Empirical Modeling of the Risk and Determinants Associated with Food-Related Illnesses

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Abstract

Each year one in six Americans experience foodborne illnesses which results in a significant financial burden, up to $51 billion. Also, these food-relevant disease outbreaks present significant risks to the private sector business involved in the provision of food and food-related products. In this paper, we utilize state-level data taken from the Centers for Disease Control and Prevention data to investigate the impact of host factors associated with the agricultural work environment on foodborne-relevant risks. To measure the level of agricultural work environment, the U.S. Bureau of Economic Analysis farm income and expense is employed. We find evidence that the poor agricultural work environment can increase risks associated with foodborne outbreaks: intensive livestock farming might weaken the immune system of farmers and residents who can be more likely to get severely ill from foodborne illnesses. Compared to the agriculture producer sector, its processor sector maintains relatively higher standards for hygiene which might lead to the strong immune system of residents who are less susceptible to foodborne illness.

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Introduction

The Centers for Disease Control and Prevention (CDC) estimates each year foodborne illnesses cause 48 million episodes of foodborne illness, 128,000 hospitalizations, and 3,000 death in the United States (Scallan et al., 2011). The incidence of foodborne illnesses leads to a significant financial burden: a couple of study estimates that the aggregated annual cost of foodborne illness in the United States is ranging from \$14.1 billion to \$51.0 billion[1] (Scharff, 2011; Hoffmann et al., 2012). Anyone can get food disease, but specific groups of people are more likely to get sick easily and experience severe symptoms. People at risk include children, older adults, pregnant women, and people with weakened immune systems (CDC, 2019; Lund & O'Brien, 2011; Simon et al., 2015) because of their weak immune systems: their immune systems are still developing or weakened. In terms of occupational perspective, different work environments for farming can also influence immune system deficiency. Farmworkers are often exposed to hazardous chemicals such as pesticides, disinfectants, and air pollutants (CDC, 2018), and their exposure level varies depending on the work environment. For example, farmworkers in large animal confinement buildings are more likely to experience a higher level of those hazardous substances including chemicals and air pollutants than small-sized farmers are. Also, the work environment of employees in the processor sector is more likely to satisfy higher standards for hygiene than the work environment of employees in the producer sector. There is evidence that a poor work environment in the agriculture sector can lead to immune system deficiency (Rein, 1992; Schenker et al., 1998).

[1] The aggregated annual cost difference is originated from the different number of pathogens and valuation methods that two studies have applied.

This paper addresses the question of how the characteristics of the agriculture work environment affect risks associated with foodborne illnesses (regardless of where the infectious agriculture productions are produced and/or processed). For dependent variables to measure risks relevant to foodborne illness, we utilize state-level data taken from the CDC's National Outbreak Reporting System (NORS) database. As independent variables to characterize the agriculture work environment, U.S. Bureau of Economic Analysis (BEA) Personal Income data, especially Farm Income and Expenses is employed. By capturing the characteristics of the input costs pattern (e.g. proportion of feed expense), we indirectly measure the intensity indicator of agriculture production (ratio of feed costs over livestock sales). The basic idea for the employed intensity indicator is that the ratio of feed costs over livestock sales is higher if the intensity of livestock farming is higher. For instance, confined livestock farming (intensive livestock farming) is more likely to require more feed than grazing livestock (extensive livestock farming). Also, processing sectors are more likely to require labor more compared to the producer sector in the agriculture industry. (Nolte & Ostermeier, 2017; Morris et al., 2009). Based on the distinction, labor expenses/total costs are employed to figure out the relative composition of each sector in the agricultural industry. Using our panel data across 51 states from 1998 through 2018, fixed-effects linear regression models and the double hurdle model introduced by Cragg (1971) are employed.

Intensive Farming and Immune System

Organic dust–an aggregate of air-suspended particles sourced from plants and animals–is a major air pollutant within intensive livestock farming workplaces (Basinas et al., 2015) and repetitive organic dust exposures can cause various respiratory chronic disease and reduction in lung function, especially in large animal farming environments (May et al., 2012; Poole & Romberger, 2012). Also, several studies found that the intensive livestock farm emissions such as high level of organic dust may affect not only the respiratory health of farmers but also neighboring residents (Schulze et al. 2006; Borlee et al., 2017; van Dijk et al., 2017). The findings of those studies are consistent with the argument that continuous exposure to concentrated animal feeding operations can dampen innate immune responses (Sahlander et al., 2012).

