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Social disadvantage, healthcare utilization, and colorectal cancer screening: Leveraging longitudinal patient address and health records data

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Abstract

Background: Social disadvantage predicts colorectal cancer (CRC) outcomes across the cancer care continuum for many populations and places. For medically underserved populations, social disadvantage is likely intersectional— affecting individuals at multiple levels and through membership in multiple disadvantaged groups. However, most measures of social disadvantage are cross-sectional and limited to race, ethnicity, and income. Linkages between electronic health records (EHRs) and external datasets offer rich, multilevel measures that may be more informative.

Methods: We identified urban safety-net patients eligible and due for CRC screening from the Parkland-UT Southwestern PROSPR cohort. We assessed one-time screening receipt (via colonoscopy or fecal immunochemical test) in the 18 months following cohort entry via the EHR. We linked EHR data to housing and Census data to generate measures of social disadvantage at the parcel- and block-group level. We evaluated the association of these measures with screening using multilevel logistic regression models controlling for sociodemographics, comorbidity, and healthcare utilization.

Results: Among 32,965 patients, 45.1% received screening. In adjusted models, residential mobility, residence type, and neighborhood majority race were associated with CRC screening. Nearly all measures of patient-level social disadvantage and healthcare utilization were significant.

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CONFLICT OF INTEREST
The authors declare no potential conflicts of interest.

Conclusions: Address-based linkage of EHRs to external datasets may have the potential to expand meaningful measurement of multilevel social disadvantage. Researchers should strive to use granular, specific data in investigations of social disadvantage.

Impact: Generating multilevel measures of social disadvantage through address-based linkages efficiently uses existing EHR data for applied, population-level research.

Keywords

Social disadvantage; Electronic health record; Geographic information systems; Colorectal cancer; Cancer in minority and medically underserved population

Introduction

Social disadvantage drives health disparities in the United States. Persons experiencing social disadvantage belong to social groups that have reduced agency due to historical or current mistreatment, compared to groups higher in the social hierarchy, and have poorer health and suboptimal health behaviors (1). Researchers are increasingly aware that individuals are often concurrent members of several disadvantaged social groups (termed “intersectionality”), which makes the detrimental effects of social disadvantage challenging to measure and even more difficult to overcome (2–4). However, measurement of social disadvantage frequently is limited to race, ethnicity, income, and health insurance status, limiting investigations into meaningful social determinants of health in systemically disadvantaged groups. Leveraging residential address information in electronic health records (EHRs) and linking this information to external datasets may more fully characterize aspects of social disadvantage at multiple levels.

Leveraging electronic health records

Standard approaches to measuring social disadvantage – for example, via cross-sectional measures such as neighborhood disadvantage measured at one time point, or via surveys regarding patient history of social disadvantage (5,6) – face limitations. Problems arising from these approaches include large required investment for survey data collection, recall bias, and inability to measure chronic exposure to disadvantage. Although there have been recent calls to use the EHR to routinely collect standardized social and behavioral variables that serve as indicators of social disadvantage (7–9), EHRs do not typically house these data.

Barriers to collecting social disadvantage data have prompted researchers to leverage EHRs through address linkage with external geospatial data to create rich, comprehensive indicators of social disadvantage (10–13). Here we define *geospatial data* as data describing some characteristic (e.g., poverty) of a geographic place, whether a point location or larger area. There are two key advantages of address-based linkages. First, through geocoding of residential addresses and subsequent linkage with Census and other geospatial datasets such as tax authority records about housing parcels, EHR data can be used to derive measures of social disadvantage at multiple levels (e.g., patient, residential neighborhood, clinic location). Second, longitudinal patterns of changes or persistence in social disadvantage can be constructed at low cost (e.g., residential address history, smoking cessation pattern) because EHR data are updated each time a patient interacts with the healthcare system.

Analyses of longitudinal data may illuminate cycles of social disadvantage otherwise obscured by standard, cross-sectional indicators. Changes in residence, for example, may indicate housing instability or homelessness (14,15). However, limited guidance exists for analysis of disadvantage assessed longitudinally and through geospatial data linkage with EHR data.

