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

Modhurima Dey Amin, Jill J. McCluskey, Ron C. Mittelhammer,
Sophie T. Wu, and Haley F. Oliver*

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: *Listeria monocytogenes*, grocery store, delis

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 U.S. Centers for Disease Control and Prevention (CDC) announced that 16 confirmed listeria cases had been reported in six states. The consequences were substantial; 13 cases resulted in hospitalizations, there was a death, and also one pregnancy loss (CDC, 2022). The CDC estimates that roughly 48 million Americans contract foodborne illnesses every year. Of these, an estimated 128 thousand are hospitalized, and three thousand Americans die. Only 15 pathogens are responsible for over 95% of the deaths caused by known foodborne pathogens (Scallan et al., 2011). Hoffmann, Macculloch, and Batz (2015) estimate that these 15 pathogens impose a \$15.5 billion economic burden annually on U.S. residents, measured by both the number of deaths and severity of illnesses. Just three foodborne pathogens account for the majority of deaths: *Salmonella* (28%), *Toxoplasma gondii* (24.2%), and *Listeria monocytogenes* (*Lm*)¹ (18.9%); and

Modhurima Dey Amin is an assistant professor in the Department of Agricultural Economics at Texas Tech University. Jill J. McCluskey (corresponding author, mccluskey@wsu.edu) is a regents professor and director of the School of Economic Sciences at Washington State University. Ron C. Mittelhammer is a regents professor in the School of Economic Sciences at Washington State University. Sophie T. Wu is a senior research assistant in the School of Health, Social Work and Sport at the University of Central Lancashire. Haley F. Oliver is a professor in the Department of Food Science, director of the USAID Feed the Future Innovation Lab for Food Safety, and assistant dean of Ag Online Programs at Purdue University. Jill McCluskey and Ron Mittelhammer acknowledge funding from the National Institute of Food and Agriculture, U.S. Department of Agriculture. We are grateful to the grocery store chains that participated in this study.

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¹ *Lm* is a bacterium that 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

their combined economic burden is estimated to be 63% of those caused by all foodborne pathogens (Hoffmann, Maculloch, and Batz 2015).

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 non-white 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 (Boer et al., 1997; Burke, 1993; Lejano and Iseki, 2001; Lejano, Piazza, and Houston, 2002; Sadd et al., 1999). 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. 2005; 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 the aggregate true cost may have been underestimated in past studies (Fahs, Mittelhammer, and McCluskey, 2009; McCluskey et al., 2005; Shang and Tonsor, 2017). Understanding the prevalence and factors affecting *Lm* infections warrants research attention.

Researchers have studied 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 Tsoleva, 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, such as 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 value safer food and are willing to pay higher prices, especially individuals with high incomes (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 U.S. 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

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., 2005), 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 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 meats are the RTE-food category that carry 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 (Gibson et al. 2013; Maitland et al. 2013; Pradhan et al., 2011; Lianou and Sofos, 2007). Hoelzer et al. (2011) find that in grocery stores *Lm* is more prevalent on nonfood contact surfaces than on food contact surfaces.

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.

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 Peter, 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 such as 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, listeriosis in pregnant women grew from 5.09 to 12.37 per hundred thousand for Hispanic women but only from 1.74 to 2.80 for non-Hispanic women (Silk et al., 2012). Mook et al. (2010) document a significant increase in listeriosis in pregnant women who are 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 (Bermudez-Millan 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 where individuals choose residential locations based on the attributes of areas, 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 McConaha, 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, 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 was collected over the period 2010 to 2013 by sampling 74² grocery store delis in California, Indiana, Minnesota, Missouri, New York, and North Carolina. 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: (1) stores had to be willing to participate in the study, and (2) 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 time 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 0-to-1 scale. 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 zero 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 U.S. Census Bureau (2010) at the tract level. Store data is matched with demographic information

² Data on *Lm* prevalence was 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 systemic reason for nondisclosures of addresses, and so omitted data bias is not expected.

