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Assessment of Sociodemographic and Geographic Disparities in Cancer Risk from Air Toxics in South Carolina

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Abstract

Populations of color and low-income communities are often disproportionately burdened by exposures to various environmental contaminants, including air pollution. Some air pollutants have carcinogenic properties that are particularly problematic in South Carolina (SC), a state that consistently has high rates of cancer mortality for all sites. The purpose of this study was to assess cancer risk disparities in SC by linking risk estimates from the U.S. Environmental Protection Agency's 2005 National Air Toxics Assessment (NATA) with sociodemographic data from the 2000 US Census Bureau. Specifically, NATA risk data for varying risk categories were linked by tract ID and analyzed with sociodemographic variables from the 2000 census using R. The average change in cancer risk from all sources by sociodemographic variable was quantified using multiple linear regression models. Spatial methods were further employed using ArcGIS 10 to assess the distribution of all source risk and percent non-white at each census tract level. The relative risk estimates of the proportion of high cancer risk tracts (defined as the top 10% of cancer risk in SC) and their respective 95% confidence intervals (CIs) were calculated between the first and latter three quartiles defined by sociodemographic factors, while the variance in the percentage of high cancer risk between quartile groups was tested using Pearson's chi-square. The average total cancer risk for SC was 26.8 people/million (ppl/million). The risk from on-road sources was approximately 5.8 ppl/million, higher than the risk from major, area, and non-road sources (1.8, 2.6, and 1.3 ppl/million), respectively. Based on our findings, addressing on-road sources may decrease the disproportionate cancer risk burden among low-income populations and communities of color in SC.

Keywords

cancer risk; environmental justice; Geographic Information Systems (GIS); National-Scale Air Toxics Assessment (NATA); South Carolina

INTRODUCTION

Ambient monitoring for criteria air pollutants (CAPs) (i.e., carbon monoxide, lead, nitrogen dioxide, ozone, particulate matter, and sulfur dioxide) is available nationwide, which makes it possible to assess exposure to these pollutants in urban and rural areas. However, less is known about the distribution, exposure, and risk related to a wide range of hazardous air pollutants (HAPs). In an effort to track the spatial distribution and contribution of HAPs to cancer and non-cancer risks, the US Environmental Protection Agency (USEPA) monitors these pollutants through the National-Scale Air Toxics Assessment (NATA).

The NATA database was primarily developed to inform national and localized efforts to characterize air pollution sources, emissions, and health risks (USEPA 2012). NATA estimates are source-specific, thereby allowing a detailed examination of emission sources that may contribute to cancer, respiratory, and neurological risk. By linking NATA data with US Census Bureau characteristics, we have the necessary tools to perform a more in-depth

analysis of the factors driving cancer risk within a specified population or geographic region.

Research has shown that physical environments with high levels of HAPs may increase cancer risk (Woodruff et al. 1998). For example, a study conducted by Apelberg et al. assessed the relationship between sociodemographic factors including race/ethnicity and cancer risk estimates in Maryland (MD) at the census tract level using 2000 census data (Apelberg et al. 2005). Based on the results, race/ethnicity and estimated cancer risk from air toxics were significantly associated within census tracts. In addition, cancer risk estimates in MD were highest when the level of socioeconomic disadvantage increased, the proportion of white residents decreased, and the proportion of African-American residents increased (Apelberg et al. 2005). However, cancer risk declined as the proportion of Hispanic residents increased throughout the state (Apelberg et al. 2005).

Previous work using NATA data has been performed in states that have a high density of populations living in urbanized areas (Apelberg et al. 2005). However, this work did not account for the influence of rurality on air toxic emissions or cancer risk that is particularly important in a state such as South Carolina (SC) where a large number of residents live in sparsely populated rural areas. SC is comprised of 46 counties with a total population of 4,012,012 residents (U.S. Census Bureau 2001). There are roughly 1,584,888 residents (U.S. Census Bureau 2001) who live in counties considered rural and over 315 census tracts that would be considered rural based on the U.S. Census Bureau's definition of rurality.

SC is a state where communities of color and low-income populations experience a greater burden of exposure to several pollution sources, including air toxics, due to the spatial distribution of pollution-emitting hazards (Burwell et al. 2013; Rice L et al 2014a, b; Svendsen et al. 2014; Wilson et al. 2012a, b; Wilson et al. 2013). In our present study, we assess the impact of sociodemographic factors on estimated cancer risk associated with air toxics in SC with a specific focus on comparing differences in cancer risk in urban and rural areas. While there is a paucity of literature on the influence of urban versus rural effects and cancer risk, we hypothesize that urban-rural differences may drive cancer risk disparities for different racial/ethnic and socioeconomic groups in SC.