Colorectal cancer (CRC) screening and social disadvantage

Social disadvantage exerts negative impacts across the colorectal cancer (CRC) screening continuum (16). Specifically, researchers have identified disparities related to male sex, minority race or ethnicity, rural residence, disability, being under- or un-insured, and having low incomes and foreign nativity (16–27). Composite measures representing social disadvantage that encompass income, education, and/or occupation (28) are consistent predictors of CRC screening, incidence, stage at diagnosis, and survival across populations and places (29–31). However, because these measures are composites, they are difficult for researchers to interpret, and inference associated with them does not identify specific modifiable targets for intervention (32,33). In addition, many past studies of social disadvantage do not account for healthcare utilization, thus impeding our understanding of which facets of social disadvantage are robust predictors of CRC screening behavior and outcomes, beyond access to care.

The goal of this paper is to highlight how geospatial EHR data linkages can enrich patient-level data employed in colorectal cancer screening research. First, we develop and explore new multilevel and longitudinal measures of social disadvantage derived from EHR data from a large, urban, safety-net healthcare system linked with external geospatial datasets. Second, we investigate associations between measures of social disadvantage and CRC screening while controlling for key covariates such as patient healthcare utilization. Last, we discuss how analyses including our multilevel, longitudinal measures of social disadvantages and healthcare utilization compare with those in the extant current cancer screening literature.

Materials and Methods

Sample

We conducted secondary analyses of data from patients in a larger cohort study about the CRC screening process conducted in the Parkland Hospital and Health System (hereafter, “Parkland”), the safety-net healthcare system in Dallas County, TX. Study details are described in detail elsewhere (34). The cohort comprised patients from Parkland who completed a primary-care appointment between January 1, 2010 and July 31, 2012 (hereafter, “index visit”) and were age-eligible for screening (classified as average-risk for CRC and non-adherent for screening). Age-eligible patients were 50–64 years old. We excluded patients with above-average risk classification (i.e., previously diagnosed with CRC, with partial or total colectomy, or with a positive fecal immunochemical test (FIT) 24 months prior to the index visit). We also excluded those adherent to CRC screening defined as having EHR documentation for: (1) colonoscopy within 10 years, (2) sigmoidoscopy within 5 years, or (3) FIT within 12 months, relative to the index visit. Finally, we excluded patients whose address at the index visit was outside Dallas County (because the health system does not cover preventive services for non-county residents), was invalid (e.g., no valid street numbers or names, P.O. boxes), or could not be geocoded.

Data

Patient-level data were extracted from the Parkland EHR. Housing data were downloaded from the local tax authority, the Dallas Central Appraisal District, and comprised 2014 boundary (i.e., location) and attribute (e.g., parcel and building characteristics) data associated with every Dallas County real-estate property. Patient-level housing disadvantage variables were created by linking parcel (i.e., land ownership attribute and location data collected by municipal tax authorities) and EHR data. Neighborhood-level data were downloaded from the American Community Survey 5-year estimates for 2008–2013 (35). We obtained additional address look-up data (location-enabled data to which non-geocoded addresses are matched) from ESRI's StreetMap Premium, which details street information for the United States (36).

Measures

The binary outcome was completion of either FIT or colonoscopy (sigmoidoscopy is no longer used at Parkland) during the 18-month follow-up period after the index visit.

We grouped indicators of social disadvantage into four broad categories: (1) patient-level social disadvantage, (2) patient-level housing disadvantage, (3) neighborhood-level physical disadvantage, and (4) neighborhood-level social disadvantage. Measures of *patient-level social disadvantage* included: sex, race/ethnicity (non-Hispanic [NH] White, NH African American, Hispanic, and NH other), and language (English, Spanish, other, unknown). We included patient age and a number of health and healthcare utilization measures as covariates because age, health, and healthcare utilization are strongly associated with CRC screening (17,20,25).

Given prior studies showing association of housing characteristics with health behaviors, including cancer screening, we identified a number of housing-related factors possibly associated with CRC screening (37–43). We defined five patient-level *housing disadvantage* variables – type, value, and proximity to healthcare facility of the participant's place of residence at the time of the index visit. We considered housing type at index visit as multiple family residence (MFR) if unit information was included with the index visit address, and single-family otherwise. Housing value was measured in tertiles of the natural log of parcel value per square foot of living space. We measured proximity to healthcare as street network distance (in miles) to the index visit primary care facility. We also measured housing stability including whether (yes/no) and how many times (continuous) the patient moved residence during the follow-up period. We calculated the number of unique addresses (continuous) in the EHR during the follow-up period. Because addresses are recorded when patients have interactions with the healthcare system, the number of unique addresses and moves recorded for a patient may be correlated with healthcare utilization. Therefore, we also calculated numbers of unique addresses (continuous) and moves (continuous) per healthcare system interaction.