Also, more intensive animal husbandry leads farm employees to be exposed to many types of antibiotics as well as animal diseases transmittable to humans. Consequently, the prevalence of antibiotic resistance in animal farms and the surrounding environment has been extensively reported. (Alam & Zurek, 2004; Schmid et al., 2013; Hille et al., 2017; Markland et al., 2019) Although the occurrence of antibiotic exposure is possibly naturally happening in some cases, intensive animal farming is a primary contributor to the increased environmental burden of antibiotic-resistant genes (Hille et al., 2017; Li et al., 2019; Ma et al., 2019). Intensive livestock farming may increase the odds that agricultural workers and neighboring residents are exposed to germs exposed to antibiotics and/or animal diseases transmittable to humans from animals (Support how feed can increase the occurrence of a foodborne outbreak) which impact their immune system adversely.

In general, a single species of livestock is raised in intensive livestock farming for productivity. The limited biodiversity can lead to the abundant occurrence of animal diseases which can be transmitted to humans. Morand (2020) found a positive relationship between the number of infectious and parasitic diseases recorded in humans and the total number of animal species. It concluded that outbreaks of human infectious diseases are linked to limited biodiversity.

Different Work Environment by Agriculture-related Sector

As a diverse industry that includes multiple occupational and environmental exposures and widely varying work (Kirkhorn & Garry, 2000), the food industry consists of four sectors: the farm service sector; the producer sector; the processor sector; and the marketer sector. From an epidemiological and industrial hygiene perspective, the processor sector is more likely to maintain the hygiene level of their workplace strictly than the producer sector does. Therefore, poor hygiene conditions in the producer sector can contribute to a weakened immune system among farmers.

Factors relevant to foodborne illnesses

A robust body of literature has dealt with factors affecting the occurrence of foodborne illnesses. Many studies investigated various agents that contaminate food: germs (bacteria, viruses, and parasites), chemicals, and toxins (Scallan et al.,2011; Geissler et al., 2017; Marsh et al., 2018 among others). Scallan et al. (2011) revealed the main etiology, cause of disease, is norovirus which accounts for 58% of foodborne illnesses while nontyphoidal salmonella spp. is the leading cause of foodborne-related severe outcomes (hospitalizations and deaths), 35% and 28% respectively.

Transmission method and food vehicle is another focus on research of foodborne illnesses (Harvey et al., 2016; Barrett et al., 2017; Chai et al., 2017; Marus et al., 2019). For example, Marus et al. (2019) investigate how *Salmonella* can be transmitted to humans via animal contact as well as food and characterize two results of outbreaks related to food transmission and outbreaks related to animal contact transmission. Barrett et al. (2017) found that scombrotoxin and tuna are more responsible etiology-fish pairs for outbreaks and hospitalizations.

The setting of exposure was also investigated by some studies (Gould et al., 2013; Angelo et al., 2017; Marlow et al., 2017). Marlow et al. (2017) investigated the epidemiology of foodborne outbreaks in correctional institutions. They found that the annual median number of outbreak-relevant illnesses per 100,000 population in correctional institutions is higher than the number in other places, which represent a disproportionate number of outbreak-associated foodborne illnesses. However, there is a limited number of studies that illustrate how host factors such as the immune system are related to risks associated with foodborne illnesses.

This paper contributes to explain the impact of the host factors on the risks associated with foodborne illnesses. To our best knowledge, it is the first study to focus on the influence of host factors affecting the risks of foodborne illness, immune status, in an agricultural setting. Since the proportion of disease transmitted by food differs by host factor, especially the immune system (Scallan et al., 2011), it can help model risks associated with food-related illness more accurately. Another contribution is the use of extensive datasets that allows empirical analysis over wider geographical regions (51 states) and a longer period (21 years). In addition, a better understanding of the factors associated with widespread food-related illnesses is critical to the development of effective management and risk mitigation mechanisms. Considering the growing interest in food liability insurance, the findings of this study can provide a better understanding of factors associated with disease outbreaks with both insurer and the insured. Lastly, the result offers some insights into how to allocate public healthcare resources efficiently by estimating the frequency of foodborne outbreaks based on the characteristics of residents.

Conceptual Framework

This study's conceptual framework focuses on the measurement method of different work environments by input cost patterns. A large body of immunology studies confirms that a poor agricultural work environment (e.g., intensive livestock farming and producer sector with a low hygiene standard) can weaken an immune system that farmworkers and neighboring residents have. Therefore, the accurate indicator of the work environment using agricultural input patterns is key to estimate the immune system of residents and, as a result, the likelihood of foodborne illnesses. In this analysis, we integrate findings of immunology studies and insights into economic analysis so that we can properly measure the host factor (status of the immune system) which is closely related to the likelihood of foodborne illness incidence (Figure 1).

