THE UNIVERSITY OF KANSAS

CANCER CENTER

Historical Redlining and Breast Cancer Screening A Spatial Analysis in the KU Cancer Center Catchment Area

Introduction

Research Question: How does redlining affect percentage of breast cancer screening in the KUCC Catchment area, and what roles do rurality, gender pay gap, income inequality, and mammogram facility availability play?

- **Redlining Context:** Established in 1933, redlining labeled neighborhoods of people of color as hazardous, causing systemic housing, infrastructure, and healthcare. disinvestment in
- Health Impact: Redlining's legacy worsens health outcomes, including higher chronic disease rates and limited access to preventive care like mammograms.
- **Breast Cancer Disparities:** Breast cancer is the most common cancer among women, with underserved communities facing lower screening rates and higher incidence.
- **Regional Screening Rates:** Kansas (74.5%) and Missouri (75.0%) screening rates highlight disparities, requiring targeted interventions in underserved areas.

Methodology **O**J

Data

- Breast Cancer Screening Data: Obtained from PLACES (CDC) and the OPTIK Cancer In Focus website.
- **Redlining Data:** Historical redlining data from the Mapping Inequality project (University of Richmond) was integrated with U.S. Census tracts to analyze spatial distribution.
- **Socioeconomic Variables:** Included rurality, mammogram facility availability, income inequality, gender pay gap, and female uninsured rates to examine their impact on screening.

Methods

- Logistic Regression (LR): Univariate LR models assessed redlining and other factors on screening, while multivariable models evaluated their combined impact
- Geographically Weighted Logistic Regression (GWLR): Examined local variations in breast cancer screening and the influence of tractlevel socioeconomic factors



Figure 1: Breast Cancer Screening (%) by Figure 2: Redline by Census Tracts **Census tract**

Results

 Table 1: Summary Statistics

Variable	Mean (SD)	Media (Min, M
Breast Cancer Screening (%)	74.1 (4.3)	74.0 (56.9, 84
Redline	$\begin{array}{c} 11.3 \\ (29.3) \end{array}$	0.0 (0,100
Rurality	3.49 (2.49)	3 $(1,9)$
Mammograms	0.11 (0.34)	$\begin{array}{c} 0 \\ (0,3) \end{array}$
Gender Pay Gap	0.19 (0.21)	0.21 (-3.58,0.
Income Inequality	0.41 (0.06)	0.40 (0.14,0.'

Table 2: Univariate Logistic Regression

Variable	Estimat
Redline*	-0.022
Mammograms	0.004
Rurality*	-0.013
Income Inequality*	-0.718
Gender Pay Gap*	0.077

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

Table 4: Geographically Weighted Logistic Regression (GWLR) Model Coefficients

Variable	Mean (SD)
Redline	-0.045 (0.018)
Mammograms	-0.013 (0.007)
Rurality	0.005 (0.009)
Income Inequality	$2.537 \\ (0.054)$
Gender Pay Gap	0.254 (0.032)



Figure 5: Spatial Distribution of OR for Redlining

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Figure 4: Spatial Distribution of Key Factors by Census Tract

Table 3: Multivariable Logistic Regression Models

Variable	Full Model		Final Model	
	Estimate [95% CI]	Odds Ratio [95% CI]	Estimate [95% CI]	Odds Ratio [95% CI]
Redline	-0.012 [-0.03, 0.01]	0.99 [0.97,1.01]	-	_
Mammograms*	0.037 [0.02, 0.06]	1.03 [1.02, 1.06]	0.04 [0.02,0.06]	1.04 [1.02, 1.06]
Rurality*	-0.012 [-0.01, -0.01]	0.99 [0.98, 0.99]	-0.012 [-0.01, -0.01]	0.99 [0.99, 0.99]
Income Inequality*	-0.699 [-0.80, -0.60]	0.50 [0.45, 0.55]	-0.71 [-0.80, -0.62]	0.49 [0.45, 0.54]
Gender Pay Gap*	0.082 [0.05, 0.11]	1.09 [1.05, 1.12]	0.085 [0.05, 0.12]	1.09 [[1.05, 1.12]]
AIC BIC	$13758 \\ 13789$		13757 13783	

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



Figure 6: Spatial Distribution of OR for Income Inequality

Odds Ratio

Odds Ratio

0.99

0.98

0.97





Figure 7: Spatial Distribution of OR for Gender Pay Gap Odds Ratio: rurality



37.5°N 37.0°N 94°W 96°W 98°W Figure 8: Spatial Distribution of OR for Mammograms

Odds Ratio: CTMammograms

39.5°N

39.0°N

38.5°N

38.0°N







Mammogram centers by Census Tract





Discussion

Logistic Regression (LR)

- Univariate LR Analysis: Redlining, rurality, income inequality, and the gender pay gap significantly influence breast cancer screening (%), with redlining, rural, and high-income-inequality areas showing lower odds of screening.
- Multivariate LR Analysis: In the final model, only the number of mammogram facilities, rurality, income inequality, and the gender pay gap remained significant predictors, while redlining was not statistically significant.

Geographically Weighted Logistic Regression (GWLR)

- The odds ratio for redlining across all census tracts is less than 1, indicating that redlined areas have lower odds of breast cancer screening compared to non-redlined areas.
- All census tracts show odds ratios greater than 1 for income inequality and the gender pay gap.

Conclusion

To improve breast cancer screening rates, targeted interventions should focus on addressing the disparities in redlined and economically underserved areas.

References

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Mammogram Score