Because context and composition of neighborhoods are associated with health and health behaviors, we also identified a number of neighborhood-level factors potentially associated with colorectal cancer screening (30,44–46). Neighborhood-level indicators of *physical* and *social disadvantage* were measured at the block-group level at the time of the index visit. Block groups are Census-defined small areas (average 600–3000 people). As the smallest unit for American Community Survey data tabulation, block groups offer the greatest precision for measuring neighborhoods and are increasingly used in the cancer literature (47–49). We measured two indicators of physical disadvantage: percentage area of a patient's block-group that was (1) vacant, and (2) legally zoned for multi-family residences (e.g., apartments). We linked geocoded patient address at the index visit to the parcel data, overlaid block-group boundaries, and aggregated parcel characteristics to the block-group boundaries to calculate these variables. Social disadvantage was measured using three indicators: majority race/ethnicity of the block group (White, African American, or Hispanic), percentage of block-group residents living at or below the federal poverty level (FPL), and percentage aged 18 or older with at least a high school degree.

Indicators of healthcare utilization and health status were measured at the patient level. Healthcare utilization factors assessed at index visit included designation of a primary care provider (yes/no), and indicator variables for the patient's primary care clinic (11 clinics total). We also measured the number of primary care, emergency department (ED), and missed visits of any type during the follow-up period. Because this was a safety-net system, we measured two aspects of healthcare coverage—payer type at index visit (Medicare, Medicaid, commercial, uninsured, other), and number of times payer type changed during the follow-up period. Health status was measured with the Charlson comorbidity index (0, 1–2, 3+), calculated in the year prior to the index visit.

Of the 23 measures in our analysis, these 7 used longitudinal information collected at multiple time points in the EHR: comorbidity; change in payer type; number of primary care, ED, and missed visits; number of unique addresses; and number of residence changes.

Geocoding

We designed our geocoding procedure to facilitate linkage to housing data. We cleaned and geocoded all addresses for each patient using a hierarchical geocoding process modeled after those described in published studies and best-practice guides for geocoding cancer registry data (50–52). Our hierarchical geocoding algorithm used parcel and street-level information. Each address passed through the parcel address locator first, and then unmatched addresses were passed to the street-level address locator. Locational information generated from a street-level geocode was adjusted to correspond to the nearest parcel.

Analysis

We used summary statistics to describe multiple facets of social disadvantage for our patient population and calculated unadjusted odds ratios to assess correlations of our social disadvantage measures with CRC screening. We assessed correlations among housing and neighborhood measures and used this information to inform our multilevel model fitting. Specifically, we selected measures with Pearson correlations ≤ 0.50 to avoid introducing multi-collinearity into our models. We fitted adjusted, sequential, logistic regression models to assess associations between CRC screening and all social disadvantage measures and covariates. All models were multilevel and included random effects at the block group level to estimate contextual effects of neighborhood-level measures while accounting for our nested data structure. First, we estimated an empty model with only block group-level random effects to estimate multilevel variation. Next, we sequentially added measures to examine independent contributions of each set of social disadvantage variables as follows: patient-level age, social disadvantage, and health and healthcare utilization factors (Model 1), patient-level housing disadvantage (Model 2), and neighborhood-level physical and social disadvantage (Model 3). We compared model fit using Akaike Information Criterion (AIC).

Address cleaning procedures were performed in R (53). Geocoding, spatial merging, and geoprocessing for area-based neighborhood measurements were performed in ArcMap version 10.3 (54). Network distance from residence to primary care clinic was calculated using Network Analyst in ArcMap 10.3. Statistical analysis was performed in Stata version 14 (55).

Results

We identified 45,225 patients who completed an index visit during the specified enrollment period. During the 18-month follow-up period, these patients reported 128,473 addresses; of these, 1,461 were invalid (e.g., not complete or missing). We excluded 12,278 patients (8,815 for out-of-county addresses, 2,650 for invalid addresses, and 814 for missing data). Our final sample comprised 32,965 patients eligible and due for screening. During the 18-month follow-up period, 45% of patients (n= 14,863) received CRC screening, the majority (85.6%) of whom completed FIT.

