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Are Incomes and Food Safety Risk Related in Retail Food Environments?

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We investigate the relationship between the level of food safety risk in retail food establishments and average incomes in surrounding communities. Building on the environmental justice literature, we hypothesize that there is a relationship between community income levels and levels of food safety risk. Using data on the prevalence of *Listeria monocytogenes* (*Lm*) obtained from grocery store delis, we find that stores located in census tracts whose residents are in lower income quartiles have greater Lm prevalence. An indicator for American Indian and Alaskan Native residents also has a positive statistically significant relationship with food safety risk.

Key words: delis, grocery store, *Listeria monocytogenes*

Introduction

Exposure to foodborne pathogens is potentially lethal in the short term and can cause long-term disabilities, such as kidney failure. For example, on just one day, November 9, 2022, the US Centers for Disease Control and Prevention (CDC) announced that 16 confirmed listeria cases had been reported in six states. The consequences were substantial: 13 hospitalizations, one death, and one pregnancy loss (Centers for Disease Control and Prevention (CDC), 2022). The CDC estimates that roughly 48 million Americans contract foodborne illnesses every year. Of these, an estimated 128,000 are hospitalized, and 3,000 Americans die. Only 15 pathogens are responsible for over 95% of the deaths caused by known foodborne pathogens (Scallan et al., 2011). Hoffmann, Macullough, and Batz (2015) estimate that these 15 pathogens impose an annual economic burden of $15.5 billion on U.S. residents, measured by both the number of deaths and the severity of illnesses. Just three foodborne pathogens account for the majority of deaths: *Salmonella* (28%), *Toxoplasma gondii* (24.2%), and *Listeria monocytogenes* (*Lm*) (18.9%);[1] their combined economic burden is estimated to be 63% of those caused by all foodborne pathogens (Hoffmann, Macullough, and Batz, 2015).

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[1] The *Lm* bacterium is commonly found in many host environments, including soil, water, and animals. Humans and animals can become infected by ingesting food that has been contaminated with *Lm*, resulting in listeriosis. *Lm* is a facultative anaerobic bacterium, meaning that it is capable of surviving in the presence or absence of oxygen, and is one of the most virulent foodborne pathogens. Elderly adults, infants, pregnant women, and individuals with weakened immune systems are more susceptible to listeriosis (e.g., Mook et al., 2010). Listeriosis can last from a few days to several weeks (Ivanek et al., 2004), and almost all listeriosis cases (99%) are foodborne (Scallan et al., 2011). In extreme cases, *Lm* can travel through the bloodstream or penetrate the central nervous system, causing meningitis and/or brain infection in immunocompromised

In this article, we conduct a case study of grocery store environments to investigate whether consumers located in lower income census tracts experience a higher risk of *Lm*. Consistent with the environmental justice literature, a testable hypothesis is that low-income and nonwhite populations are more likely to experience higher *Lm* exposure. Minority and low-income communities have experienced a disproportionate share of stationary sources of air pollution—including treatment, storage, and disposal facilities—and toxic release inventory facilities (Burke, 1993; Boer et al., 1997; Sadd et al., 1999; Lejano and Iseki, 2001; Lejano, Piazza, and Houston, 2002). If this is also the case with food pathogens, then the average income of a census tract surrounding a grocery store may be a useful coincident indicator of *Lm* risk and incent additional prevention measures to thwart the negative impacts of listeriosis—a harmful and potentially deadly foodborne illness mainly transmitted via the consumption of contaminated foods (Scallan et al., 2011).

Previous studies show a pattern of substantial associated economic losses from medical costs, productivity loss, and death from foodborne illnesses (Ivanek et al., 2004; Buchanan and Lindquist, 2000). Moreover, there are additional psychological costs from the disutility caused by foodborne illnesses, including suffering, worry, and lost leisure time (Teisl and Roe, 2010). Other economic impacts include the costs of food safety recalls and consumer demand as well as supply disruptions, suggesting that past studies may have underestimated the true aggregate cost (McCluskey et al., 2005; Fahs, Mittelhammer, and McCluskey, 2009; Shang and Tonsor, 2017). Understanding the prevalence and factors affecting *Lm* infections warrants research attention.

