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RESEARCH ARTICLE

Contaminated water and the Food Safety Modernization Act

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Abstract
We develop a theoretical framework and present a corresponding empirical analysis of the Food and Drug Administration's irrigation water quality regulatory standard under the Food Safety Modernization Act using lettuce as a case study. We develop a stochastic price endogenous partial equilibrium model with recourse to examine the standard's efficacy under various scenarios of foodborne illness severity, standard implementation, demand response to foodborne outbreaks, and irrigation costs. The stringency of regulation is evaluated with endogenous producer response to regulatory requirements and corresponding implications for economic surplus. The baseline results show that in the case of the lettuce market, the proposed microbial irrigation water quality regulation in the Food Safety Modernization Act (FSMA) is not cost effective relative to the existing Leafy-Greens Marketing Agreements relying on water treatment for mitigation of microbial contamination. However, FSMA can be cost effective if water treatment is sufficiently expensive.

Keywords: foodborne illness; Food Safety Modernization Act; food safety regulation; irrigation; partial equilibrium; water quality

JEL Classification: D61; D78; Q11; Q18

Introduction

Food safety is a critical public health concern for consumers and producers (Bellemare and Nguyen 2018; Bar and Zheng 2019; Ollinger and Bovay 2020). Despite the economic significance of foodborne diseases and reoccurring illnesses from the consumption of fresh fruits and vegetables, there is a lack of studies on the economic efficiency of ex-ante prevention of food contamination in the fresh produce sector. Nevertheless, in response to numerous foodborne disease outbreaks, the Food Safety Modernization Act (FSMA) was enacted in 2011 to improve food safety and prevent foodborne illnesses, particularly in fresh fruits and vegetables.[1] Pursuant to FSMA, the Food and Drug Administration

[1]The final FSMA rule went into effect in 2016 (the U.S. Food and Drug Administration 2020).

(FDA 2014) proposed preventative standards for growing, harvesting, packing, and storage of fresh produce intended for human consumption without processing. According to the FDA, irrigation carries a significant risk of introducing pathogens to the fresh produce supply. Therefore, regulating irrigation water quality is prioritized for foodborne disease prevention (FDA 2012a). The FDA rules require periodic testing of irrigation water and restrict the use of water that exceeds the maximum allowable number of colony-forming units (CFU) of *Generic E. coli* as an indicator microorganism.[2]

According to the FDA's FSMA regulation, if a) the statistical threshold value (STV) of *E. coli* exceeds 410 or b) the moving geometric mean (GM) exceeds 126 CFU per 100 ml of water from any five consecutive irrigation surface water samples or one groundwater sample, then irrigation from the contaminated sources should cease unless water is treated, or harvest should be delayed allowing for microbial die-off (FDA 2014). Growers can delay harvest for up to four days to allow for the die-off of pathogens. The produce that is out of compliance based on half-log reduction of *E. coli* CFUs after four days must be discarded.

FSMA rules overlap with the Leafy-Greens Marketing Agreement (LGMA) program, adopted in 2007 in response to the 2006 *E. coli* outbreak linked to spinach. Like FSMA, LGMA aims to protect public health by decreasing foodborne illnesses from leafy greens. The food safety practices in LGMA include environmental assessments, water testing and recordkeeping, soil amendments, worker practices, and field sanitation. LGMA includes shippers and sellers in California and Arizona, who deliver roughly 90% of leafy greens in the U.S. (California Leafy-Greens Marketing Agreements 2022). LGMA irrigation water quality standard is based on a rolling geometric mean of *Generic E. coli* from five samples. However, if less than five samples are taken before irrigation, the maximum acceptance criteria depend on the number of samples. If only one sample has been collected, *Generic E. coli* must be less than or equal to 126 CFU/100 ml. If the acceptance criterion is exceeded, two samples must be taken, and a geometric mean should be below 126 CFU/100 ml.

Although FSMA and LGMA have similar testing and microbial water quality requirements, there are also some differences. FSMA standard allows more choices as remedial action relative to LGMA. The remedial actions under FSMA include treating contaminated water, delaying harvest, or extending the period between harvest and storage to allow for microbial die-off. The LGMA requires treating irrigation water to continue production. LGMA requires monthly testing, while FSMA requires a minimum of five (one) samples for untreated surface (ground) irrigation water. Finally, LGMA requires testing water that is either directly or indirectly applied to the produce, while FSMA requires testing only directly applied water (Calvin et al. 2017).