MATERIALS AND METHODS

National Scale Air Toxics Assessment (NATA)

The USEPA's NATA dataset is a comprehensive evaluation of hazardous air pollutants (HAPs), emission sources, and critical locations that are used to estimate cancer risk. There are approximately 187 HAPs addressed in the NATA data that the Clean Air Act (CAA) requires the USEPA to regulate (USEPA 2014). While NATA data has been collected since 1996, we used the most recent cancer risk estimates from 2005 in our analysis. There were five types of emission sources documented in the NATA dataset: 1) on-road, 2) non-road, 3) major, 4) area, and 5) background sources. Furthermore, the USEPA's NATA dataset included estimates of cancer risk for each source as well as total cancer risk calculated as the sum of risk from the aforementioned emission sources. A detailed description of the

methodology used to derive cancer risk from HAPs may be found in the NATA technical methods document for 2005 (USEPA 2011).

Census Data

The 2000 census data (American Factfinder 2000) were downloaded at the tract level from the US Census Bureau and linked with cancer risk data using the Federal Information Processing Standards (FIPS) code (FIPS PUBS 2008). Many of the sociodemographic factors analyzed in this study have also been used in previous research (Apelberg et al. 2005; Morello-Frosch and Jesdale 2006; Linder et al. 2008). Specifically, the variables representative of race/ethnicity, socioeconomic status (SES), and geographic characteristics included: 1) percent Hispanic, 2) percent non-white (inclusive of all races except non-Hispanic whites), 3) percent homeownership, 4) per capita income, 5) median household (HH) income, 6) percent poverty, 7) percent unemployment, 8) percent of homes built pre-1950, 9) percent without a high school (HS) education, and 10) percent urban area.

Statistical Methods

NATA and 2000 US Census data were linked by FIPS codes, analyzed in R, and mapped using ArcGIS version 10 (esri, Redlands, CA). Correlations between cancer risk from each emission source and each sociodemographic factor were calculated and tested. These correlations allowed us to observe the agreement between different sources of cancer risk regarding their connection with sociodemographic factors. To comprehensively evaluate the association of cancer risk from emission sources with sociodemographic factors in different landscapes (rural versus urban), we applied multiple linear regression models stratified by urban status. Specifically, we applied the model twice so that there was one for rural and urban area respectively.

$$Cancer\ Risk = \alpha + \sum \beta_i \times x_i$$

where x_i is one of the following demographic variables: % non-white, % Hispanic, % homeownership, per capita income, median HH income, % poverty, % unemployment, % homes built pre-1950, and % < HS education. Urban areas were defined as census tracts with 100% urban area, while rural areas were characterized as census tracts with 0% urban area. Collinearity in regressors was examined via Pearson correlations.

To compare cancer risk, we first categorized the census tracts into four groups according to quartile measures of each sociodemographic factor, denoted by Q1 to Q4 (Apelberg et al. 2005). For example, group 1 (Q1) was composed of census tracts with sociodemographic measures in the 25th percentile, group 2 (Q2) was between the 25th and 50th percentile, etc.... Next, we recorded the census tracts as high risk tracts if their cancer risk was in the top 10% for SC. Finally, relative risk (RR) estimates were calculated as a ratio of the proportion of high cancer risk in each group defined by quartiles of sociodemographic factors. Moreover, RR estimates were used to measure the difference in cancer risk in census tracts grouped in Q1 compared to Q4, where Q1 was designated as the reference

group. A chi-square test was then used to evaluate the statistical difference of the proportion of risk in Q1 and other quartiles for each sociodemographic factor.