Researchers have studied the general relationships between income and infectious diseases. Semenza and Giesecke (2008) note that populations with poor educational attainment and low income are disproportionately affected by infectious diseases in every European Union member state. The general population can also be threatened by transmission of highly prevalent infectious diseases in subpopulations, so that the scale and distribution of income in a community can play a crucial role in determining the vulnerability of the population (Semenza, Suk, and Tsolova, 2010). A decrease in income has been found to be associated with declines in health indices for individuals (Van Kippersluis et al., 2009). From a broader perspective, there is evidence that the prevalence of infectious diseases (e.g., tuberculosis) is inversely related to wealth and its distribution over populations (Suk et al., 2009).

A logical extrapolation from the preceding observations is to hypothesize that food safety risk follows similar patterns. Several studies find that consumers, especially individuals with high incomes, value safer food and are willing to pay higher prices (e.g., Buzby et al., 1998; Neill and Holcomb, 2019). Minor and Parrett (2020) use a difference-in-difference approach to estimate that a change in US Department of Agriculture rules reduced meat-related *Lm* illnesses by about 60 cases per year. Our analysis supplements the policy findings of that study by suggesting that a strategy for additional reduction in illness could include increased monitoring and interventions in in-store grocery delis with locations in lower-income areas. To the best of our knowledge, the literature lacks research into the relationship between neighborhood incomes and food safety levels of retailers, perhaps due to the lack of reliable data on foodborne illnesses and uncertainty over the source of pathogens. The current study contributes research on this issue utilizing an exclusive dataset that includes the prevalence of *Lm* measured by sampling deli surfaces located in retail grocery stores.

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individuals. Listeriosis can lead to stillbirth in pregnant women (Mateus et al., 2013). *Lm* can survive and grow at refrigerator temperatures with low potential hydrogen (pH) and high salt concentrations (Gandhi and Chikindas, 2007). The persistent nature of *Lm* makes it difficult to control or eradicate from the environment. Previous studies show that approximately 90% of human listeriosis cases are linked to ready-to-eat (RTE) foods (Pradhan et al., 2011), and deli meat is the RTE food category that represents the major listeriosis risk to consumers. However, the CDC has not recommended avoidance of any products sold at delis because a common source of infection has been difficult to identify due to large product variation. Although *Lm* cannot survive elevated temperatures, it can persist in retail facilities due to post-processing cross-contamination of RTE foods, product contamination from the environment, or both (Lianou and Sofos, 2007; Pradhan et al., 2011; Gibson et al., 2013; Maitland et al., 2013). Hoelzer et al. (2011) find that *Lm* is more prevalent on nonfood contact surfaces in grocery stores than on food contact surfaces.

Associations between *Lm* Prevalence and Socioeconomic Factors

There are many possible reasons for why *Lm* might be related to socioeconomic variables. Inadequate access to food retailers or financial pressures may encourage individuals to store food for longer than the food product's intended shelf life, which could result in exposure to higher *Lm* loads (Swaminathan and Gerner-Smidt, 2007). Gillespie et al. (2010) use laboratory surveillance data on listeriosis cases in England between 2001 and 2007 to demonstrate that the incidence of human listeriosis is positively related to neighborhood deprivation, measured by a number of socioeconomic factors including income, education, employment, health deprivation and disability, living environment, barriers to housing and services, and crime and disorder. A second explanation is food consumption patterns, which can be correlated with socioeconomic factors. Some high-risk foods (e.g., sliced deli meats, raw milk and cheeses, and unheated frankfurters) are more likely to be contaminated. Rates of listeriosis are higher among Hispanic populations who consume fresh Mexican-style cheeses (Ray et al., 2004; MacDonald et al., 2005; Jackson, Iwamoto, and Swerdlow, 2010; Jackson et al., 2011). Between 2004 and 2009, instances of listeriosis in pregnant women grew from 5.09 to 12.37 per 100,000 for Hispanic women but only from 1.74 to 2.80 per 100,000 for non-Hispanic women (Silk et al., 2012). Mook et al. (2010) document a significant increase in listeriosis in pregnant women among a number of ethnic minorities in England and Wales between 2001 and 2008.