Several studies have examined the FSMA rule. Using an equilibrium-displacement model, Ferrier et al. (2018) estimate that FSMA increases consumer fruit and vegetable prices by 0.49% and 0.14%, respectively. Also, FSMA decreases vegetable and fruit producers' welfare by 0.59% and 0.86%, respectively. Bovay and Sumner (2017) also use an equilibrium-displacement model to show that wholesale tomato prices increase by up to 2.4% if demand for safer produce rises relative to the scenario with more foodborne outbreaks and no FSMA. Bovay (2017) uses GAP (Good Agricultural Practices) standards to estimate the likely effects of FSMA on demand for tomatoes from Florida and California and finds that GAPs do not increase demand for fresh tomatoes. Hence, FSMA is not likely to increase demand for fresh produce, which implies reduced farmer profits because a price

[2]*Generic E. coli* is found in more than 90% of human and animal feces and in non-fecal sources (FDA 2014). Many irrigation water sources in the Western U.S. exceed the FDA standards for *E. coli* (Dadoly and Michie 2010).

increase does not offset FSMA regulation costs. In addition, prior studies also showed that, due to scale economies, small farms are disproportionately burdened by FSMA costs (Lichtenberg and Page 2016; Bovay and Sumner 2017; Adalja and Lichtenberg 2018; Bovay et al. 2018).

Our objective is to evaluate the economic merits of the FSMA irrigation water quality regulation as an ex-ante control strategy for foodborne disease in the lettuce market. A theoretical model is developed as a framework for the analysis. Conditions for optimal microbial water quality regulatory stringency are derived as a function of water scarcity, regulation costs, illness severity, and illness prevention efforts of distributors and consumers. Next, the optimality conditions are examined empirically using lettuce as a case study. The FDA rule is examined relative to the existing LGMA guidelines.

The empirical model integrates a dose–response formulation (Lichtenberg 2010; Pang et al. 2017) in a stochastic two-stage partial equilibrium framework (Dantzig 1955; Lambert et al. 1995) with recourse. In such models, stage one decisions are made before the stochastic state of nature is revealed. Stage two activities take place after the stochastic state of nature is revealed and are conditional on the decisions made in stage one. In the first stage, before the stochastic irrigation water quality is revealed, farmers make planting and irrigation decisions for the upcoming growing season. In the second stage, water treatment and harvest activities are subject to the FSMA guidelines on the acceptable microbial quality of irrigation water and harvest delay.

The objective function maximizes consumer and producer surplus minus illness costs and costs of standard implementation. This approach extends the FDA (FDA 2014) cost/benefit (CBA) analysis by explicitly accounting for producer and consumer surplus changes. The constraints include demand and supply balance, land use restrictions, stochastic water quality equations, yield and irrigation relationships, harvest, water treatment, storage delay constraints reflecting STV and GM standards, and illness dose–response specifications.

We use lettuce as a case study for several reasons. First, all lettuce is consumed fresh without processing. As such, lettuce is one of the primary targets of FSMA regulation. Second, lettuce is highly perishable. Hence, delay in harvest as a response strategy mandated by FSMA can have significant implications for supply and profitability. Third, several recent severe foodborne disease outbreaks have been traced to contaminated lettuce. For example, according to the Centers for Disease Control and Prevention (CDC), in June 2018, an outbreak of *E. coli* was traced to romaine lettuce irrigated with contaminated water that affected 210 people in at least 36 states with 96 hospitalizations and 5 deaths (CDC 2018). In January 2019, another *E. coli* outbreak was linked to romaine lettuce with 167 cases, including 85 hospitalizations (CDC 2020, 2019).

This study contributes to prior literature with an economic evaluation of ex-ante food contamination prevention in the fresh produce sector, focusing on the lettuce market as a case study. We provide a theoretical framework and develop a stochastic partial equilibrium model to examine the stringency of microbial irrigation water quality standard. To our knowledge, this paper is first to examine the food safety-related irrigation water quality standard as proposed by the FDA using an economic framework that includes consumer and producer surplus and a detailed pathogen exposure and dose–response formulations. The results shed new light on the merits of additional regulatory requirements and examine the sensitivity under various parametric assumptions.