Table 1 describes patient-level social disadvantage and patient health and healthcare utilization characteristics for the final sample. On average, patients were ~55 years old, female (61%), and African American (37%) or Hispanic (39%). Most spoke English (66%) or Spanish (29%). The overwhelming majority (76%) was uninsured. In the 18-month follow-up period, patients had on average 4 primary care visits, less than one ED visit, and 2 missed appointments. Of the 11 patient-level social disadvantage and healthcare utilization characteristics, screened and non-screened patients had similar values for age only, and had significant differences for every other measured characteristic.

Table 2 describes patient-level housing disadvantage for the final sample. Patients lived on parcels with an average value of $29.08 per square foot located an average of 9 miles away from the primary care clinic of record. Only 18% lived in multiple-family housing at index visit. On average, patients recorded 0.20 unique addresses and 0.04 residence changes per visit, which corresponds to on average to 1 residential address change (i.e., move) per every 25 total healthcare visits. For every other housing measure besides distance to clinic, screened and non-screened patients had significantly different values.

Table 3 describes neighborhood-level physical and social disadvantage. Patients lived in block groups where an average of 24% of residents earned below the federal poverty level and 28% were high school graduates, 11% of block group area was vacant, and 6% of block group area was multiple-family residences. Most patients lived in block groups that were majority White (38%) or Hispanic (39%). Of the five neighborhood-level physical and social disadvantage measures, screened and non-screened patients differed only on majority race/ ethnicity block-group population.

The magnitude of correlations among housing and neighborhood variables was generally relatively low (Supplementary Table 1). Distance to primary care clinic was significantly and negatively correlated with neighborhood-level measurements of percent poverty and percent high school graduate residents. One pairwise correlation exceeded the 0.50 threshold: between the per-visit numbers of unique addresses and moves ($\rho = 0.5326$; $p < 0.001$). Therefore, in our multilevel models we only include the per-visit number of unique addresses.

Table 4 presents results from logistic regression analyses. All patient-level social disadvantage and patient-level health and healthcare utilization measures except age were significantly associated with screening in univariate analyses, and most associations held in our sequential multivariate logistic regression models. Measures associated with increased odds of screening across all models included: speaking Spanish (vs English), having a primary care provider on record (vs no provider), having a change in payer type during follow-up, and more primary care visits during follow-up. Measures associated with decreased odds of screening across all models included: White (vs any other race), having a missing language value (vs all others), having a Charlson comorbidity score of 3 or more (vs 0), commercial payer type (vs none), Medicaid or Medicare (vs none), and a higher number of ED visits during follow-up. Three measures had changes in statistical significance across models: age (negative association became significant in univariate models), sex (univariate association lost significance), and mid-range comorbidity scores (negative association became significant in univariate models). The direction of association changed across models only for one measure: the number of missed visits (positive association became negative).

Some patient housing social disadvantage measures were significantly associated with screening. Housing value, distance to clinic, residential mobility, and housing type were associated with screening in the unadjusted odds ratios. After accounting for patient-level social disadvantage and health and healthcare utilization characteristics, screening advantages associated with the middle tertile of parcel housing values and living closer to the clinic disappeared. Only residential mobility during follow-up and multi-family residence at index visit remained significantly associated with decreased odds of screening. These housing social disadvantage measures remained statistically significant even after accounting for neighborhood-level physical and social disadvantage.

Out of five neighborhood physical and social disadvantage measures, only one was significantly associated with screening in the unadjusted models – patients who lived in majority African American block groups were more likely to be screened. This remained the sole significant neighborhood-level measure after accounting for patient-level social disadvantage, health and healthcare utilization characteristics, and housing social disadvantage. In sensitivity analyses including Census tract level random effects, results were similar.

Model 2, which estimates effects of housing disadvantage in addition to patient-level disadvantage and health and healthcare utilization, was our most efficient model (AIC=38416.4). Addition of neighborhood physical and social disadvantage in the model (Model 3) generated a slightly less efficient model (AIC of 38420.1); however, the difference in AIC scores between models 2 and 3 is very small.

Discussion

By linking longitudinal EHR data with secondary geospatial datasets, we identified nine intersectional measures of social disadvantage and investigated which were associated with CRC screening in our safety-net population. EHR-derived measures of patient social disadvantage, health and healthcare utilization, and some housing measures were associated with screening. In addition, the majority race of the patient's neighborhood was associated with screening.