Figure 1. Diagram of Conceptual Framework

Feed and Livestock Intensity

According to the classification of World Census of Agriculture (WGA) 2020, there are three main types of livestock (farm) systems of the holding: the grazing system; the industrial system; the mixed system. The grazing system is characterized by livestock grazing mainly on grasses and other plants. In this system, more than 90% of the dry matter fed to animals comes from grazed grasses. On the other hand, the industrial system refers to intensive livestock farming in which the majority of the animal feed is off-farm produced. Note that in the industrial system a single species of animal is raised and fed in feedlot or other in-house feeding systems (Moss et al., 2016).

The most common indicators in terms of grassland are cattle grazing or grazing intensity (livestock units per day of grazing per ha and year) and the ratio of livestock heads, which also linked to concentrated food for cattle (Caviglia-Harris, 2005; Temme and Verburg, 2011; Egorov et al., 2014; Teillard et al., 2012; Allan et al., 2014). The indicators can also measure the intensity of livestock farming in the grazing system.

By borrowing the idea of the livestock intensity measurement in the grazing system, we can measure livestock intensity in the industrial system by feed consumption. The feed costs per livestock share are higher in area A if the proportion of intensive livestock farming is higher in area A.

Labor-intensive Processor Sector

In the agriculture industry, the producer sector and processor sector have a distinctive level of labor intensity. Nolte & Ostermeier (2017) found that the processor sector is labor-intensive compared to the producer sector using wage data. Also, Morris et al. (2009) confirmed that commercial agriculture can generate a large number of jobs in off-farm operations, such as processing and packaging jobs. Thus, the labor cost share (farm labor expenses/total costs) is higher in area A if the proportion of the processor sector in the agricultural industry is higher in area A.

Along with conceptual predictions, our hypothesis is the following:

Work environment condition measured by two proposed indicators influences the likelihood of foodborne illness incidence.

Data Description

Centers for Disease Control and Prevention (CDC) data

In this article, Centers for Disease Control and Prevention (CDC) National Outbreak Reporting System dataset (NORS) is utilized to measure risks associated with food-related illnesses. Since

1971 CDC has collected various types of reported outbreaks. (e.g., Foodborne, Waterborne, Animal Contact, Environmental, Person to Person) According to CDC, a foodborne outbreak is defined as, “an incident in which two or more persons experience a similar illness resulting from the ingestion of a common food.” In the CDC outbreak data, we utilize the number of reported illnesses, hospitalizations, and deaths for each outbreak in addition to the primary mode of transmission and etiology (Table 1). In terms of the primary mode of transmission, this analysis focuses on foodborne outbreaks which have “Food” as a primary mode of transmission. And this analysis includes all types of etiology including unknown etiology. In our analysis, the CDCNORS dataset includes 21,307 reported foodborne outbreaks in 51 states from 1998 through 2018. We aggregate by year and geographic area (state). Outbreaks can geographically divide into two groups: single-state outbreaks and multistate outbreaks. In single-state outbreaks, exposures to the source of the outbreak (e.g., food, water, animal) occur in a single state. However, it occurs in multiple states in case of multistate outbreaks. We drop multistate outbreaks which account for 2.26% (497 foodborne outbreaks). To make the data balanced, we add zeros if a foodborne outbreak in a state was not reported in a year. For example, if a foodborne outbreak in North Carolina was not reported in 2017, the number of illnesses, outbreaks, hospitalizations, deaths relevant to the foodborne outbreak are zeros. Rather than counts of incidences (e.g., the number of illnesses), their ratio (e.g., the number of illnesses per 1million population) is more relevant to the model because the ratio can adjust the scale effect. For example, one death in a state with high resident populations is a different meaning to one death in a state with low resident populations. Although the CDC NORS data is comprehensive and collective data, it has some limitations. First, it covers only a part of reported illnesses that are identified as relevant to outbreaks. Also, it is possible for outbreaks to be underreported because reporting to CDC is voluntary.

U.S. Bureau of Economic Analysis (BEA) Personal Income data, Farm Income and Expenses

To investigate how farm expenses would affect risks associated with foodborne-related illness, the BEA personal income data is employed, especially the farm income and expenses. To be specific, the following input costs are used: labor, feed, and seed expenses (Table 1). In the appendix, an extensive list of independent variables can be found. Note that for the comparison purpose, seed cost per crop sales is included which is comparable to feed cost per livestock sales.

