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Introduction

Research Question: How are historical redlining grades (A to D) and social vulnerability associated with breast cancer screening prevalence across KUCC census tracts, after accounting for spatial clustering and temporal trends?

- Redlining (1930S HOLC):** This practice labeled many neighborhoods often communities of color as “hazardous,” restricting credit and investment and contributing to sustained disinvestment in housing and healthcare access. HOLC assigned grades from A (“Best”) to D (“Hazardous”), with lower grades signaling greater disinvestment risk.
- Lasting impact:** Historically, redlined neighborhoods often have persistent socioeconomic disadvantage and reduced access to preventive services today.
- Place-based barriers:** Within the KUCC catchment area, census tracts overlapping historically redlined neighborhoods often face high social vulnerability and constrained healthcare access (e.g., greater distance to mammography centers), creating barriers that limit timely breast cancer screening beyond individual-level determinants.

Research Goal: To quantify how historical redlining and present-day social vulnerability jointly influence breast cancer screening and to identify geographic areas with persistently low screening to guide targeted interventions.

Methodology

Data

- Study Period:** 2016-2024
- Study Location:** Kansas University Cancer Center (KUCC) census tract
- Outcome:** Breast Screening prevalence (proportion) (0,1).

- Data sources :**
- Breast Cancer Screening Data:** Obtained from PLACES (CDC) and the KUCC In Focus OPTIK Data warehouse.
 - Redlining Data:** Historical redlining data from the Mapping Inequality project (University of Richmond) was integrated with U.S. Census tracts to analyze spatial distribution.
 - SVI Data:** SVI from the CDC/ATSDR Social Vulnerability Index dataset (census-tract-level SVI).

Method

- Model:** Bayesian spatiotemporal beta regression with,
 - spatially structured random effects (ICAR) to capture geographic clustering,
 - AR(1) temporal random effects to capture year-to-year dependence,
 - space-time interaction for local deviations over time.

Mediation Analysis: Estimated how much of the redlining–screening association is explained by individual tract-level factors (mediator-specific indirect effects).

Funding

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Results

Table 1: Bayesian Spatiotemporal Model Results (OR 95% Cr.I)

Predictors	Mean (β)	OR (95% Cr.I)	Directions
HOLC redlining Grade			
Grade A	--	--	
Grade B	-0.044	0.957 (0.893, 1.022)	4.3% Lower ↓
Grade C*	-0.064	0.938 (0.896, 0.991)	6.2% Lower ↓
Grade D*	-0.065	0.937 (0.892, 0.988)	6.3% Lower ↓
Social Vulnerability Index			
1 st quintile	--	--	
2 nd quintile	0.060	1.062 (0.999, 1.116)	6.2% Higher ↑
3 rd quintile	0.056	1.058 (0.995, 1.109)	5.8% Higher ↑
4 th quintile	0.049	1.050 (0.988, 1.104)	5.0% Higher ↑
5 th quintile*	0.073	1.075 (1.012, 1.138)	7.5% Higher ↑
Below 150% Poverty	-0.012	0.988 (0.968, 1.011)	1.2% Lower ↓
No high school diploma*	-0.062	0.940 (0.916, 0.963)	6.0% Lower ↓
No health insurance	-0.016	0.984 (0.958, 1.010)	1.6% Lower ↓
In multiunit structures	0.009	1.009 (0.989, 1.027)	0.9% Higher ↑
In mobile homes*	-0.017	0.983 (0.971, 0.996)	1.7% Lower ↓
In crowded conditions	0.006	1.006 (0.988, 1.024)	0.6% Higher ↑
With no vehicle	-0.002	0.998 (0.981, 1.015)	0.2% Lower ↓
Nearest mammogram Distance (miles)	-0.032	0.968 (0.934, 1.006)	3.2% Lower ↓

*Note: Statistically significant at the 5% significance level (i.e., p < 0.05)