A third explanation that relates specifically to the association between *Lm* prevalence and income is the handling of foods by low-income populations (Bermúdez-Millán et al., 2004; Trepka et al., 2006; Henley, Stein, and Quinlan, 2012). The argument is that lower-income food handlers might be either less well trained or less aware of safe-food handling processes, resulting in greater prevalence of foodborne illnesses among those they serve.

Yet another explanation of the potential relationship between income and access to safer food is "residential sorting", a process by which individuals choose residential locations based on an area's attributes, including prices. Such sorting can lead to nonrandom assignments of environmental amenities (Graff Zivin and Neidell, 2013; De Silva, Hubbard, and Schiller, 2016). Spatially delineated public goods and environmental amenities can expose poor and less educated residents to environmental disamenities (Cameron and McConnaha, 2006). Preferences over residential neighborhoods can depend on such things as employment opportunities, commuting costs, and social and environmental conditions (Tiebout, 1956; Roback, 1982).

On the other hand, residents of an area contribute to neighborhood features. Consequently, attributes of a location and its selection by individuals are mutually endogenous (e.g., Cutts et al., 2009; Kabisch and Haase, 2014). Local amenities are often "bundled" (e.g., access to high-quality education and transportation versus lack of clean air in urban areas). If amenities are normal goods, then wealthier people have a greater willingness to pay to reside in areas with better local amenities. Grocery stores with better food safety records may be one such amenity.

Data

The data used in this study were collected over 2010–2013 by sampling 74 grocery store delis in California, Indiana, Minnesota, Missouri, New York, and North Carolina.[2] University researchers collaborated with corporate sanitarians to sample stores without regard to perceived food safety challenges, facility sizes and configurations, or area demographics. Fully randomized selection of stores was infeasible for two main reasons: (i) stores had to be willing to participate in the study and

[2] Data on *Lm* prevalence were originally collected from 100 in-store delis, but 26 stores opted not to disclose their addresses, preventing their data from being matched with census tract information. Since the *Lm* data needed to be linked with store location, our analysis is limited to the 74 stores that provided addresses. There was no identifiable systematic reason for nondisclosures of addresses, and so omitted data bias is not expected.

(ii) stores needed to be sufficiently close to one of the participating universities since the specimens were biologically vulnerable and required overnight shipping on ice to the universities.

A variety of surfaces (referred to as “sites”) within each store were tested for the prevalence of *Lm* in delis by collecting samples with sponge swabs from such areas as slicers, counter touch points, floors, sinks, food contact surfaces in deli cases, deli case handles, deli case coils, cleaning tools, mobile carts, and door handles of walk-in coolers. Data collection followed a longitudinal approach, with repeated sampling over varying periods, including pre- and post-operation of the delis and before and after cleaning. The derived *Lm* prevalence risk is a constructed measure that reflects the varied conditions under which samples were taken, including store structural and operating characteristics and the timing of data collection.

The dependent variable is the predicted risk of an in-store deli exhibiting *Lm* prevalence, measured on a scale from 0 to 1. The construction of the prevalence risk measure was guided by Firth (1993), who implemented a bias-corrected logistic regression model for in-store delis based on the types of sample information described above. As noted by Forauer, Wu, and Etter (2021), the various store configurations, including scheduled shift patterns in the in-store deli, seasonal operational and environmental changes, infrastructure modifications, and cleaning regimens, in addition to food handling variability and the diversity of *Lm* strains, necessitates using a prediction methodology that explicitly accounts for diverse store-specific conditions. The method utilized for collecting and analyzing the deli observations is supported by Hammons et al. (2015) as providing observations that are both associated with the presence of *Lm*, and useful for constructing scientifically robust probability-based *Lm* prevalence risk scores. Further details of the specific dependent variable construction methodology used to calculate the *Lm* prevalence risk values analyzed as the dependent variable in this paper can be found in Wu et al. (2020).

The risk prevalence scores were aligned with the demographics of the census tracts in which stores were located. As noted above, the resulting tracts do not constitute a purely random sample due to distance conditions relating to university testing laboratories and the condition of stores’ willingness to participate in the study. However, the feasible distances for overnight shipment of samples were relatively large, and there was no apparent systematic pattern in stores’ willingness to participate. The samples themselves offer accurate, scientifically collected quantitative information on the prevalence of *Lm* in grocery store delis, as defended in the literature noted above. At the least, the observed risk values can be used to analyze the effects of neighborhood sociodemographic characteristics on a conditional basis.