RESULTS

There were 867 census tracts in SC with a population ranging from 197 to 16,745 persons per tract (average = 4,627). The geographic area of the tracts ranged from 0.12 to 319.66 square miles (average = 35.69 square miles). Table 1 presents a statistical summary of sociodemographic measures and NATA cancer risk by mean and percentile measurements. The mean Hispanic population (2.4%) in SC was five times lower than the national average (12.5%). In contrast, the state's poverty rate (15.8%) was slightly higher than the national average (11.3%). The mean total cancer risk for SC was 26.8 people per million (ppl/million), which was significantly lower than the 2005 national cancer risk estimate (50.0 ppl/million) (Palma et al. 2011). The estimated mean cancer risk from on-road sources (5.8 ppl/million) was higher than the risk from other sources (except for background sources (15.3 ppl/million)); however, the lowest mean cancer risk was found among non-road sources (1.3 ppl/million). Furthermore, the variation in cancer risk between the 5th and 95th percentiles of on-road sources reflected a wide range in risk (1.0 and 14.0 ppl/million, respectively) while major sources demonstrated a smaller range in risk (0 and 5.0 ppl/million, respectively).

Table 2 depicts the correlation and significance between NATA cancer risk by source and sociodemographic characteristics. Race-related variables had lower correlations with total cancer risk than other sociodemographic factors except per capita income and median HH income. Furthermore, the correlation between total cancer risk and race/ethnicity was strongest for the percentage of Hispanic residents (0.10). All sociodemographic measures were correlated with total cancer risk with the exception of median household income. The correlation between total cancer risk and percent urban area (0.64) was highest among all sociodemographic factors. In addition, the correlation of percent urban area with area (0.57), on-road (0.64), non-road (0.54), and background cancer risk (0.31) were the highest among all sociodemographic factors.

Table 2 also illustrates that area source cancer risk had a higher correlation with race/ethnicity and income-related factors than other sources of cancer risk. Moreover, percent had a higher correlation with cancer risk from different emission sources with the exception of total and non-road emissions compared to other racial/ethnic characteristics. When considering all income-related variables, percent homeownership was most correlated with cancer risk associated with all emission sources with the exception of background sources. The correlation of percent homeownership was over 0.50 for total, area, and on-road source cancer risk and -0.23 and -0.48 for major and non-road source cancer risk, respectively. The pattern of correlation was similar between total cancer risk and cancer risk from different sources.

In Table 3, we used multiple linear regression models to examine the impact of the urban-rural effect on the relationship between total cancer risk and sociodemographic measures. In urban areas, only the percentage of homes built pre-1950 (regression coefficient $\beta = 0.118$, p

value <0.01) had a statistically significant impact on cancer risk after controlling for other sociodemographic measures. Specifically, a 10% increase in the percentage of homes built pre-1950 increased cancer risk by roughly 1.2 ppl/million. When considering rural areas, percent non-white ($\beta=-0.065$, p value <0.01) and percent $<$ HS education ($\beta=-0.126$, p value <0.01) were the only statistically significant variables. Therefore, a 10% increase in the percentage of non-whites would decrease cancer risk by 0.7 ppl/million while an increase in the percent $<$ HS education population would decrease cancer risk by 1.3 ppl/million.

Table 4 shows results for RR and the percentage of high cancer risk tracts (total cancer risk) by quartile for sociodemographic measures in SC. With the exception of per capita income, all RR in terms of Q4 versus Q1 were significantly different from 1, which demonstrates the difference in high risk tracts found between quartiles. The RR for Q4 versus Q1 was 17.8 for percent urban area, meaning that the percentage of high risk tracts in Q4 was 17.8 times that found in Q1. In addition, the RR for percent poverty was 3.6, which indicates that the percent of high risk tracts in Q4 was 3.6 times that found in Q1. The RR estimates for percent home built pre-1950, unemployment, median household income, and homeownership were similar to the aforementioned variables where the percent of high risk tracts were higher in Q4 than Q1. In reference to the race/ethnicity related variables, the percentage of high risk tracts was 3.7 times higher in Q4 compared to Q1 for percent non-white and 2.1 times higher in Q4 than Q1 for Hispanic populations.

Figure 1 depicts RR for Q4 versus Q1 for major, area, on-road, and non-road source cancer risk in urban (solid line) and rural (dashed line) areas. For major source cancer risk documented in Figure 1, RR was significantly higher than 1 for the variable homes built pre-1950 in urban areas while RR values were significantly lower than 1 for percent non-white in rural areas. For area source cancer risk, with the exception of racial/ethnic variables and percent $<$ HS education, RR values were significantly different from 1 for all variables in urban areas. In contrast, the RR values were significantly different from 1 for percent homeownership in rural areas. Therefore, tracts with a high percentage of Hispanic, non-white, or homeownership populations had a lower percent of high cancer risk. Regarding on-road source emissions in urban areas, percent homeownership and percent homes built pre-1950 had RR values significantly different from 1, which indicates that these factors may be associated with high cancer risk (Figure 1). With the exception of percent Hispanic, percent homeownership, percent unemployment, and percent home pre-1950, rural areas had RR values that were significantly different from 1 for the remaining sociodemographic factors.

