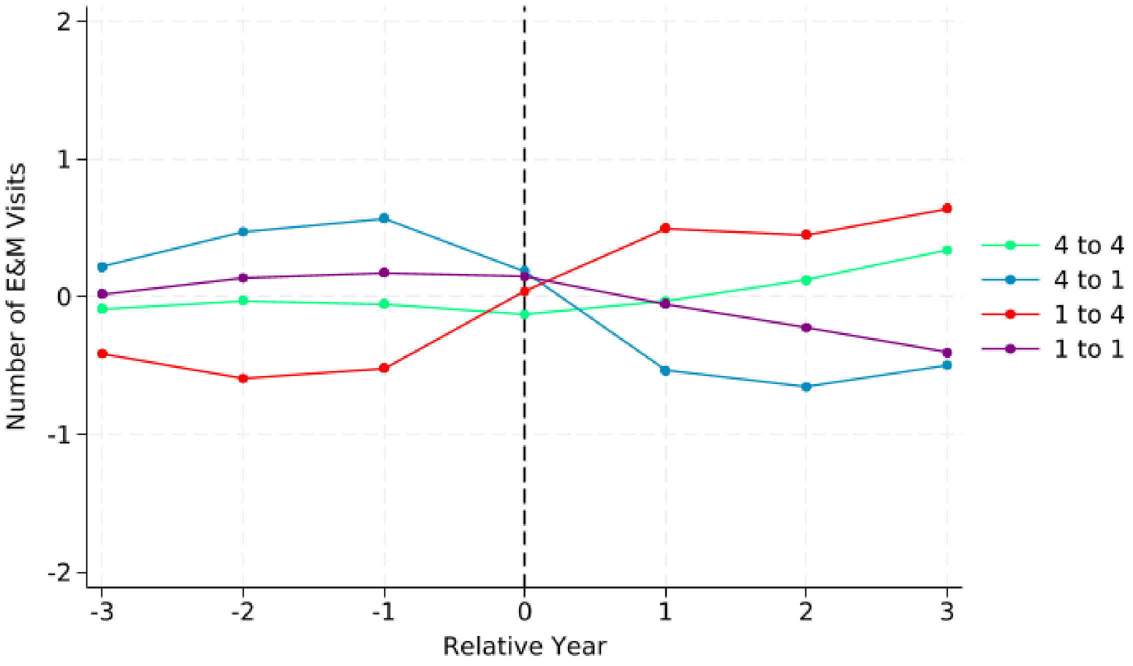
Figure. Changes in Number of E&M Visits by Move Type, Black Movers