Our study is useful for researchers interested in leveraging multilevel measures of social disadvantage to investigate social determinants of health and intersectionality, because it demonstrates a novel approach to measuring the multilevel context in which patients reside. In prior cancer screening studies, context primarily was typically measured only at the neighborhood-level using Census data (e.g., Census tract or block group measures). We demonstrate how linking the EHR to more granular parcel data facilitates creation of additional measures of housing disadvantage (housing type, size, value, stability, and proximity to healthcare facility) at very precise spatial scales. In doing this, we explored social disadvantages associated with CRC screening in a way that uses the EHR to (1) measure multilevel social disadvantage, and (2) improve characterizations of health and healthcare utilization.

Measuring multilevel social disadvantage using the EHR

Our models that incorporated housing disadvantage employed one familiar measure of housing disadvantage (distance to clinic). Distance to primary care clinic is a common but notoriously inconsistent geospatial predictor of screening in observational studies (56). In intervention studies focused on removing geographic barriers to CRC screening (e.g., via use of mobile screening units or mailed screening test kits), interventions removing the need for in-person visits to clinics have consistently generated significant increases in screening (57,58). In our study, clinic distance was not significant, perhaps because our study was conducted in a single urban county in which less than 2% of patients lived more than 15 miles from a community-based clinic.

We explored the utility of three novel longitudinal or parcel-based measures of housing disadvantage (number of residence changes per visit in the follow-up period [i.e., housing instability], living in an multi-family residence at the index visit, and housing value per square foot of parcel space). Two of these novel measures of housing disadvantage (housing instability and multi-family residence at index visit) were significantly associated with screening in adjusted models. Our results agree with previously published studies indicating that housing stability and type are associated with preventive health behaviors, particularly for low-income and older populations such as ours (37, 38). Housing value was insignificant in our study. Because housing value and distance to clinic reflect socioeconomic status, housing wealth, and spatial accessibility of medical care, they may be related to screening in other populations or places such as rural areas (39, 40, 59, 60) where there may be more variation in these factors.

Although previous studies indicate associations between neighborhood factors and CRC screening (22, 30, 61), only 1 of 5 neighborhood variables was associated with screening in our study. Patients who resided in majority African-American neighborhoods had higher odds of screening, regardless of individual race and ethnicity. This result corresponds to emerging trends in the cancer screening and outcomes literatures that point to differing cultural acceptance and tolerance of the CRC screening process (62), but differs from literature showing that African Americans are less likely to be screened than Whites (63). Furthermore, the finding implies that patients who are not African American, but live in a majority African American neighborhood, are more likely to be screened.

In contrast to much of the extant neighborhoods and cancer literature that employs larger areal units (30, 47, 64), we developed very precise, granular measures of housing and neighborhood disadvantage. In our study, patient address data were first extracted from the EHR before they were geocoded and linked to geospatial databases. For future studies, the comparative ease and precision of using very small (vs large) geographic units likely will depend on study purpose and resources. To our knowledge, there are no examples of EHR systems with built-in geocoding capabilities, but geocoding and geospatial linkage has been included recently in data processing protocols for health information exchanges (65). Future work is needed to better integrate GIS functionality into EHR systems. If housing and neighborhood social disadvantage indicators were available within EHR systems, this information could be leveraged for delivery of clinical care or screening promotion interventions. For example, healthcare systems could geographically target screening promotion interventions to neighborhoods located very far from primary care clinics or located in hotspots of extreme social disadvantage.

Improving characterizations of healthcare utilization using the EHR

In comparison to previous CRC screening studies, we characterized healthcare utilization more fully by mining the EHR using 2 familiar measures (primary care provider and payer type) and 4 new, longitudinal measures (change in payer type during follow-up; number of primary care, ED, and missed visits during follow-up). Although studies of CRC screening that include both comprehensive healthcare utilization measures and contextual neighborhood factors are rare, a number of our findings are concordant with previous research:-- CRC screening was positively associated with having a primary care provider, engagement with preventive healthcare, and prior appointment-keeping behavior (25,66–73) but was negatively associated with reliance upon the emergency department as a source of primary care (74).