For some variables found in Figure 1, RR values for a specific source were significantly different from 1 in both rural and urban areas. This phenomenon was demonstrated among area sources for percent homeownership in which RR was significantly less than 1 in rural and urban areas. When considering non-road sources, percent homeownership and percent homes built pre-1950 had RR values that were significantly different from 1 in both rural and urban areas. Specifically, percent homeownership had a RR value that was significantly less than 1 in urban areas while significantly greater than 1 in rural areas. The reverse was true for percent homes built pre-1950 in which RR values were significantly higher than 1 in urban areas and significantly lower than 1 in rural areas.

We also wanted to determine the spatial distribution of cancer risk by percent non-white and percent poverty at the census tract level. Figure 2 is a choropleth map that depicts the distribution of percent non-white and total cancer risk across SC. There were large clusters of total cancer risk located in densely populated areas in the north, northwest, central, and western regions of the state near the Georgia border. Specifically, the cancer risk clusters were primarily found in higher population density counties such as Greenville, Richland, York, and Aiken (Land Area and Population Density 2010). Regarding the percentage of non-white residents across the state, there appears to be some overlap with the higher quartiles of total cancer risk that can be further supported by the correlation reported in Table 2 (0.09).

DISCUSSION AND CONCLUSION

In this analysis, we assessed cancer risk disparities associated with hazardous air pollutants using estimated cancer risk from the USEPA's NATA dataset and sociodemographic measures at the census tract level in SC. This research aimed to not only increase the body of knowledge for exposure science, but to further inform policy and drive emissions reduction efforts among vulnerable populations. Consistent with other studies, we found a strong association between sociodemographic measures and estimated cancer risk. For example, area source emissions had a higher correlation with race/ethnicity (0.19 for % non-white) and income-related (-0.56 for % homeownership) variables than other risk sources which may indicate that facilities producing these emissions may be more numerous in communities with a higher percentage of low-income and non-white populations. Moreover, area source cancer risk had a higher correlation with race/ethnicity and other income-related factors. As a result, facilities producing area source emissions may also be located in or near communities comprised of predominately low-income and non-white populations.

Despite the significant influence of area sources on cancer risk, our findings are consistent with studies conducted in Maryland and California, which found that on-road source emissions were the greatest contributor to cancer risk (Apelberg et al. 2005; Morello-Frosch et al. 2002). In addition, similar results were found in a study that was conducted on segregation, deprivation, air toxics, and lifetime cancer risk (Rice et al. 2014b). Furthermore, our results indicated that on-road source risk was significantly related to all sociodemographic factors. When examining the correlation between percent urban and cancer risk, on-road emission sources had the strongest correlation of all sociodemographic measures with the exception of total cancer risk. This correlation between on-road emissions sources and cancer risk may be present due to the significant increase (62%) in vehicle miles traveled in SC since 1987 (Gregory 2014).

For example, Harvard University's diversity data index reported Greenville and Columbia, SC in the largest 100 metropolitan areas (Diversitydata 2012). However, these urban areas had a low percentage of shared commuting by public transportation, which may indicate that there are more vehicles on the highway in these particular areas. For example, Greenville and Columbia had 0% and 1.0% shared commuting by public transportation respectively on a scale of 0–28% (Diversitydata 2012). These transportation patterns may be indicative of

disproportionate exposures to vehicles emissions and may best explain why on-road sources were the greatest contributor to cancer risk among all sociodemographic categories.

Additional research found that there are 4,621 public vehicles and 3,559,779 private and commercial vehicles in use in SC (SCIWAY 2012), whereby many emit high levels of hazardous pollutants that are associated with poor health outcomes. Moreover, the state was ranked 33rd for having a ratio of 770 vehicles per 1,000 people (SCIWAY 2012) which may be attributable to the lack of a mass transit system. The impact of this vehicle ratio is apparent in Figure 2, where the distribution of percent total cancer risk across SC appears to be highest in high population density counties (Greenville, Richland, York, and Aiken). Perhaps future studies should focus on the implications of traffic exposure on adult cancer, especially among vulnerable populations with co-morbidities that are also influenced by traffic induced air pollution.