Back

The Importance of Place-by-Race Effects: Num. E&M Visits



(a) White Place Effect Moves, White Movers

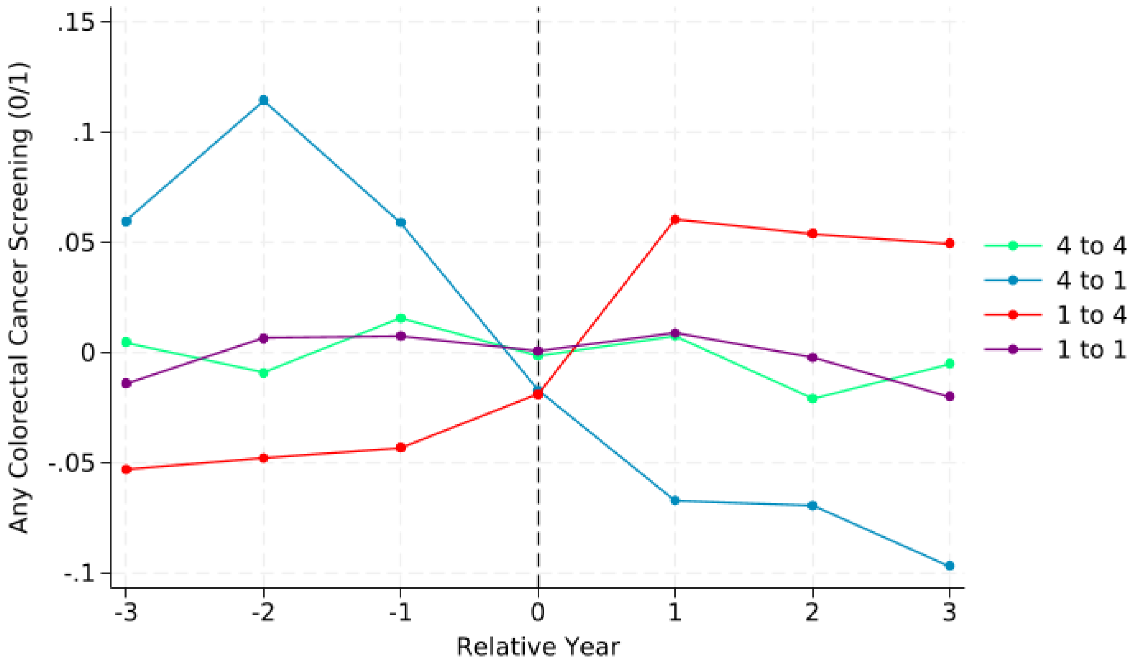


(b) Black Place Effect Moves, White Movers

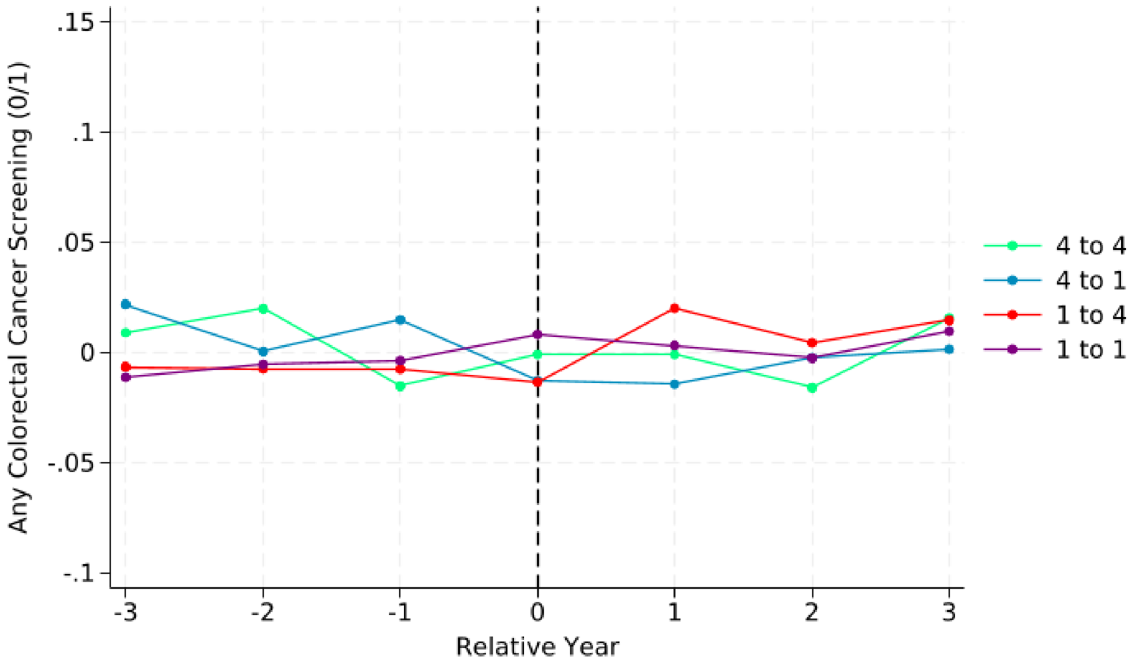
Figure. Changes in Number of E&M Visits by Move Type, White Movers