Table 1. Summary of Dependent and Independent Variables Used in the Empirical Model (N=1,071)

Models Empirical Specification and Estimation Strategy

To empirically test the conceptual prediction (or equivalently estimate the impact of agricultural work environment on risks associated with food-related outbreaks), we first utilize a panel linear regression model (PLM) with fixed effects:

$$FoodRisk_{it} = \beta_1 Main_{it} + \beta_2 X_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

where $FoodRisk_{it}$ is the food-related risk in state i in year t. In our data, the following four relative variables measure the food-related risk: Illness; Hospital; Outbreak; $Main_{it} = (Labor_{it}, Feed_{it})$ is a 1×2 vector of independent variables that includes two measurements of agriculture work environment: labor expenses per total sales (Labor); and feed expenses per livestock sales (Feed); $X_{it} = \left(X_{it}^1, \dots, X_{it}^k\right)$ is a 1×k vector of time-varying covariates that include the proportion of age groups with the weak immune system(Age under five or over 65) $WeakAge_{it}$; α_i is the state fixed effect to capture the unobservable time-invariant state variations such as demographic characteristics or health conditions; γ_t is the year (or time) fixed effects to capture annual characteristics that affect food-related disease occurrence; β_1 is the parameter to be estimated (with β_1 as our main coefficient of interest); and ε_{it} is the idiosyncratic error term.

Since one of our dependent variables, death has a large number of zeros (87.4%. For detail, see Table 1 and Figure 2), Cragg's Double Hurdle model (DH) is employed which is initially proposed by Cragg(1971) to address the issues associated with excessive zeros. DH model combines two models (hurdles):

1. Selection Model: binary model (e.g., probit) to predict zeros
2. Outcome Model: Truncated (at zero) normal model to predict a nonzero dependent variable

Figure 2. Histogram of Dependent Variables

The selection model (probit model) determines the boundary points of the dependent variable. It judges whether the hurdle can be cleared (dependent variable>0) or not (dependent variable=0). The outcome model (linear/exponential regression model with (truncated) normal distribution) determines its nonbounded values (dependent variable>0). Therefore, the second model determines the value of the outcome conditional on having cleared the hurdle. For example, one of our dependent variables is the number of outbreaks in state *i* at year *t*. The hurdle model can be characterized by the relationship

$$y_{it} = s_{it} h_{it}^*$$

where y_{it} is the observed number of outbreaks at state *i* at year *t*. s_{it} is a selection variable and h_{it}^* is a continuous latent variable. The selection variable (s_{it}) is 1 if the dependent variable is not bounded and 0 otherwise. If the lower limit that binds the response variable y_{it} is zero, the selection model is given by

$$s_{it} = \begin{cases} 1 & if\ z_{it}\gamma + \varepsilon_{it} > 0 \\ 0 & otherwise \end{cases}$$

where z_{it} is a vector of explanatory variables with a vector of their coefficients γ and ε_{it} is a standard normal error term.

Also, the continuous latent variable h_{it}^{*} is observed only if $s_{it} = 1$. The outcome model can be either the linear model or exponential model:

Linear model: $h_{it}^{*} = x_{it}\beta + e_{it}$ or Exponential model: $h_{it}^{*} = exp(x_{it}\beta + e_{it})$

where x_{it} is a vector of explanatory variables to predict non-zero dependent variables with a vector of their coefficients β and e_{it} is an error term. For the linear model, e_{it} has a truncated normal distribution with lower truncation point $-x_{it}\beta$. For the exponential model, the error term has a normal distribution. It does not necessary that explanatory variables for two models z_{it} and x_{it} are the same. That is the key distinction between Cragg's model and Tobit's (for corner-solution) model. The key limitation to the Tobit model is that the probability of a positive value and the actual value is determined by the same underlying process, the same parameters (Burke, 2009).

In the double hurdle (DH) model, the identical covariates are used in both selection and outcome model: $(Labor_{it}, Feed_{it}, WeakAge_{it})$ with time and state fixed effects.