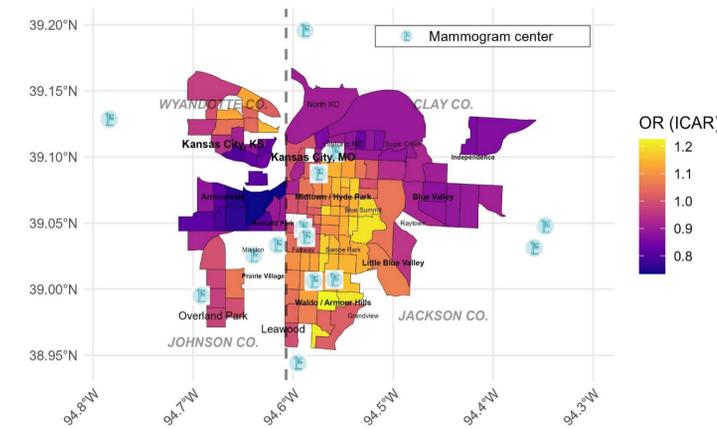


Figure 1: Spatial Variation in Breast Cancer Screening (ICAR Spatial Effects, OR) with Mammography Centers

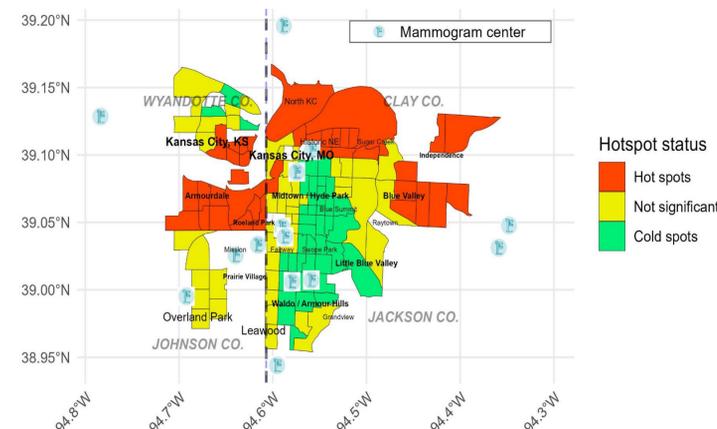


Figure 2: Breast Cancer Screening Hotspots and Cold spots with Mammography Centers