Back

The Importance of Place-by-Race Effects: Colorectal Cancer Screen



(a) Black Place Effect Moves, Black Movers

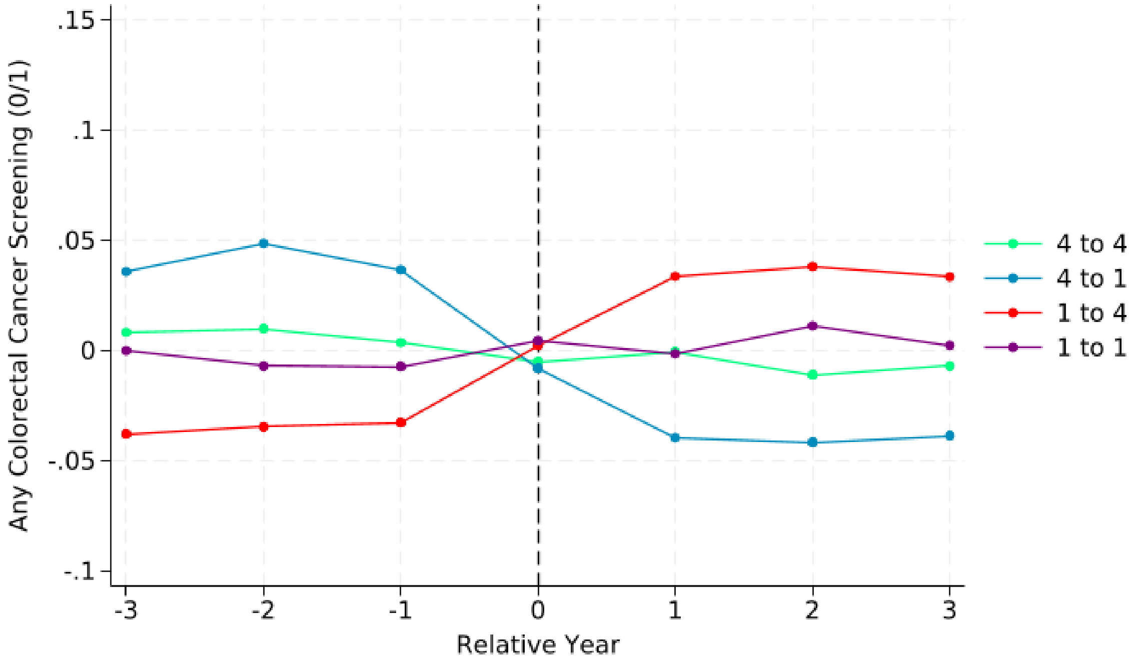


(b) White Place Effect Moves, Black Movers

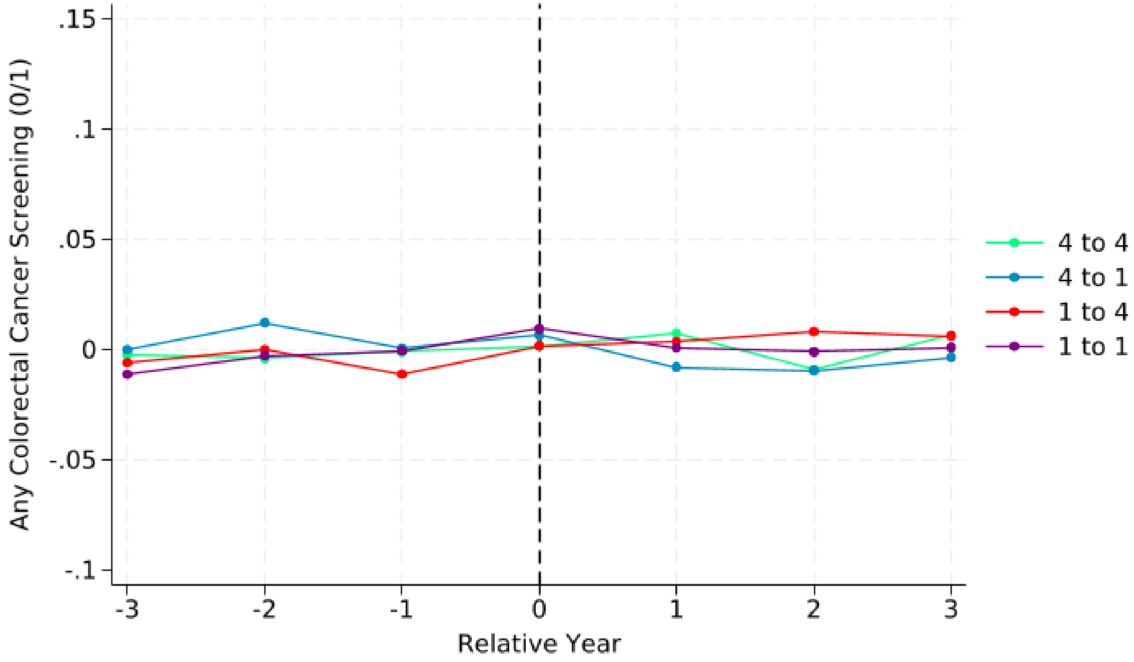
Figure. Changes in Colorectal Cancer Screening by Move Type, Black Movers

Back

The Importance of Place-by-Race Effects: Colorectal Cancer Screen



(a) White Place Effect Moves, White Movers



(b) Black Place Effect Moves, White Movers

Figure. Changes in Colorectal Cancer Screening by Move Type, White Movers

Back

How Correlated are Place Effects?