Table 1 presents variable descriptions and data summary statistics. The average prevalence risk of *Lm* at a deli was 13.67%, and there was high variation in this risk measure across stores. Of the 74 observations, 44 had 0 calculated prevalence risk, while the others had varying positive levels of prevalence risk across the *Lm* sites tested. No deli was found to have a *Lm* risk of 100%.

The demographic information is from the American Community Survey (ACS) dataset of the US Census Bureau (2010) at the tract level. Store data are matched with demographic information using geographic information system (GIS). The tract-level demographic information includes income per capita, education, and racial characteristics of the population as well as population density and urbanization.

As shown in Table 1, mean real income per capita across the sampled tracts is $31,661, which is moderately above the $27,180 level reported for all US tracts. Income quartiles (in 2010 dollars) support a more nuanced view of the distribution of income, with values $22,245, $28,737, and $35,812 associated with the defining boundaries of quartiles 1, 2, and 3, respectively. Our use of income quartiles is motivated by Figure 1, which depicts a scatter plot of *Lm* percentages versus per capita real incomes. From Figure 1, it is apparent that there is substantial variability in the observations, but there appears to be some degree of negative association between income and prevalence risk. The prevalence risk appears somewhat higher in census tracts with lower per capita income.

Table 1. Summary Statistics (*N* = 74 delis)

Variable	Description	Mean	Std. Dev.
Dependent variable			
Lm prevalence (%)	% of sampled sites where Lm was found	13.666	23.439
Explanatory variables			
Income	Per capita annual real income (thousand $)	31.661	14.833
Income Quartile1	=1 if census tracts with per capita income in 1st quartile (<$22,245), 0 otherwise	0.243	0.432
Income Quartile2	=1 if census tracts with per capita income in 2nd quartile ($22,455 to $28,737), 0 otherwise	0.257	0.440
Income Quartile3	=1 if census tracts with per capita income in 3rd quartile ($28,737 to $35,812), 0 otherwise	0.243	0.432
Income Quartile4	=1 if census tracts with per capita income in 4th quartile (>$35,812), 0 otherwise	0.257	0.440
White	White population (%)	73.726	22.167
African American	African American population (%)	13.829	19.018
Hispanic	Hispanic population (%)	8.816	10.948
Asian	Asian American population (%)	4.889	5.381
Pacific Islanders	Native Hawaiian and Other Pacific Islander (%)	0.165	0.437
American Indian	American Indian and Alaska Native (%)	0.462	0.351
College	Population at least went to college (%)	64.273	15.979
Store age	Age of the deli in years	4.230	1.643
Population density	Number of people per mile in the tract	3,476	2,891
Urban	Urban residence (%) in the tract	0.981	0.126
State indicator variables			
California	13 stores	0.176	0.383
Indiana	11 stores	0.149	0.358
Minnesota	10 stores	0.135	0.344
Missouri	10 stores	0.135	0.344
North Carolina	10 stores	0.135	0.344
New York	20 stores	0.270	0.447

Notes: Store-level information and *Lm* estimates are obtained from scientific surveys in 2010–2013 (see Simmons et al., 2014, for details). Sociodemographic variables are from the 2020 US Census.

Because our dataset does not contain a large number of observations, a single high-valued income data point could substantially impact the estimated relationship between *Lm* prevalence risk and income. Two observations in the dataset in the $80,000 range are 3 standard deviations from the mean, and five observations lie between 2 and 3 standard deviations from the mean. While these observations are not necessarily "outliers," they can notably influence estimated relationships. The dashed curve in Figure 1 represents a quadratic fit, while the red line displays *Lm* prevalence risk averages by income quartiles. Continuous transformations, such as squared (we also examined the log of income), accentuate the influence of large income values; the estimated relationship appears to be consistently deviant from the mean levels of *Lm* prevalence risk, especially in the first and third quartiles. Segmenting by quartiles suppresses these ranges of consistent under- and overpredictions. However, a two-dimensional analysis clearly does not capture all relevant factors, and our statistical analysis provides greater resolution in the identification of the relationship.