Among income-related variables, percent homeownership was more correlated with source risk (0.55 for total risk, -0.23 for major source, -0.56 for area source, -0.54 for on-road source, and -0.48 for non-road source risk) excluding the risk associated with background source emissions. While there was a high correlation between homeownership and all sources of cancer risk (excluding background sources), being a homeowner was considered a protective factor. Specifically, cancer risk decreased by 0.25 ppl/million for every one percent increase in homeownership. This implies that homeowners may be less likely to live in high-traffic areas or near major or area emission sources such as coal-fired plants or TRI facilities.

Furthermore, sociodemographic measures examined in this study had a different influence on cancer risk in rural versus urban landscapes. For example, a 10% increase in the percentage of homes built pre-1950 in urban areas would increase cancer risk by 1.2 ppl/million. In contrast, increasing the percent non-white population and the percentage of persons with less than a high school education in rural areas demonstrated a more protective effect that would lead to a decrease in cancer risk (0.7 and 1.3 ppl/million, respectively). In addition, percent urban area had a higher correlation with all emissions sources when compared with other factors, which illuminates the importance of the relationship between percent urban area and exposure to emission sources that increase cancer risk. There were also differences in high cancer risk by sociodemographic factors in rural versus urban areas (Figure 1), which reiterates the fact that future studies should evaluate disparities in cancer risk for rural and urban geographies separately.

There are a few limitations of this research. For example, we used NATA data to assess cancer risk at the census tract level across the state; however, we were unable to account for individual-level exposures to air toxics. Also, NATA does not include all air toxics that individuals can be exposed and only provides estimated lifetime cancer risk associated with a select number of hazardous air pollutants. The NATA dataset does not include toxins that individuals can be exposed to via consumption of contaminated water or food, nor does this dataset take into account other factors that can contribute to cancer risk including occupation, family history, health behaviors, diet, lifestyle, and genetics.

Additionally, we linked census data from 2000 with NATA data from 2005, and as a result, cancer risk may be overestimated or potentially underestimated among our study population. This study only focused on estimated lifetime cancer risk and did not explore an association between lifetime estimated cancer risk, cancer incidence, and cancer mortality for populations in SC. To assess the utility of NATA cancer risk estimates in cancer prevention and control activities in the state of SC, future research will examine association between air toxics, estimated lifetime cancer risk, cancer incidence, and cancer mortality in relation to race/ethnicity, socioeconomic status, and geography.

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HIGHLIGHTS

- On-road source emissions were the greatest contributor to cancer risk.
- Sociodemographic measures were strongly associated with estimated cancer risk.
- There were differences in cancer risk in urban versus rural landscapes.
- Non-white and urban communities were most impacted by cancer risk disparities.

Figure 1.
Relative Risks for Different Sociodemographic Measures and Cancer Risk Sources for Urban and Rural Areas

Figure 2.
Map Percent Non-White and Total Cancer Risk in South Carolina

Table 1
Descriptive Statistics for Sociodemographic Measures and NATA Cancer Risk in South Carolina

Sociodemographic Measures	Mean	5 th Percentile	25 th Percentile	50 th Percentile	75 th Percentile	95 th Percentile
% Non-White	36.7	4.7	15.7	31.6	53.4	88.6
% Hispanic	2.4	0.5	0.9	1.5	2.5	7.1
% Homeownership	69.8	28.4	61.4	75.5	84.4	89.6
Per Capita Income *\$10,000	1.9	1.0	1.4	1.7	2.1	3.2
Median HH Income *\$10,000	3.7	1.8	2.8	3.5	4.2	6.3
% Poverty	15.8	3.4	8.3	13.6	20.6	36.2
% Unemployment	3.9	1.0	2.2	3.3	4.7	7.9
% Homes Built Pre-1950	13.7	0.6	4.2	9.6	18.7	42.7
% < HS Education	25.1	4.8	14.6	26.9	33.9	44.7
% Urban Area	46.1	0.0	0.3	30.6	99.3	100.0
Cancer Risk (persons per million)						
Major	1.8	0.0	1.0	1.0	2.0	5.0
Area	2.6	1.0	1.0	2.0	3.0	5.0
On-Road	5.8	1.0	3.0	5.0	8.0	14.0
Non-Road	1.3	0.0	1.0	1.0	2.0	3.0
Background	15.3	12.0	13.0	16.0	17.0	18.0
Total	26.8	16.0	20.0	26.0	32.0	42.0