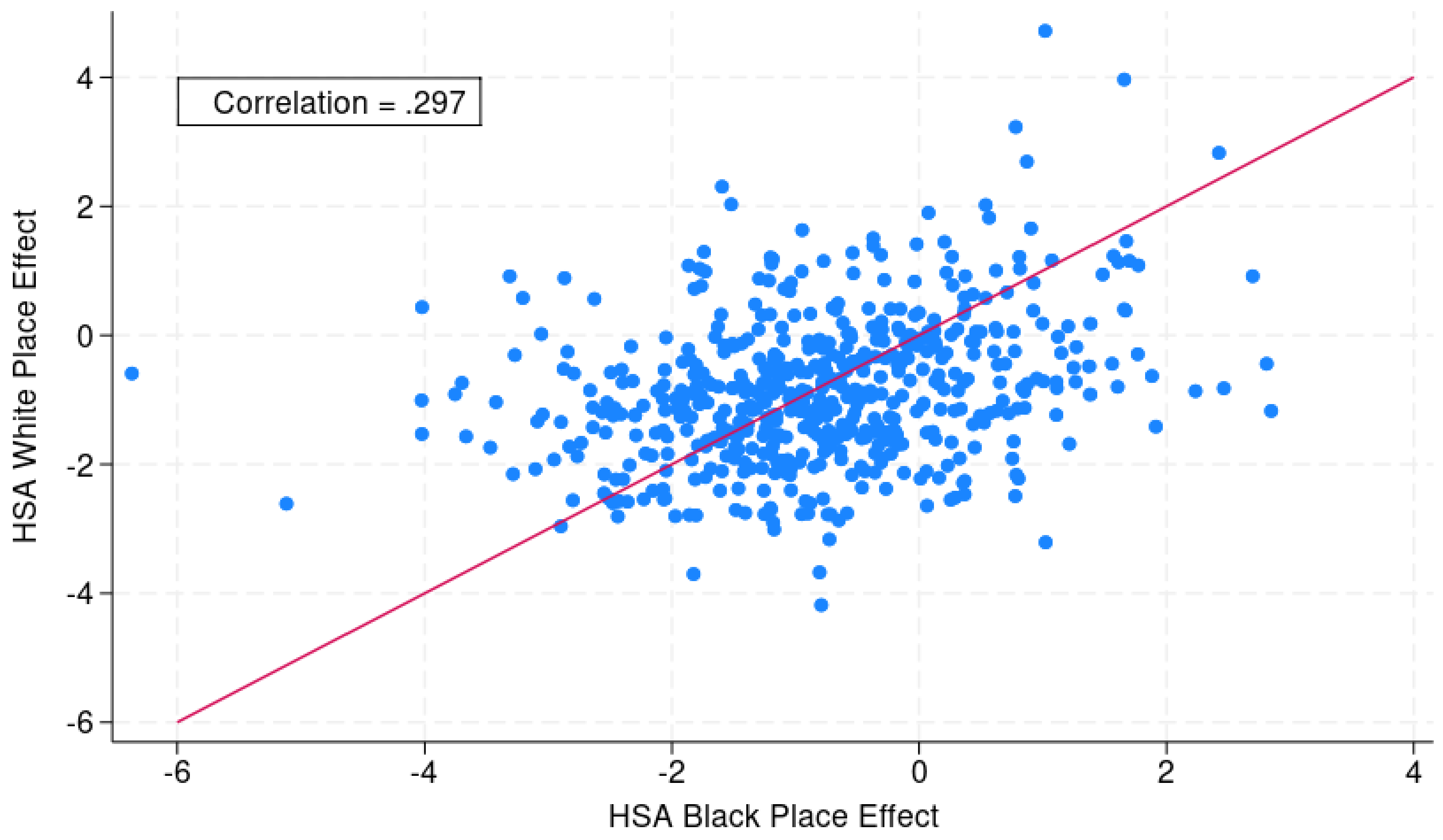


Figure. Correlation between Black and White HSA Place Effects, Number of E&M Visits

Back

How Correlated are Place Effects?