Regarding education, an average 64.27% of adults in the sample had at least some college education and/or an associate degree. The race and ethnicity variables include indicators for white,

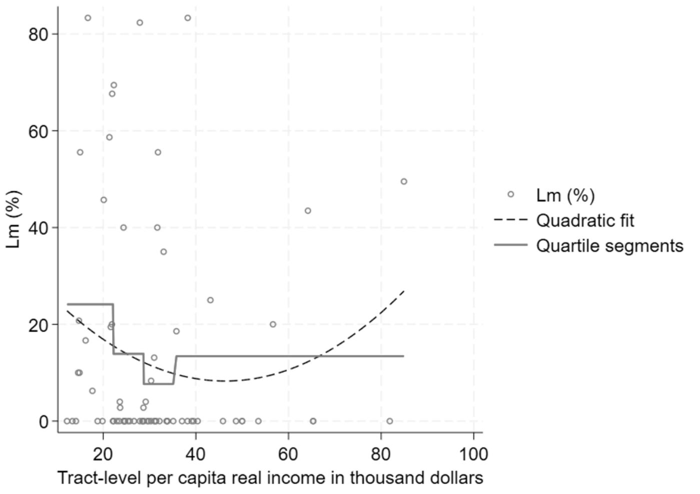

Figure 1. Calculated Prevalence of *Listeria monocytogenes* (%) vs. Census-Tract Income

Notes: The dashed curve represents a quadratic fit, and the red line shows *Lm* averages by income quartiles. A continuous model, like quadratic or log, overemphasizes the impact of one high-income observation and underrepresents the impact of three at zero. Moreover, the estimated LM prevalence is especially and consistently deviant from quartile means in the first and third quartiles. Segmenting by quartiles suppresses these consistent ranges of under and over predictions.

African American, Hispanic, Asian, Pacific Islanders, and American Indian. The majority of the population (73.73%) in the sampled tracts was white, and 13.83% of the sampled population was African American. Among other race and ethnicity categories, 8.82% of the sampled population was Hispanic, 4.89% was Asian, and less than 1% of the sampled population was Pacific Islander and American Indian.

Two additional variables are included to measure population density and level of urbanization in a census tract. The census tracts generally have population sizes ranging between 1,200 and 8,000, with an average size of 4,000 inhabitants. On average, there were nearly 3,500 people per square mile across tracts, with 98.1% of them being urban residents. State indicator variables are included as well as the ages of sampled in-store delis to account for retail store operating longevity and experience.

Empirical Analysis

Given the notable number of observations indicating 0 prevalence risk of *Lm*, a censored Tobit-type regression model was implemented to estimate the relationship between prevalence risk and explanatory variables. The Tobit model is consistent with the dependent variable representing a constructed prevalence risk score ranging from 0 to 1 and having a probability characterization. Moreover, for *Lm* prevalence risk even when observed as 0, there can still be an underlying latent risk of *Lm* that might lie below the detectable level until it reaches a certain threshold. The Tobit model can account for the association between predictor variables and both the latent and observed prevalence of *Lm*. The analysis provided by this type of model is to be interpreted in the context of representing the degree of *Lm* prevalence risk resulting from the cumulative effects of preparation, transportation, and storage of ready-to-eat food (Bortolussi, 2008). The Tobit model is specified in classical form as

$$\begin{aligned} y_i^* &= \boldsymbol{x}'_i\boldsymbol{\beta} + \epsilon_i, \quad i = 1,2,\dots n, \\ y_i &= 0 \text{ if } y_i^* \leq 0, \\ y_i &= y_i^* \text{ if } y_i^* > 0, \end{aligned} \tag{1}$$

where $n = 74$ is the number of sample observations; y_i^* is the unobserved latent variable used to facilitate modeling the mixed discrete–continuous nature of the dependent variable, y_i, which is the detected level of listeria prevalence risk; $\boldsymbol{x}_i$ is a vector of explanatory variables that includes income, education, race, unemployment, urbanization, and state indicator variables (six states); and $\boldsymbol{\beta}$ is a vector of parameters to be estimated. The residual term, ϵ_i, is specified in classical Tobit model form as normally and independently distributed with mean 0 and constant variance σ^2. The parameter vector $\boldsymbol{\beta}$ is estimated via maximum likelihood.