Theoritical framework

The regulator's problem is to maximize social welfare (SW) in terms of consumer and producer surplus minus the cost of irrigation, expected damages from foodborne illnesses due to water contamination, and cost of implementing water quality standard with respect to irrigation w and water quality standard (θ). The notation is summarized in Table A.1.

$$\max_{\theta,w} SW = \int_0^X P(X(w),\theta)dX - cw -$$

$$\left[\int_0^\theta S(\mu, X(w);\alpha)f(\mu)d\mu + S(\theta, X(w);\alpha)\int_\theta^z f(\mu)d\mu\right] - R(\theta;\beta) \quad (1)$$

where SW is the social welfare and $P(X(w), \theta)$ is the inverse demand for fresh produce X and water quality standard (θ). $X(w)$ is the production function of X in terms of irrigation w. $S(\mu, X(w);\alpha)$ is the monetary value of damages from foodborne illnesses as a function of water quality μ, consumption X, and consumer and producers prevention efforts α. $f(\mu)$ is probability distribution of water quality with low (high) values of μ corresponding to better (worse) microbial quality, $\mu \in \{0: z\}$ (Figure A.1, top panel). Water quality is stochastic because farmers are not able to accurately forecast water quality without testing shortly before each irrigation. Therefore, after planting decisions are made, the quality of water used for irrigation during the growing season is random. $R(\theta;\beta)$ is the cost of implementing the water quality standard with β as the shift parameter. c is the cost of irrigation water. The term in the square brackets is the expected damage from foodborne illnesses.

The water quality standard (θ) truncates the left tail of water quality distribution. If microbial water quality is poorer than the regulatory standard ($\mu \geq \theta$), then foodborne illness damages are expressed in terms of θ because the regulatory standard truncates microbial contamination of water, ensuring that microbial content does not exceed θ (second term in the square brackets). On the other hand, if water contamination does not exceed the regulatory standard, $\mu < \theta$, then the observed damages depend on the actual water quality μ (first term in the square brackets) (Figure A.1).

The first-order conditions with respect to water quality standard and irrigation (equations A.1 and A.2) lead to the following propositions (derivations in Appendix A, equations A.3–A.17):

a) *An increase in the opportunity cost of irrigation water decreases water use and optimal regulatory efforts, i.e.,* $\frac{\partial\theta}{\partial c} \geq 0$ *and* $\frac{\partial w}{\partial c} \leq 0$.

Costly irrigation water (e.g., corresponding to greater water scarcity or more expensive irrigation) decreases production. Thus, expected illness damages decrease, while the marginal benefit of output increases. Hence, the optimal microbial water quality standard is less stringent.

b) *Assuming substitution,* $S_{\theta\alpha}<0$ *(complementary,* $S_{\theta\alpha}>0$*) between regulatory stringency and prevention efforts by consumers and distributors greater prevention efforts by consumers and/or distributors have ambiguous effects on (increase) stringency of water quality standard and ambiguous effect on (increase) water use,* $\frac{\partial\theta}{\partial\alpha} = ?$ *and* $\frac{\partial w}{\partial\alpha} = ?0$ ($\frac{\partial\theta}{\partial\alpha} \leq 0$ *and* $\frac{\partial w}{\partial\alpha} \geq 0$).

Substitution ($S_{\theta\alpha}<0$) implies that marginal productivity of regulation decreases with greater consumer prevention. On the other hand, complementarity ($S_{\theta\alpha}>0$) implies that marginal productivity of regulatory standard stringency is enhanced as consumers' and distributors' efforts increase. In the context of irrigation water contamination and associated foodborne illness, substitution is more plausible, and the theoretical result shows an ambiguous effect of greater consumer and distributor efforts on optimal stringency and irrigation. The effect depends on the relative magnitudes of changes in marginal benefits of standard stringency versus the marginal benefits of irrigation as consumers' and distributors' efforts change.

c) *Increasing implementation costs result in a less stringent optimal standard and lower water use, i.e.,* $\frac{\partial \theta}{\partial \beta} \geq 0$ *and* $\frac{\partial w}{\partial \beta} \leq 0$.

Greater marginal costs of regulation result in less stringent standards, which increases expected damages from foodborne illness. Hence, irrigation and production decrease to balance marginal benefits of lettuce consumption and marginal damages from expected illness.