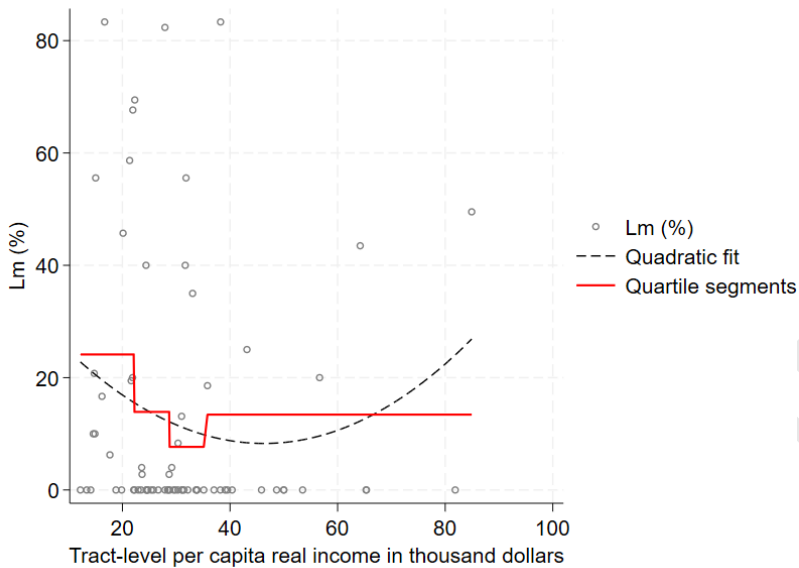


Figure 1. Calculated Prevalence of *Listeria monocytogenes* (%) vs. Census-Tract Income.

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.

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 U.S. tracts. Income quartiles (in 2010 dollars) support a more nuanced view of the distribution of income, with the values \$22,245, \$28,737, and \$35,812 being 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 it appears there is some degree of negative association between income and prevalence risk. The prevalence risk appears somewhat higher in census tracts with lower per-capita income.

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 data set in the \$80,000 range are three standard deviations from the mean, and five observations lie between two and three 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 and 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 over predictions. However, a two-dimensional analysis clearly does not capture all relevant factors, and a more resolute identification of the relationship is provided in the statistical analysis presented ahead.

Table 1. Summary Statistics

Variable	Description	Mean	Std. Dev.
<i>Dependent variable</i>			
<i>Lm prevalence (%)</i>	% of sampled sites where <i>Lm</i> was found	13.666	23.439
<i>Explanatory variables</i>			
Income	Per capita annual real income (thousand \$)	31.661	14.833
Income Quartile1	=1 if Census Tracts with per capita income in 1 st quartile (< \$22,245), 0 otherwise	0.243	0.432
Income Quartile2	=1 if Census tracts with per capita income in 2 nd quartile (\$22,455 to \$28,737), 0 otherwise	0.257	0.440
Income Quartile3	=1 if Census tracts with per capita income in 3 rd quartile (\$28,737 to \$35,812), 0 otherwise	0.243	0.432
Income Quartile4	=1 if Census tracts with per capita income in 4 th 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 Islanders (%)	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
<i>State Indicator Variables</i>			
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
Sample size (number of delis)		74	

Note: Store level information and *Lm* estimates are obtained from scientific surveys in 2010-13 (see Simmons et. al., 2014 for details). Sociodemographic variables are from the US Census 2010.

Regarding education, the average number of adults in the sample who had at least some college education and/or an associate degree was 64.27%. The race and ethnicity variables include indicators for white, African American, Hispanic, Asian, Pacific Islanders, and American Indian. The majority of the population (73.73%) in the sampled tracts were white, and 13.83% of the sampled population were African American. Among other race and ethnicity categories, 8.82% of the sampled population were Hispanic, 4.89% were Asians, and less than 1% of the sampled population were Pacific Islanders 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 zero 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 zero, there can still be an underlying latent risk of *Lm* that might lie below the detectable level until it reaches a certain threshold. With the Tobit model, the association between predictor variables and both the latent and observed prevalence of *Lm* can both be accounted for. 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

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

where $n = 74$ is the number of sample observations, y_i^* is the unobserved latent variable used to facilitate modelling the mixed discrete-continuous nature of the dependent variable, y_i , which is the detected level of listeria prevalence risk, x_i is a vector of explanatory variables that include income, education, race, unemployment, urbanization, and state indicator variables (six states), and β 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 zero and constant variance σ^2 . The parameter vector β 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

$$(2) \quad L_i = \frac{1}{\sigma} \phi \left(\frac{y_i - x_i' \beta}{\sigma} \right)$$

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

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

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

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

where D_i is an indicator variable that takes the value 1 when $y_i > 0$.