The likelihood function value for a nonzero observation on *Lm* prevalence risk, which is represented in the model by $y_i = y_i^* > 0$, is given by

$$L_i = \frac{1}{\sigma}\phi\left(\frac{y_i - \boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma}\right), \tag{2}$$

where ϕ refers to the standard normal density function. For a 0-valued observation on *Lm* prevalence risk, represented in the model by $y_i^* \leq 0 \Rightarrow y_i = 0$, the likelihood function value is defined by

$$L_i = 1 - \Phi\left(\frac{x_i'\beta}{\sigma}\right), \tag{3}$$

where Φ is the standard normal cumulative distribution function. The likelihood function, L, for the entire sample is then given by

$$L(\beta,\sigma) = \Pi_{i=1}^{n} L_i = \Pi_{i=1}^{n}\left[\frac{1}{\sigma}\phi\left(\frac{y_i - x_i'\beta}{\sigma}\right)\right]^{D_i}\left[1 - \Phi\left(\frac{x_i'\beta}{\sigma}\right)\right]^{1-D_i}. \tag{4}$$

The unconditional marginal effect of an explanatory variable, x_{ij}, on the *latent variable* is represented directly by the corresponding Tobit coefficient

$$\frac{\partial E y_i^*}{\partial x_{ij}} = \beta_j. \tag{5}$$

The unconditional and conditional marginal effects (McDonald and Moffitt, 1980; Maddala, 1983) of x_{ij} on the observed data relating to actual *Lm* prevalence risk, y_i, are given, respectively, by

$$\frac{\partial E y_i}{\partial x_{ij}} = \beta_j \Phi(z_i) \tag{6}$$

and

$$\frac{\partial E\left[y_i \mid y_i^* > 0\right]}{\partial x_{ij}} = \beta_j\left(1 - z_i\frac{\phi(z_i)}{\Phi(z_i)} - \frac{\phi(z_i)^2}{\Phi(z_i)^2}\right) \tag{7}$$

where $z_i = \boldsymbol{x}_i'\boldsymbol{\beta}/\sigma$.

The effect in equation (6) measures the overall effects of a change in x_{ij} on the percentage of *Lm* prevalence risk. The conditional marginal effect in equation (7) measures the effects of changes in x_{ij} on *Lm* prevalence risk given that the prevalence risk was detected as being positive.

Estimation Results

The possibility of heteroskedastic errors is accounted for in the estimated variances of estimators provided in Table 2. Estimated marginal effects are presented for both the observed *Lm* prevalence risk and the value of the underlying latent risk variable. In the model specification, the lowest income quartile is designated as the default benchmark category. Note that despite the fact that the number

Table 2. Tobit Estimation Results (N = 74)

Dependent Variable	**Tobit Estimates**	**Unconditional Marginal Effects**	**Conditional Marginal Effects**
***Lm* Prevalence**	$\boldsymbol{\beta}$	$\boldsymbol{\beta_j \Phi(z)}$	$\boldsymbol{\beta_j \left(1 - z\frac{\phi(z)}{\Phi(z)} - \frac{\phi(z)^2}{\Phi(z)^2}\right)}$
1	**2**	**3**	**4**
2nd income quartile	−19.833**	−6.967**	−5.748**
	(9.789)	(2.899)	(2.541)
3rd income quartile	−26.717*	−8.620**	−7.393**
	(14.474)	(3.341)	(3.310)
4th income quartile	−26.522	−8.723*	−7.420*
	(18.505)	(4.565)	(4.427)
African American (%)	−0.128	−0.055	−0.042
	(0.263)	(0.114)	(0.086)
Hispanic (%)	−0.887	−0.383	−0.291
	(0.732)	(0.317)	(0.239)
Asian (%)	0.537	0.232	0.176
	(0.817)	(0.352)	(0.267)
Pacific Islanders (%)	17.101	7.389	5.605
	(10.586)	(4.594)	(3.453)
American Indian (%)	42.591**	18.403**	13.960**
	(16.765)	(7.279)	(5.407)
College (%)	0.306	0.132	0.100
	(0.392)	(0.168)	(0.128)
Store age	−6.149***	−2.657***	−2.015***
	(1.769)	(0.724)	(0.538)
Population density (log)	−6.283	−2.715	−2.059
	(5.162)	(2.206)	(1.672)
Urban (%)	70.590	30.502	23.137
	(46.598)	(19.681)	(14.940)
California	−4.831	−1.951	−1.516
	(19.587)	(7.372)	(5.886)
Indiana	69.555***	52.241***	42.899***
	(10.395)	(9.209)	(9.062)
Minnesota	37.688**	24.910*	18.400
	(16.798)	(13.954)	(11.226)
Missouri	4.327	1.996	1.483
	(13.917)	(6.797)	(4.972)
North Carolina	−20.076	−6.238**	−5.426*
	(14.323)	(3.055)	(3.168)
Base intercept	−26.883		
	(46.667)		
Pseudo-R^2	0.181		