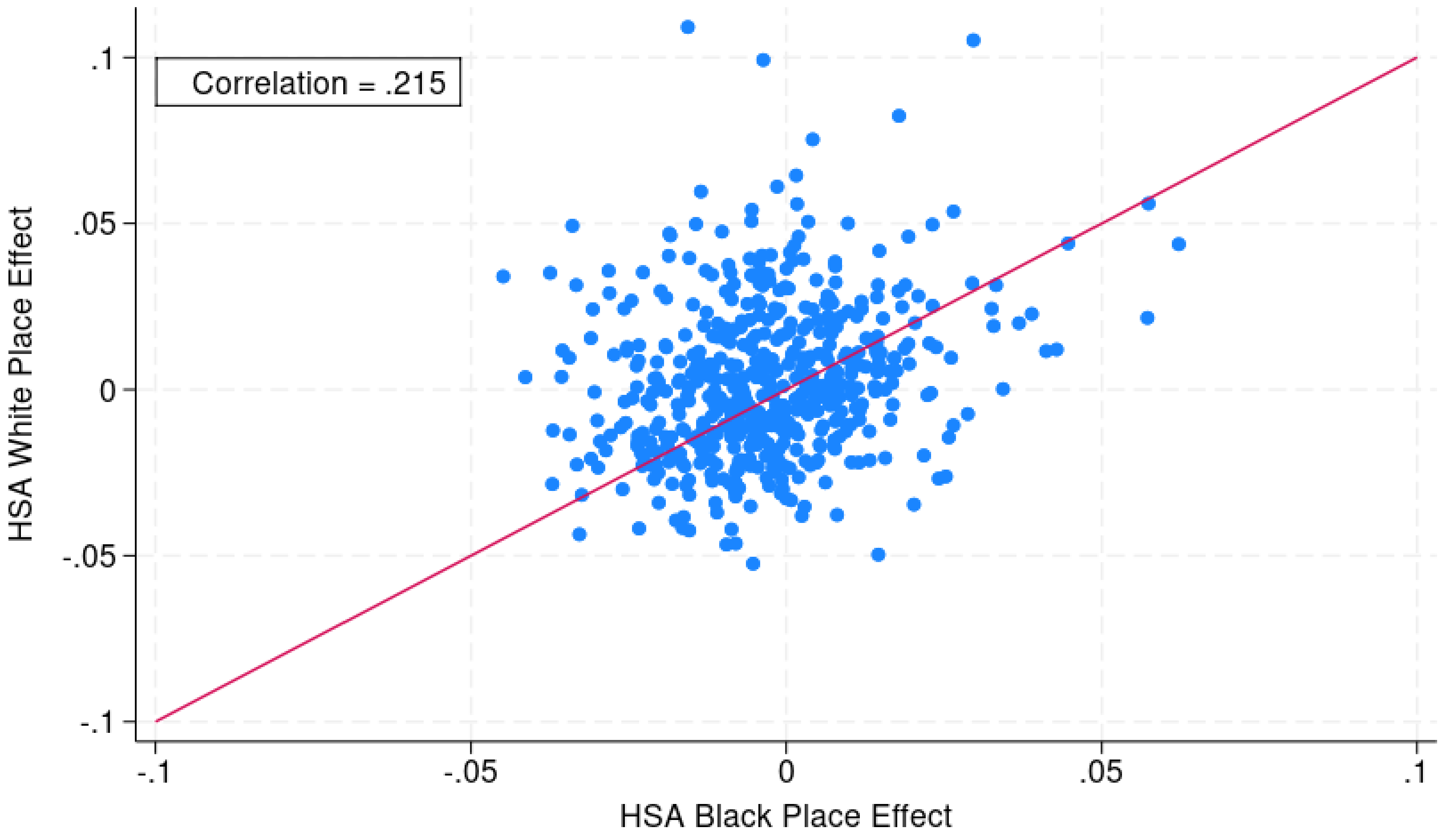
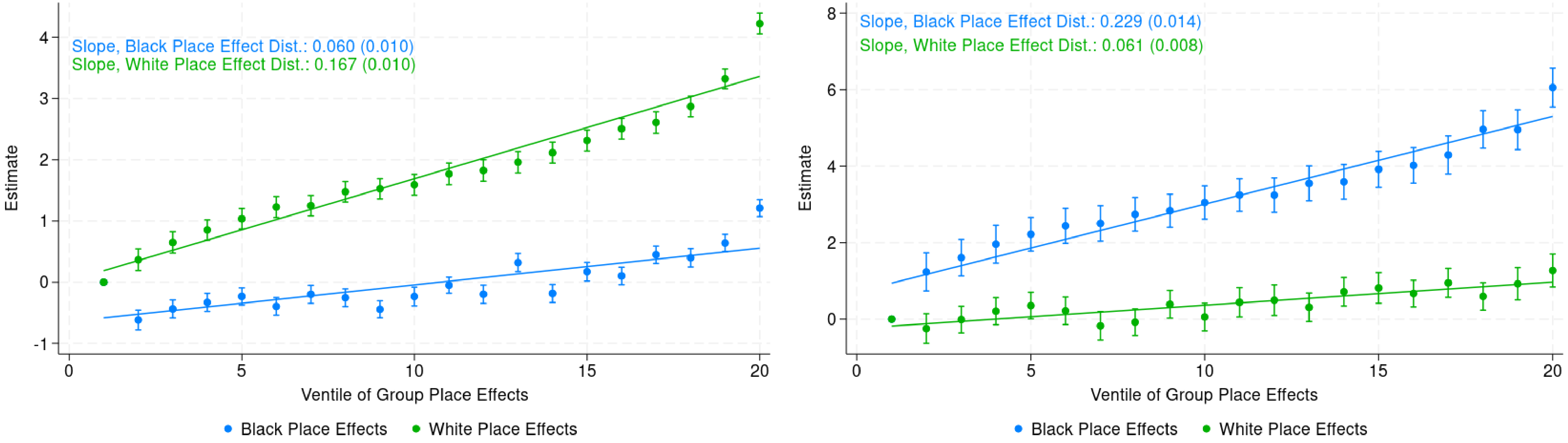


Figure. Correlation between Black and White HSA Place Effects, Colorectal Cancer Screening

Back

How Correlated are Place Effects?