Results and Discussion

Table 2 shows estimate results from two specifications for four dependent variables (*Illness, Hospital, Death, Outbreak*) using data that covers 51 states over 21 years. We begin by employing base model specification that includes *Labor* (Labor expenses/Total cost) and *Feed* (Feed costs

/Livestock sales) with two fixed effects. In all models except 4b, the signs of coefficients on *Labor* are negatives for all food-related risks which is for a priori expectation. If the share of labor cost (*Labor*) increases by 0.1 (10 %p), the number of illnesses per 1 million population is likely to be reduced by 51.5 using model (1a) estimates. However, the coefficients of *Labor* are only significant when illness and hospital are employed as dependent variables. Also, the signs of *Feed* coefficient are consistent with what we expected, positive. If the ratio of feed cost to livestock sales increases by 0.1 (10 %p), the number of illnesses per 1 million population is likely to increase by 11.9 using model (1a) estimates. The more intensive livestock farming in the region, the higher probability of getting foodborne illness its residents might experience. The significance of Feed coefficient varies depending on dependent variables. Relatively, four different dependent variables represent risks associated with foodborne illness at different severity level. *Death* shows the most severe cases followed by *Hospital, Illness,* and *Outbreak.* Considering the different severity levels of cases, *Feed* becomes significant when cases are involved in relatively mild symptoms while *Labor* in severe symptoms.

When the demographic variable (*Weak Age*) is introduced, the signs, magnitudes, and significances of most regressor variables are restored. In general, *Weak Age* representing the proportion of age groups with weak immune system has a positive coefficient which shows how people with weak immune system increases the probability of foodborne illness. For the robustness check, double hurdle model specification is employed and results with DH model are consistent with results with PLM model.

Table 2. Regression Results, Panel Regression with Fixed Effects

Table 3. Regression Results, Double Hurdle Model with Fixed Effects

Conclusion

In this article, we show the influence of agriculture work environment conditions on foodborne-relevant risks using state-level CDCNORS and BEA data. The results demonstrate that poor agriculture work environment condition causes higher risks of foodborne illness at different levels: outbreak; illness; hospitalization; death. Notably, intensive livestock farming practice and relaxed standards for hygiene increase the probability of residents getting sick of foodborne illness.

However, this paper has several limitations. First, our dependent variables measuring foodborne-associated risks are in terms of the entire residents at state-level while our independent variables indicating the different agricultural work environment is related to farmers and neighboring residents. If our observations are agriculture producing counties, the relationship might be clearer. Our analysis can be developed with lower geography level data (e.g., county-level data).

Also, CDCNORS data provide limited information in terms of foodborne illness incidence. Among estimated 48 million foodborne illnesses, only a small proportion of illnesses is reported and identified as associated with foodborne outbreaks. Also, the definition of foodborne outbreak that CDC applies makes it harder to distinguish between zero illness due to nonexistence of foodborne illness and due to nonexistence of reported and confirmed foodborne illness. Even if the foodborne illness happens in state A, it is possible for state A to have zero illness because either it is not reported or identified.

This paper improves on previous analysis of how foodborne illness incidence is influenced by host factor (immune system) which is limitedly investigated as a factor of foodborne illness. An understanding of the factors associated with widespread food-related illnesses is critical to the development of effective management and risk mitigation mechanisms. The issue of insurance protection from the economic losses that may be associated with outbreaks has become increasingly important. The restaurant and prepared food sectors have an obvious risk of liability for alleged outbreak-related illnesses. However, there are other less obvious but equally important businesses that face the risk of an outbreak that could be tied to their farm, farmers' market, truck patch market, and similar such business. Insurers have an essential need to understand factors associated with disease outbreaks. Our findings offer insight about food product liability insurance market, such as its potential and economic benefits.

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Tables and Figures

Table 1. Summary of Dependent and Independent Variables Used in the Empirical Model (N=1,071)

Category	Variable	Variable Description	Mean	Std.dev	Min	Max	N of Zeros
Food Risk	Illness	Number of primary cases with illness/1million population	72.38	103.49	0.00	1951.71	63 (5.9%)
	Hospital	Number of primary cases hospitalized/1million population	2.29	3.66	0.00	53.94	222 (20.7%)
	Death	Number of primary cases died/1million population	0.04	0.19	0.00	3.20	934 (87.2%)
	Outbreak	Number of outbreaks/ 1million population	3.56	4.22	0.00	51.24	63 (5.9%)
Farm Input Cost	Labor	Hired farm labor costs/total costs	0.13	0.09	0.00	0.44	21 (2.0%)
	Feed	Feed purchased/livestock sales	0.27	0.11	0.00	0.93	21 (2.0%)
Demo-graphic	Weak Age	Population over age 65 or under age 5 /Total population	0.20	0.02	0.13	0.26	0 (0%)