One finding regarding healthcare utilization from our sequential multilevel models is contrary to prior work. We found that commercially insured patients were less likely to screen, compared to uninsured patients who rely on county-level medical assistance. This interesting result points to the possibility that uninsured patients in our safety-net system may be receiving County-provided coverage from Parkland such that engagement in CRC screening is enabled. Specifically, Parkland can offer uninsured patients heavily subsidized care that might be superior for CRC screening compared to commercially *under*insured patients, who might be unable to pay for high deductibles or other CRC screening costs (75). The screening gap between patients insured by Medicaid or Medicare and non-insured patients who use the County-provided funding may exist because patients insured by Medicare in our sample have comorbidities related to conditions that qualify them for coverage but disqualifying them for screening (i.e., receipt of Social Security Disability Insurance or diagnosis of end stage renal disease).

Notably, we found that change in payer type during follow-up was associated with decreased likelihood of screening. In contrast, previous studies had shown that low socioeconomic status patients who switch from traditional HMO to high-deductible healthcare plans substitute stool-based exams for endoscopic tests (76, 77), and that adults who experience gaps in healthcare coverage are less likely to engage in preventive care (78).

Limitations

Our study faces several limitations. First, we were unable to distinguish whether tests were completed for screening or diagnostic purposes. However, because the vast majority (85.6%) of tests completed were FITs, which are solely screening tests, this is unlikely to substantively impact our results. Second, we were unable to include information about patient education because it is not recorded in the Parkland EHR. Third, because our study is based on data recorded in the EHR, we were unable to observe residential address information that changed between interactions with the healthcare system. For example, if a patient moved twice between visits to the healthcare system, only the second new address was captured within the EHR, thus appearing as one move rather than two. Fourth, we did not take into account loss to follow-up, but sensitivity results from analyses that excluded patients without at least one visit in the 18 months following the index visit were not substantively different from our presented results. Fifth, we were unable to assess whether patients received screening at other health systems. However, because Parkland is the main safety-net provider in the county it is unlikely that our predominantly uninsured patients went elsewhere to receive CRC screening.

Conclusion

By linking our EHR data with two external geospatial datasets, we were able to create rich, longitudinal, multilevel measurements of social disadvantage. Results from our multilevel models indicate that researchers should use granular contextual data, like parcel data, in investigations of social disadvantage and health. Through the continued application of these new linkage methods and multilevel measures to EHR data from heterogeneous patient populations, we can create more nuanced measures of social disadvantage using data that are routinely collected in EHRs across the United States. Future work will be needed to determine whether and how such granular geospatial measures can be integrated into EHRs to inform screening promotion interventions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1:

Patient-level social disadvantage and patient health and healthcare utilization characteristics by colorectal cancer (CRC) screening test use during 18-month follow-up period for age- and screening-eligible sample (N=32,965); Pct: Percent; SD: Standard deviation; IQR: Interquartile mean; ED: Emergency department.

	Overall		Screened		
	N (Mean)	Pct (SD)	N (Mean)	Pct (SD)	P-value
Patient Social Disadvantage					
Age	(55.17)	(4.06)	(55.14)	(4.12)	0.3
Sex					
Female	19,862	0.6	9,256	0.62	<0.001
Male	13,103	0.4	5,607	0.38	
Race/Ethnicity					
African American	12,202	0.37	5,009	0.34	<0.001
Hispanic	12,860	0.39	6,766	0.46	
Other	1,853	0.06	784	0.05	
White	6,050	0.18	2,304	0.15	
Language					
English	21,914	0.66	8,854	0.6	<0.001
Spanish	9,562	0.29	5,344	0.36	
Other	1,343	0.04	641	0.04	
Unknown	146	0.01	24	0	
Charlson index[1]					
0	18,525	0.56	8,549	0.58	<0.001
2-Jan	12,332	0.37	5,586	0.38	
3+	2,108	0.06	728	0.05	
Healthcare Utilization Factors					
Clinic[2]					<0.001
Patient has primary care provider	15,160	0.46	7,440	0.5	<0.001
Payer type					
Commercial	2,051	0.06	498	0.03	<0.001
Medicaid	2,862	0.09	938	0.06	
Medicare	2,399	0.07	888	0.06	
Other	637	0.02	347	0.02	
Uninsured	25,016	0.76	12,192	0.82	
Payer type changed[3]	6,684	0.2	3,151	0.21	<0.001
# primary care visits[3]	(4.18)	(2.75)	(4.71)	(2.63)	<0.001
# ED care visits[3]	(0.85)	(2.79)	(0.83)	(2.25)	0.05
# missed care visits[3]	(2.27)	(2.77)	(2.31)	(2.71)	<0.001
Total	32,965	1	14,863	45.12	

[1]Measured in year prior to index visit

[2]Clinic indicators not shown

[3]Measured in 18-month follow-up period.