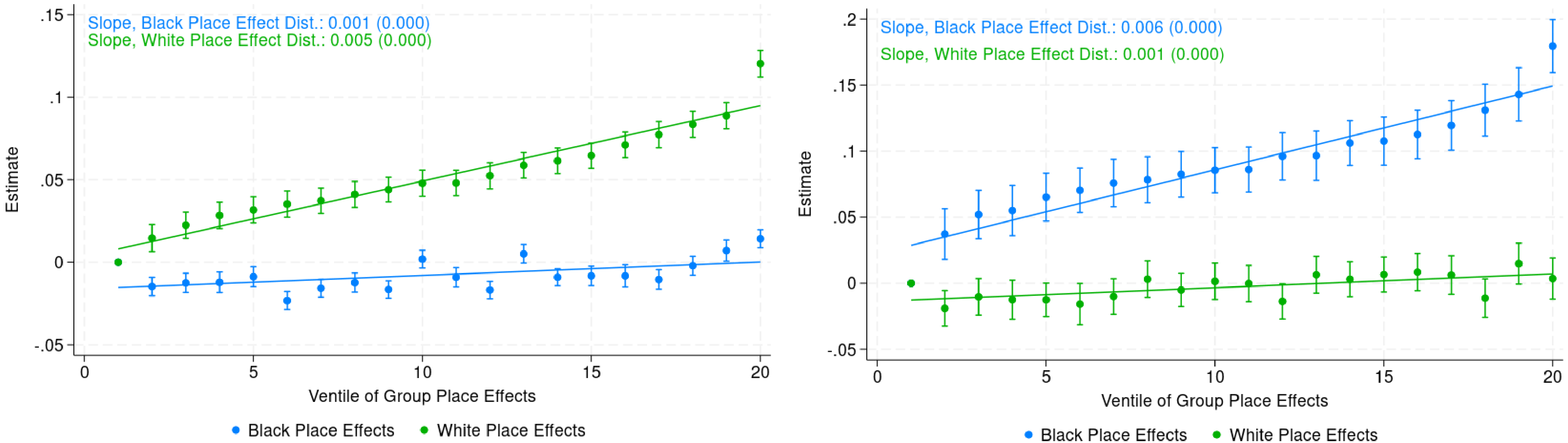
(a) White Movers,
Number of E&M Visits

(b) Black Movers,
Number of E&M Visits

Figure. Causal Effect of Moving Up Place Effects Distribution by Race, Number of E&M Visits

Back

How Correlated are Place Effects?



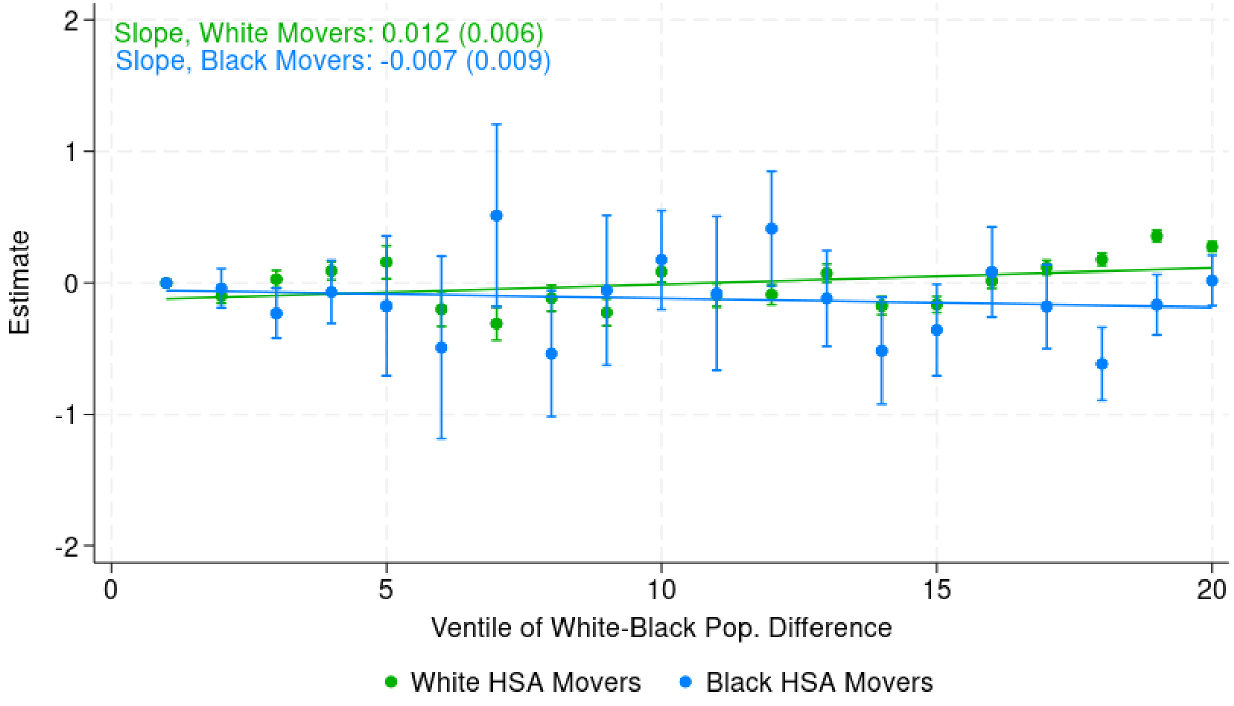
(a) White Movers,
Colorectal Cancer Screening