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

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

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

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

and

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

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 heteroscedastic 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 despite the fact that the number 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

³ The environmental justice argument asserts that lower-income minority populations should 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.

Table 2. Tobit Estimation Results

(1) Dependent variable <i>Lm</i> prevalence	(2) Tobit Estimates β	(3) Unconditional Marginal Effects $\beta_j \Phi(z)$	(4) Conditional Marginal Effects $\beta_j \left(1 - z \frac{\phi(z)}{\Phi(z)} - \frac{\phi(z)^2}{\Phi(z)^2}\right)$
2 nd Income quartile	-19.833** (9.789)	-6.967** (2.899)	-5.748** (2.541)
3 rd Income quartile	-26.717* (14.474)	-8.62** (3.341)	-7.393** (3.31)
4 th Income quartile	-26.522 (18.505)	-8.723* (4.565)	-7.42* (4.427)
African American (%)	-0.128 (0.263)	-0.055 (0.114)	-0.042 (0.086)
Hispanic (%)	-0.887 (0.732)	-0.383 (0.317)	-0.291 (0.239)
Asian (%)	0.537 (0.817)	0.232 (0.352)	0.176 (0.267)
Pacific Islanders (%)	17.101 (10.586)	7.389 (4.594)	5.605 (3.453)
American Indian (%)	42.591** (16.765)	18.403** (7.279)	13.96** (5.407)
College (%)	0.306 (0.392)	0.132 (0.168)	0.1 (0.128)
Store Age	-6.149*** (1.769)	-2.657*** (0.724)	-2.015*** (0.538)
Population density (log)	-6.283 (5.162)	-2.715 (2.206)	-2.059 (1.672)
Urban (%)	70.59 (46.598)	30.502 (19.681)	23.137 (14.94)
California	-4.831 (19.587)	-1.951 (7.372)	-1.516 (5.886)
Indiana	69.555*** (10.395)	52.241*** (9.209)	42.899*** (9.062)
Minnesota	37.688** (16.798)	24.91* (13.954)	18.4 (11.226)
Missouri	4.327 (13.917)	1.996 (6.797)	1.483 (4.972)
North Carolina	-20.076 (14.323)	-6.238** (3.055)	-5.426* (3.168)
Base Intercept	-26.883 (46.667)		
Pseudo R-squared	0.181		

Note: ***, **, * denote significance at the .01, .05, and .10 levels, respectively. Heteroskedastic robust standard errors are given in parentheses. Observations =74. 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.

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 on *Lm* prevalence risk, including the effects of African American, Hispanic, Asian, and Pacific Islander percentages are all statistically insignificant. However, the American Indian and Alaska Native population percentage is positively associated with *Lm* prevalence risk and is statistically significant at 5%, where a one-percent 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 having a larger population 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 that supports greater awareness and established adherence to food safety protocols, which 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 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, such as education, population density, and degree of

⁴The census tracts chosen for this study were chosen based on the locations of the stores who participated and not explicitly to represent U.S. 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 five-year 2010 American Community Survey is as follows: The first quartile is less than \$18,529, the second quartile between \$18,529 and \$24,112, the third quartile is between \$24,112 and \$32,121, and the fourth quartile is greater than \$32,121. The mean income is \$27,182. Comparatively, in our data, the first quartile is less than \$22,245, the second is between \$22,245 and \$28,737, the third is between \$28,737 and \$35,812, and the fourth is greater than \$35,812. The mean of our data is \$31,660. Even so, 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.

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 that was 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 *Listeria monocytogenes* 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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