Table 2:

Patient-level housing disadvantage by colorectal cancer (CRC) screening test use during 18-month follow-up period for age- and screening-eligible sample (N=32,965)

	Overall		Screened		
	N (Mean)	Pct (SD)	N (Mean)	Pct (SD)	P-value
Housing Social Disadvantage					
Log of parcel value per sq. ft.					
T1: −0.71–3.68 ($0.50-$39.58)	10,713	0.33	4,806	0.32	0.02
T2: 3.68–4.05 ($39.58-$57.40)	11,140	0.34	5,168	0.35	
T3: 4.05–12.96 ($57.40-$423,430)	11,093	0.34	4,889	0.33	
Network distance to clinic (mi)	(12.83)	(6.38)	(12.90)	(6.45)	0.86
# unique addresses per visit[1]	(0.20)	(0.26)	(0.12)	(0.11)	<0.001
# residence changes/moves per visit[1]	(0.04)	(0.14)	(0.03)	(0.08)	<0.001
Lived in MFR	5,778	0.18	2,517	0.17	0.04
Total	32,965	1.00	14,863	45.12	

Pct: Percent; SD: Standard deviation; IQR: Interquartile mean; Sq.Ft.: Square foot; Mi: Miles; T: Tertiles

[1]Measured in 18-month follow-up period.

Table 3:

Neighborhood-level physical and social disadvantage by colorectal cancer (CRC) screening test use during 18-month follow-up period for age-and screening-eligible sample (N=32,965); Pct: Percent; SD: Standard deviation; IQR: Interquartile mean; MFR: Multiple family residence; HS: High school.

	Overall		Screened		
	N (Mean)	Pct (SD)	N (Mean)	Pct (SD)	P-value
Neighborhood Physical Disadvantage					
% area vacant parcels	(0.11)	(0.13)	(0.11)	(0.13)	0.59
% area devoted to MFR	(0.06)	(0.11)	(0.06)	(0.11)	0.20
Neighborhood Social Disadvantage					
% Poverty	(0.24)	(0.16)	(0.24)	(0.16)	0.90
% HS graduates	(0.28)	(0.10)	(0.28)	(0.10)	0.43
Majority race/ethnicity					
White	12,426	0.38	6,661	0.37	0.04
African American	7,748	0.24	4,288	0.24	
Hispanic	12,772	0.39	6,876	0.39	
Total	32,965	1.00	14,863	45.12	

Table 4.

Logistic regression odds ratios (OR) and 95% confidence intervals (CI)