(b) Black Movers,
Colorectal Cancer Screening

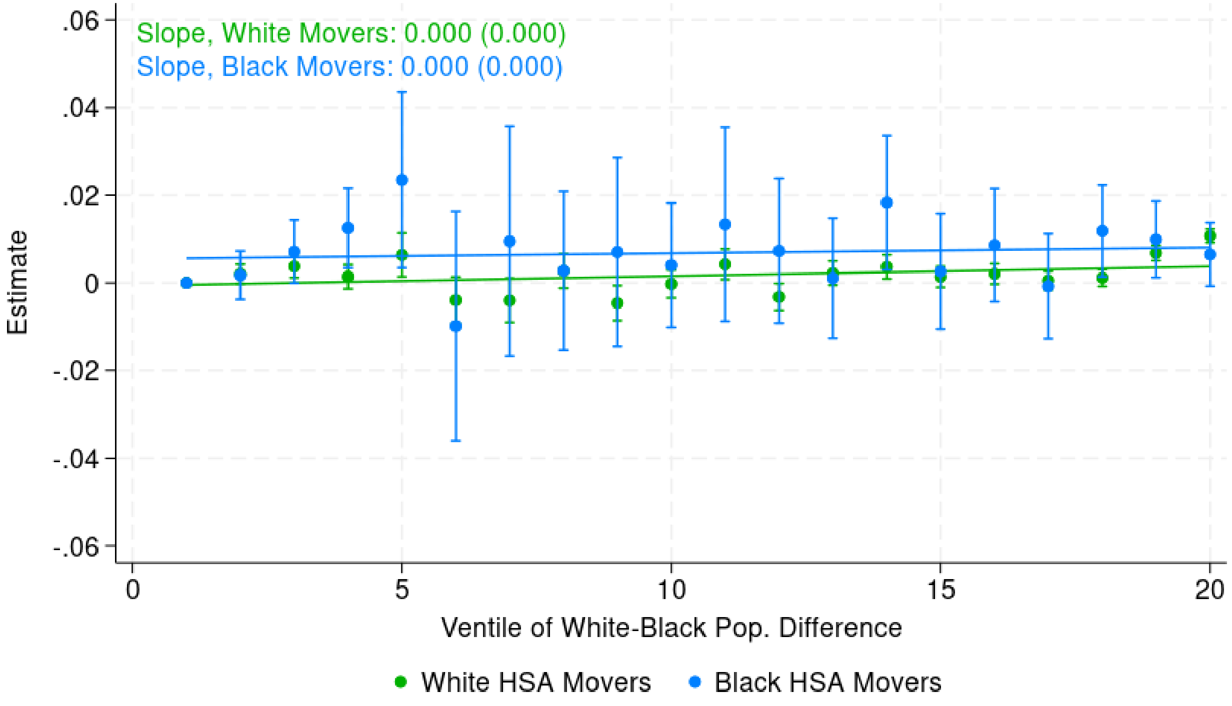
Figure. Causal Effect of Moving Up Place Effects Distribution by Race, Colorectal Cancer Screening

Back

Access Unchanged by Moves Across the Geographic Distribution



(a) Number of E&M Visits



(b) Colorectal Cancer Screening

Figure. Causal Effect of Moving Up the Differential Geographic Distribution

Back

References

Almond, D. V., Chay, K. Y., & Greenstone, M. (2006). Civil Rights, the War on Poverty, and Black-White Convergence in Infant Mortality in the Rural South and Mississippi. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.961021

Alsan, M., Chandra, A., & Simon, K. (2021). The Great Unequalizer: Initial Health Effects of COVID-19 in the United States. *Journal of Economic Perspectives*, *35*(3), 25–46. https://doi.org/10.1257/jep.35.3.25