Notes: Single, double, and triple asterisks (*, **, ***) denote significance at the 10%, 5%, and 1% levels, respectively. Heteroskedastic robust standard errors are given in parentheses. The base intercept refers to New York, and the first income quartile represents the benchmark income category. Columns 2, 3, and 4 represent equations 16 (Tobit regression coefficients), 17 (unconditional marginal effects on observed *Lm* prevalence), and 18 (conditional marginal effects on *Lm* prevalence given the latent risk is above the threshold), respectively.

of observations available to conduct the statistical analysis ($N = 74$) was not large, it is notable that the estimated effects associated with the income variables, which is a principal focus of this study, nevertheless exhibit robust statistical significance.[3]

Column 2 of Table 2 presents the marginal effects of explanatory variables on the latent variable underlying the observed *Lm* prevalence risk outcomes. The value of the latent variable is estimated to decrease when tracts are characterized by higher income quartiles, and the decreases are statistically significantly different from the baseline income effect (i.e., the lowest income category) for two of the three marginal effects. Census tracts with average incomes in the lowest quartile are estimated to experience a higher propensity for infections, with the prevalence risk estimated to gradually decline at higher quartiles.

Columns 3 and 4 of Table 2 represent the unconditional and conditional marginal effects of explanatory variables on the prevalence risk of *Lm*, respectively. All of the marginal effects of income on food safety risk are statistically significant and decrease as income quartiles increase. Census tracts with higher income quartiles are associated with increasingly lower *Lm* prevalence risk compared to the lowest income quartile. In particular, tracts with per capita income between \$22,245 and \$28,737 (second quartile) are estimated to have 6.9% lower prevalence risk than tracts with income below \$22,245 (first quartile), tracts in the third quartile, spanning incomes between \$28,737 and \$35,812, are associated with 8.6% lower prevalence risk compared to the first quartile, and tracts within the fourth quartile with incomes above \$35,812 are associated with 8.7% lower prevalence risk than the first quartile.[4]

Most of the marginal effects of the race and ethnic population percentages (including those for African American, Hispanic, Asian, and Pacific Islander) on *Lm* prevalence risk are statistically insignificant. However, the American Indian and Alaska Native population percentage is positively associated with *Lm* prevalence risk and is statistically significant at the 5% level, where a 1% increase in this population is associated with an increase in prevalence risk of 18.4%. The conditional marginal effects associated with positive values of *Lm* prevalence risk are similar in outcomes. The results suggest that, holding income and other variables constant, prevalence risk is higher in census tracts with larger populations of American Indian and Alaska Native residents.

Store age is statistically significant and inversely associated with *Lm* prevalence risk. The rationale for this association may be that stores providing higher levels of safety have more operating experience, which supports greater awareness and established adherence to food safety protocols and also supports business sustainability and longevity. The effects of education, population density, and urbanization on the prevalence risk of *Lm* were statistically insignificant.

Estimated coefficients on the state indicator variables for Indiana and Minnesota were statistically significant in the unconditional sense, with the latent prevalence risk of *Lm* estimated to be 52% and 24.9% greater in tracts from these two states, respectively, relative to the baseline of New York.