	Unadjusted		Model 1		Model 2		Model 3	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Level 1: Patient								
Constant			0.51 ***	(0.37, 0.716)	2.60 ***	(1.81, 3.75)	2.75 ***	(1.88, 4.03)
Patient Social Disadvantage								
Age	1.00	(0.99, 1.00)	0.99 **	(0.99, 1.00)	0.99 ***	(0.98, 0.99)	0.99 ***	(0.98, 0.99)
Sex (referent group: female)	0.86 ***	(0.82, 0.90)	1.00	(0.95, 1.05)	1.03	(0.98, 1.09)	1.03	(0.98, 1.09)
Race/Ethnicity (referent group: White)								
African American	1.13 ***	(1.06, 1.21)	1.19 ***	(1.11, 1.28)	1.28 ***	(1.19, 1.38)	1.28 ***	(1.19, 1.38)
Hispanic	1.81 ***	(1.70, 1.92)	1.27 ***	(1.16, 1.38)	1.32 ***	(1.20, 1.44)	1.31 ***	(1.20, 1.44)
Other	1.19 ***	(1.07, 1.33)	1.31 ***	(1.14, 1.50)	1.40 ***	(1.12, 1.50)	1.30 ***	(1.12, 1.50)
Language (referent group: English)								
Spanish	1.87 ***	(1.78, 1.96)	1.37 ***	(1.18, 1.59)	1.41 ***	(1.21, 1.65)	1.41 ***	(1.21, 1.65)
Other	1.35 ***	(1.21, 1.96)	1.52 ***	(1.40, 1.64)	1.55 ***	(1.43, 1.68)	1.55 ***	(1.43, 1.68)
Unknown	0.29 ***	(0.19, 0.45)	0.41 ***	(0.26, 0.64)	1.01	(0.61, 1.69)	1.02	(0.61, 1.70)
Charlson index (referent group: 0)[1]								
1–2	0.97	(0.92, 1.01)	0.88 ***	(0.84, 1.93)	0.81 ***	(0.77, 0.86)	0.81 ***	(0.77, 0.86)
3+	0.62 ***	(0.56, 0.68)	0.68 ***	(0.61, 0.76)	0.53 ***	(0.48, 0.60)	0.53 ***	(0.48, 0.59)
Healthcare Utilization Factors[2]								
Patient has primary care provider	1.35 ***	(1.29, 1.41)	1.31 ***	(1.24, 1.37)	1.25 ***	(1.19, 1.32)	1.25 ***	(1.19, 1.32)
Payer type (base is Uninsured)								
Commercial	0.34 ***	(0.30, 0.37)	0.78 ***	(0.68, 0.90)	0.84 ***	(0.73, 0.97)	0.84 *	(0.73, 0.97)
Medicaid	0.51 ***	(0.47, 0.56)	0.65 ***	(0.59, 0.71)	0.71 ***	(0.65, 0.78)	0.71 ***	(0.65, 0.78)
Medicare	0.62 ***	(0.57, 0.67)	0.77 ***	(0.70, 0.84)	0.79 ***	(0.72, 0.87)	0.79 ***	(0.72, 0.87)
Other	1.26 **	(1.07, 1.47)	1.03	(0.86, 1.23)	1.02	(0.86, 1.22)	1.02	(0.86, 1.22)
Payer type changed[3]	1.11 ***	(1.05, 1.17)	1.05	(0.99, 1.12)	0.91 ***	(0.85, 0.97)	0.91 ***	(0.85, 0.97)
# primary care visits[3]	1.18 ***	(1.17, 1.19)	1.27 ***	(1.25, 1.28)	1.11 ***	(1.10, 1.12)	1.11 ***	(1.10, 1.12)
# ED care visits[3]	0.99 +	(0.98, 1.00)	0.97 **	(0.96, 0.98)	0.91 **	(0.90, 0.92)	0.91 **	(0.90, 0.92)
# missed care visits[3]	1.01 ***	(1.01, 1.02)	0.96 ***	(0.95, 0.97)	0.95 ***	(0.94, 0.96)	0.95 ***	(0.94, 0.96)
Housing Social Disadvantage								
Parcel value (referent group: T3)								
T1	1.03	(0.98, 1.09)			1.03	(0.96, 1.10)	1.03	(0.96, 1.10)
T2	1.10 ***	(1.04, 1.16)			1.05	(0.99, 1.11)	1.05	(0.99, 1.11)

	Unadjusted		Model 1		Model 2		Model 3	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Network distance to COPC (mi)	1.00+	(1.00, 1.01)			1.00	(1.00, 1.00)	1.00	(1.00, 1.00)
# residences changes per visit[3]	0.01**	(0.01, 0.01)			0.01***	(0.01, 0.01)	0.01***	(0.01, 0.01)
Lived in MFR	0.93**	(0.88, 0.98)			0.91**	(0.85, 0.97)	0.91**	(0.85, 0.97)
Level 2: Block group								
Neighborhood Physical Disadvantage								
% area vacant parcels	0.96	(0.81, 1.13)					0.91	(0.75, 1.10)
% area devoted to MFR	1.13	(0.92, 1.38)					1.10	(0.87, 1.38)
Neighborhood Social Disadvantage								
% Poverty	1.01	(0.88, 1.16)					0.99	(0.83, 1.19)
% HS graduates	1.10	(0.88, 1.35)					1.04	(0.81, 1.34)
Majority race/ethnicity (referent group: White)								
African American	1.08*	(1.02, 1.14)					1.09*	(1.02, 1.17)
Hispanic	1.01	(0.96, 1.06)					0.99	(0.96, 1.05)
Akaike Information Criterion	--		41099		38416.4		38420.1	

*** p<0.001

** p<0.01

* p<0.05

+ p<0.10

MFR: multiple family residence

HS: High school

[1] Measured in year prior to index visit

[2] Clinic indicators not shown

[3] Measured in 18-month follow-up period.