Alsan, M., Garrick, O., & Graziani, G. (2019). Does Diversity Matter for Health? Experimental Evidence from Oakland. *American Economic Review*, *109*(12), 4071–4111. https://doi.org/10.1257/aer.20181446

Alsan, M., & Wanamaker, M. (2018). Tuskegee and the Health of Black Men*. *The Quarterly Journal of Economics*, *133*(1), 407–455. https://doi.org/10.1093/qje/qjx029

Bach, P. B., Pham, H. H., Schrag, D., Tate, R. C., & Hargraves, J. L. (2004). Primary care physicians who treat blacks and whites. *The New England Journal of Medicine*, *351*(6), 575–584. https://doi.org/10.1056/NEJMsa040609

Baicker, K., Chandra, A., & Skinner, J. S. (2005). Geographic variation in health care and the problem of measuring racial disparities. *Perspectives in Biology and Medicine*, *48*(1 Suppl), S42-53.

Baicker, K., Chandra, A., Skinner, J. S., & Wennberg, J. E. (2004). Who You Are And Where You Live: How Race And Geography Affect The Treatment Of Medicare Beneficiaries: There is no simple story that explains the regional patterns of racial disparities in health care. *Health Affairs*, *23*(Suppl2), VAR-33-VAR-44. https://doi.org/10.1377/hlthaff.var.33

Bailey, Z. D., Krieger, N., Agénor, M., Graves, J., Linos, N., & Bassett, M. T. (2017). Structural racism and health inequities in the USA: Evidence and interventions. *The Lancet*, *389*(10077), 1453–1463. https://doi.org/10.1016/S0140-6736(17)30569-X

References

Buchmueller, T. C., & Levy, H. G. (2020). The ACA's Impact On Racial And Ethnic Disparities In Health Insurance Coverage And Access To Care: An examination of how the insurance coverage expansions of the Affordable Care Act have affected disparities related to race and ethnicity. *Health Affairs*, *39*(3), 395–402. https://doi.org/10.1377/hlthaff.2019.01394

Chandra, A., Kakani, P., & Sacarny, A. (2020). *Hospital Allocation and Racial Disparities in Health Care* (w28018; p. w28018). National Bureau of Economic Research. https://doi.org/10.3386/w28018

Hoffman, K. M., Trawalter, S., Axt, J. R., & Oliver, M. N. (2016). Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(16), 4296–4301. https://doi.org/10.1073/pnas.1516047113

Jha, A. K., Orav, E. J., Li, Z., & Epstein, A. M. (2007). Concentration and quality of hospitals that care for elderly black patients. *Archives of Internal Medicine*, *167*(11), 1177–1182. https://doi.org/10.1001/archinte.167.11.1177

Mahmoudi, E., & Jensen, G. A. (2014). Has Medicare Part D Reduced Racial/Ethnic Disparities in Prescription Drug Use and Spending? *Health Services Research*, *49*(2), 502–525. https://doi.org/10.1111/1475-6773.12099

Murphy, S. L., Xu, J., & Kochanek, K. D. (2013). *Deaths: Final Data for 2010* (61(4); National Vital Statistics Reports). National Center for Health Statistics.

References

Nguyen, K. H., Wilson, I. B., Wallack, A. R., & Trivedi, A. N. (2022). Racial And Ethnic Disparities In Patient Experience Of Care Among Nonelderly Medicaid Managed Care Enrollees: Study examines racial and ethnic disparities in patient care experience among nonelderly Medicaid managed care enrollees. *Health Affairs*, *41*(2), 256–264. https://doi.org/10.1377/hlthaff.2021.01331

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, *366*(6464), 447–453. https://doi.org/10.1126/science.aax2342

Pierson, E., Cutler, D. M., Leskovec, J., Mullainathan, S., & Obermeyer, Z. (2021). An algorithmic approach to reducing unexplained pain disparities in underserved populations. *Nature Medicine*, *27*(1), 136–140. https://doi.org/10.1038/s41591-020-01192-7

Wallace, J., Jiang, K., Goldsmith-Pinkham, P., & Song, Z. (2021). Changes in Racial and Ethnic Disparities in Access to Care and Health Among US Adults at Age 65 Years. *JAMA Internal Medicine*, *181*(9), 1207–1215. https://doi.org/10.1001/jamainternmed.2021.3922

Washington, H. A. (2006). *Medical apartheid: The dark history of medical experimentation on Black Americans from colonial times to the present* (1st pbk. ed). Harlem Moon.

Williams, D. R., & Jackson, P. B. (2005). Social Sources Of Racial Disparities In Health. *Health Affairs*, *24*(2), 325–334. https://doi.org/10.1377/hlthaff.24.2.325