Figure 3: Year-wise Screening Classification (≥80.3% vs <80.3%), 2016–2024

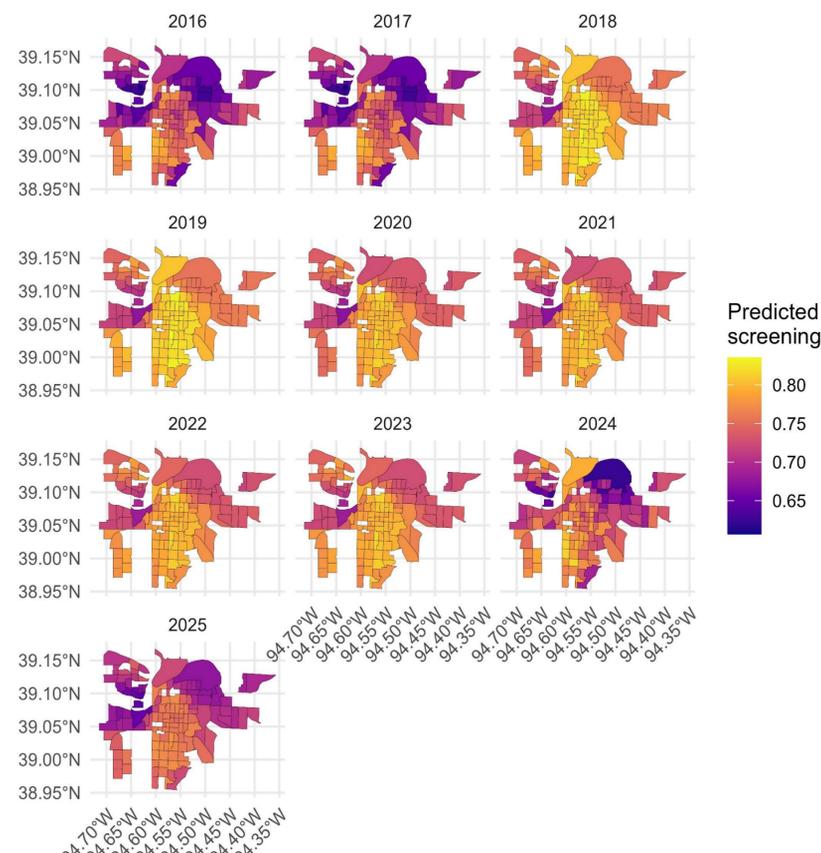


Figure 4: Year-wise Predicted Breast Cancer Screening, 2016–2024 (2025 Forecast)

Mediation Analysis

Table 2: Mediation Analysis of the Association Between Historical Redlining and Breast Cancer Screening

Mediator	Effect estimate (95% CI)	Relative effect (95% CI)
HOLC Grade D vs Grade A/B/C		
Direct	-0.05 (-0.10, 0.01)	35.2 (-9.6, 66.8)
Indirect		
Poverty*	-0.06 (-0.10, -0.03)	44.5 (22.7, 76.1)
No high school diploma*	-0.04 (-0.07, -0.01)	25.5 (6.7, 54.0)
No health insurance	-0.00 (-0.02, 0.01)	1.4 (-11.0, 15.1)
Multi-unit structures	0.00 (-0.02, 0.02)	-2.0 (-17.7, 12.9)
Mobile homes	-0.00 (-0.01, 0.01)	0.3 (-5.0, 10.6)
Crowded conditions	-0.00 (-0.01, 0.01)	0.1 (-5.5, 8.2)
No vehicle	0.01 (-0.00, 0.03)	-6.5 (-21.0, 1.9)
Nearest mammogram distance	-0.00 (-0.02, 0.01)	1.3 (-6.8, 11.8)
Total indirect	-0.09 (-0.16, -0.04)	64.8 (33.2, 109.6)
Total effect	-0.14 (-0.21, -0.08)	

*Note: Statistically significant at the 5% significance level (i.e., p < 0.05)

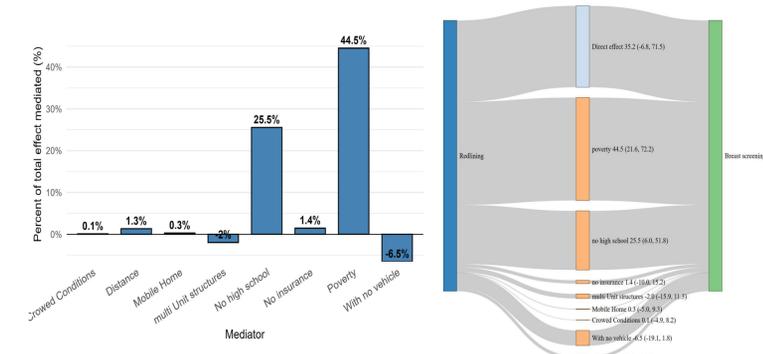


Figure 5: Mediation Pathways Linking Redlining to Breast Cancer Screening

Discussion

- Persistent disparity:** Screening was lower in historically redlined tracts (HOLC C/D) and highest vulnerability areas, even after adjustment, suggesting ongoing place-based effects of structural disadvantage.
- Geographic targeting:** Strong spatial clustering identified neighborhoods that consistently lag in screening, supporting hotspot-guided outreach and resource allocation.
- Pathways:** Mediation results indicate poverty and educational disadvantage explain a large share of the redlining–screening association, pointing to actionable intervention targets.

Conclusion

To reduce breast cancer screening disparities in the KUCC catchment area, interventions should prioritize historically redlined and high-SVI census tracts and address key barriers such as poverty, education, and access to mammography services.

References

- Centers for Disease Control and Prevention (CDC), & Robert Wood Johnson Foundation. (n.d.). PLACES: Local Data for Better Health.
Haining, R., & Li, G. (2020). Modelling Spatial and Spatio-Temporal Data: A Bayesian Approach. Chapman & Hall/CRC.