Table 2. Regression Results, Panel Regression with Fixed Effects

Dependent Variable	Illness		Hospital		Death		Outbreak	
Model	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Labor	-515.2***	-538.9***	-20.04***	-20.56***	-0.340	-0.459	-0.216	3.056
	(-2.71)	(-2.80)	(-2.83)	(-2.86)	(-0.88)	(-1.18)	(-0.03)	(0.48)
Feed	119.4**	118.8**	0.720	0.684	0.125	0.103	7.637***	8.377***
	(2.18)	(2.16)	(0.35)	(0.33)	(1.13)	(0.93)	(4.14)	(4.56)
Weak Age		383.0		8.280		3.003**		-84.44***
		(0.57)		(0.33)		(2.19)		(-3.75)
Intercept	148.0***	77.93	4.498***	3.015	0.0320	-0.535**	2.328**	18.30***
	(4.78)	(0.59)	(3.90)	(0.62)	(0.51)	(-2.01)	(2.23)	(4.18)
N	1071	1067	1071	1067	1071	1067	1071	1067
AIC	12753.7	12708.1	5706.6	5690.8	-528.0	-525.1	5491.3	5450.6
BIC	12868.1	12827.5	5821.1	5810.2	-413.6	-405.8	5605.8	5569.9
R^2	0.222	0.223	0.135	0.134	0.0663	0.0707	0.470	0.480
Adj R^2	0.166	0.166	0.0722	0.0706	-0.00109	0.00238	0.431	0.442

Notes: All columns include state and year fixed effects. T statistics are shown in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Table 3. Regression Results, Double Hurdle Model with Fixed Effects

Dependent Variable	Illness		Hospital		Death		Outbreak	
Model	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Outcome Model (Truncated Normal Model), Average Marginal Effects								
Labor	-	-515.5***	-13.96***	-14.23***	-0.0654	-0.0710	-13.06***	-12.11**
	-	(-3.74)	(-2.90)	(-2.91)	(-0.21)	(-0.23)	(-2.72)	(-2.54)
Feed	-	80.38**	2.148	2.085	0.109	0.0946	4.161***	4.599***
	-	(2.08)	(1.57)	(1.52)	(1.19)	(1.03)	(3.04)	(3.38)
Weak Age	-	-254.8		5.318		1.439		-37.97**
	-	(-0.55)		(0.30)		(1.27)		(-2.34)
Selection Model (Probit Model), Coefficients								
Labor	-31.60***	-35.41***	-6.549*	-6.544*	0.601	0.371	-31.60***	-35.41***
	(-3.35)	(-3.62)	(-1.93)	(-1.91)	(0.15)	(0.09)	(-3.35)	(-3.62)
Feed	-3.599	-3.568	1.754*	1.815*	0.472	0.290	-3.599	-3.568
	(-1.54)	(-1.52)	(1.75)	(1.79)	(0.41)	(0.24)	(-1.54)	(-1.52)
Weak Age		32.79*		-1.011		18.98		32.79*
		(1.79)		(-0.09)		(1.28)		(1.79)
N	1071	1067	1071	1067	1071	1067	1071	1067
AIC	8828.3	8824.3	2486.6	2487.1	310.9	313.0	2295.4	2263.8
BIC	9475.3	9565.2	3218.1	3228.0	987.7	999.2	3027.0	3004.7

Notes: All columns include state and year fixed effects. T statistics are shown in parenthesis. In model 1a, the outcome model result is omitted because the variance matrix is nonsymmetric or highly singular. * p<0.1, ** p<0.05, *** p<0.01.

Figure 1. Diagram of Conceptual Framework

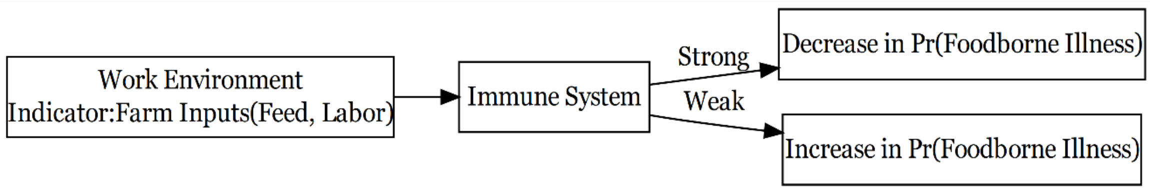

Figure 2. Histogram of Dependent Variables