Overall, our estimation results suggested that there is between a 6.9% and 8.7% higher prevalence risk of *Lm* in the lowest income quartile tracts compared to higher income quartiles, and a mean calculated prevalence risk of 13.66% (Table 1). While the income effects may seem

[3] The environmental justice argument asserts that we should expect lower income minority populations to be the worst-served group. We replicated Table 2 with the addition of interactions between higher income quartiles and minority population variables. While some of the interactions produced significant estimates, due to the limited number of observations in each category, many of the marginal effects are insignificant. To avoid overfitting, we chose the more parsimonious model without the interaction terms.

[4] The census tracts chosen for this study were chosen based on the locations of the stores that participated and not to explicitly represent US demographics. Thus, the census tracts in our data have slightly higher incomes compared to the United States as a whole. The variable *Per Capita Income in the Past 12 Months* (in 2010 dollars) in the 5-year 2010 American Community Survey is as follows: The first quartile is <\$18,529, the second is \$18,529–\$24,112, the third is \$24,112–\$32,121, and the fourth is >\$32,121. The mean income is \$27,182. Comparatively, in our data, the first quartile is <\$22,245, the second is \$22,245–\$28,737, the third is \$28,737–\$35,812, and the fourth is >\$35,812. The mean of our data is \$31,660. Despite these differences, our results remain consistent even when using the nationally representative quartile cut-off points, with higher incomes being more statistically significant, owing to the slightly elevated income levels in our selected census tracts.

numerically modest in comparison to the effects of state-level indicators as well as the effect of American Indian and Alaska Native population percentages, any increased risk is significant in public health terms, given that *Lm* can cause extreme illness and is a potentially deadly foodborne pathogen.

Concluding Remarks

Building on ideas from the environmental justice literature, this study provides an empirical analysis relating to the existence of an association between income and the prevalence of the food pathogen *Listeria monocytogenes* (*Lm*) in retail food stores. Using data on the prevalence of *Lm* collected from delis located in grocery stores, the prevalence of the pathogen was shown to exhibit a statistically significant negative association with income. Census tracts characterized by higher income quartiles have increasingly lower *Lm* prevalence risk compared to the lowest income quartile in our analysis. While most of the effects of race and ethnicity did not have a statistically significant differential impact on prevalence risk, the risk was estimated to be significantly higher among populations characterized by a greater presence of American Indian and Alaska Native individuals. Other demographic variables (e.g., education, population density, and degree of urbanization) are not associated with statistically significant differential impacts. We also find a statistically significant negative relationship between store age and risk.

The interpretation of these results requires caution, given that our sample of in-store delis was not the result of a fully randomized sampling design. Our sample was conditioned by stores' willingness to participate in the study as well as the condition of close enough proximity to university laboratories to facilitate overnight shipping of samples under ice preservation. However, the samples are accurately aligned with the demographics of the census tracts where these delis are situated, and observations of *Lm* prevalence risk are scientifically defensible and accurate. All told, our findings pertain to the selected tracts but may not be generalizable to a broader range of locations and so should be viewed in a conditional sense.

To the best of our knowledge, this study represents the inaugural attempt to employ scientifically gathered information on the prevalence of *Lm* at the store level and analyze its relationship with local sociodemographic variables. Our findings serve as an initial discourse on the potentially higher food safety risks prevalent in low-income neighborhoods. The biology of pathogens, such as *Lm*, renders the goal of their total elimination from food unrealistic. Pursuing economic efficiency suggests supplying a level of food safety for which marginal cost is equal to marginal benefit, and the results of this study are consistent with the notion that the marginal benefit expressed in the marketplace is positively associated with willingness and ability to pay. However, foodborne illnesses remain a major challenge, especially to marginalized communities, and are often underreported.

Our findings contribute to the research agenda on food safety articulated by, Hoffmann, Ashton, and Ahn (2021). Specifically, the results suggest that optimal enforcement policies might be improved by targeting additional interventions in lower-income areas, and income may be useful as a coincident indicator for localities having higher risk of *Lm* prevalence where significant increases in health benefits might result from interventions.

Policies that support increasing food safety and improving health include additional monitoring and validating of food safety protocols in select stores. Subsidizing food safety training of employees who work in stores located in low-income areas could be another policy intervention supporting the provision of safer food in higher risk populations. An overarching goal that is suggested by our analysis is to lower the cost of supplying and consuming safer food, which would enable low-income consumers, in particular, to afford healthier food choices.

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