Table 2
Correlation between NATA Cancer Risk and Sociodemographic Measures in South Carolina

Sociodemographic Measures	Total	Major	Area	On-Road	Non-Road	Background
% Non-White	0.09**	0.11**	0.19**	0.13**	<0.01	-0.19**
% Hispanic	0.10**	0.05	0.04	0.11**	0.14**	<0.01
% Homeownership	-0.55**	-0.23**	-0.56**	-0.54**	-0.48**	-0.09**
Per Capita Income	0.08*	-0.01	-0.07	0.05	0.20**	0.18**
Median HH Income	<0.01	-0.04	-0.18**	-0.03	0.1**	0.23**
% Poverty	0.14**	0.11**	0.29**	0.14**	0.1**	-0.18**
% Unemployment	0.18**	0.12**	0.26**	0.19**	0.12**	-0.08*
% Homes Built Pre-1950	0.29**	0.15**	0.37**	0.25**	0.27**	0.02
% < HS Education	-0.13**	0.02	0.04	-0.12**	-0.25**	-0.22**
% Urban Area	0.64**	0.21**	0.57**	0.64**	0.54**	0.31**

* p-value = <0.05;

** p-value = <0.01

Table 3

Multiple Linear Regression for Sociodemographic Measures in Rural and Urban Areas in South Carolina

Sociodemographic Measures	Multiple Linear Regression (regression coefficient, <beta>)	
	Coefficient in Census Tracts with Urban Area = 100%	Coefficient in Census Tracts with Urban Area = 0%
% Non-White	0.037	-0.065**
% Hispanic	0.032	-0.14
% Homeownership	-0.085	-0.022
Per Capita Income	----	----
Median HH Income	----	----
% Poverty	-0.019	0.032
% Unemployment	-0.006	0.165
% Homes Built Pre-1950	0.118**	0.025
% < HS Education	-0.029	-0.126**
	----	----

*
p-value = <0.05;**
p-value = <0.01

Note: The median household income and per capita income variables were removed from the multiple linear regression model because of their high correlation to percent populations with < HS education (-0.72 for median household income and -0.71 for per capita income, respectively).

Table 4
Relative Risk of Total Cancer Risk by Quartiles for Sociodemographic Measures in South Carolina

Sociodemographic Measure	% High Risk	RR	Sociodemographic Measure	% High Risk	RR	Sociodemographic Measure	% High Risk	RR
% Non-White			% Homes Built Pre-1950					
Q1	4.1	--	Q1	12.9	--		4.6	--
Q2	8.3	2.0 (0.9–4.3)	Q2	6.5	0.5 (0.3–0.9)		5.7	1.3 (0.6–2.8)
Q3	10.7	2.6 (1.2–5.4)	Q3	10.2	0.8 (0.5–1.3)		4.7	1.0 (0.4–2.4)
Q4	15.2	3.7 (1.8–7.5)	Q4	8.8	0.7 (0.4–1.2)		23.7	5.2 (2.7–9.9)
% Hispanic			Median HH Income			% Urban Area		
Q1	6.5	--	Q1	18.5	--	Q1	1.7	--
Q2	6.0	0.9 (0.4–1.9)	Q2	7.4	0.4 (0.2–0.7)	Q2	4.0	2.3 (0.6–8.9)
Q3	12.0	1.9 (1.0–3.5)	Q3	5.6	0.3 (0.2–0.6)	Q3	11.4	6.7 (2.0–22.2)
Q4	13.8	2.1 (1.2–3.9)	Q4	6.9	0.4 (0.2–0.7)	Q4	30.3	17.8 (5.7–55.8)
% Homeownership			% Poverty			% Unemployment		
Q1	26.3	--	Q1	5.5	--	Q1	8.8	--
Q2	6.5	0.2 (0.1–0.4)	Q2	7.5	1.4 (0.7–2.8)	Q2	7.0	0.8 (0.4–1.5)
Q3	2.8	0.1 (0.05–0.2)	Q3	5.1	0.9 (0.4–2.1)	Q3	6.1	0.7 (0.3–1.4)
Q4	1.4	0.1 (0.02–0.2)	Q4	19.6	3.6 (1.9–6.6)	Q4	16.7	1.9 (1.1–3.2)

^a Less than HS education was not included because all of the confidence intervals for relative risk included 1.