Empirical model

The empirical model uses a stochastic two-stage (Dantzig 1955) price endogenous partial equilibrium model with recourse. First-stage decisions include irrigation water quality standard stringency, planted acreage, and associated irrigation plans. In the second stage, after microbial water quality is revealed, producers can treat the contaminated water, stop irrigation, or delay harvest to allow for microbial die-off.[3] The objective function maximizes consumer and producer surplus minus aggregate costs of illness incidents and costs of implementing the regulatory standard. Variables, parameters, and their units are listed in Tables B.1 and B.2.

$$\begin{aligned} SW = \; & \frac{1}{N} * \sum\nolimits_{n,i} \left[\int p^d_{n,i}\left(\varpi_n * x^d_{n,i}\right) dx^d_{n,i} - \int p^s_{n,i}\left(x^s_{n,i}\right) dx^s_{n,i} \right] - \delta * \frac{1}{N} * \sum\nolimits_n ill_n \\ & - \varsigma * \sum\nolimits_{i,f,ct,ws,g,r} a'_{i,f,ct,ws,g,r} \\ & - \sum\nolimits_{i,f,ct,ws,g,r} \left\{ \left(M_{f,GM} - \xi_{f,GM} * \theta_{GM}\right) + \left(M_{f,STV} - \xi_{f,STV} * \theta_{STV}\right) \right\} * a'_{i,f,ct,ws,g,r} \\ & - \frac{1}{N} * \sum\nolimits_{n,i,f,ct,ws,g,tr,r} MT_f * a''_{n,i,f,ct,ws,g,d0,tr,r} \end{aligned} \tag{2}$$

where SW is the social welfare. $p^d_{n,i}\left(\varpi_n * x^d_{n,i}\right)$ and $p^s_{n,i}\left(x^s_{n,i}\right)$ are inverse demand and supply functions, respectively. The demand functions include cross-price effects to allow for substitution in the demands for two lettuce types (Leaf Romain and Head). $x^d_{n,i}$ and $x^s_{n,i}$ are quantities of demand and supply of lettuce type i in state of nature n. The expression in the square bracket is the area between demand and supply curves, representing consumer and producer surplus and includes negative demand response to foodborne outbreaks, ϖ_n as a function of the number of foodborne illnesses (see Appendix B). δ is the average cost per case of illness, and ill_n is the number of foodborne illnesses in each state of nature. ς is per acre cost of irrigation in addition to the baseline irrigation costs included in per acre

[3]Water quality is stochastic because farmers, irrigation districts, or regulators are not able to predict contamination of irrigation water with certainty unless the water is tested shortly before each irrigation. Water treatment decisions, like use of chemicals to neutralize pathogens, take place in the second stage, after microbial tests reveal the quality of irrigation water.

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marginal costs of production.[4] $a'_{i,f,ct,ws,g,r}$ is the ex-ante acreage of crop i, planted in county ct, farm type f (small and large), irrigated with water source ws (ground or surface), in production district[5] r, and irrigated g times during a growing season. The second to last term in the objective function is the cost of implementing the FSMA regulatory standard with $\xi_{f,GM}$ and $\xi_{f,STV}$ as marginal per acre cost and $M_{f,GM}$ and $M_{f,STV}$ the per acre cost of the most stringent regulatory standard such that any amount of detected *E. coli* requires discarding the affected produce. The last term provides LGMA compliance cost with $a''_{n,i,f,ct,ws,g,d0,tr,r}$ as the treated (tr) ex-post acreage of crop i harvested with 0 days of delay ($d0$). MT_f is the per acre cost of water treatment.[6] θ_{GM} and θ_{STV} are water quality standard based on GM and STV criteria, respectively. N is the number of states of nature (500). For the LGMA scenario, the second to last term in the objective function is zero.

The supply and demand balance is

$$x^d_{n,i} - x^s_{n,i} \leq 0 \qquad \forall n, i \tag{3}$$

The first-stage planting decisions are constrained by historical and synthetic crop mix acreages. These constraints (4 and 5) reflect county scale technological, managerial, and agronomic rotation requirements (McCarl and Spreen 1980; Schneider et al. 2007; Chen and Onal 2012; Elbakidze et al. 2012; Xu et al. 2022):

$$\sum_{f,ws,g,r} a'_{i,f,ct,ws,g,r} = \sum_t cmix_{i,ct,t} * \vartheta_{ct,t} + smix_{i,ct} * \tau_{ct} \forall i, ct \tag{4}$$

$$\sum_t \vartheta_{ct,t} + \tau_{ct} = 1 \ \forall ct \tag{5}$$

where $cmix_{i,ct,t}$ is the acreage of crop i (including two types of lettuce and total acreage of other vegetables) observed in year t in county ct; $smix_{i,ct}$ is the synthetic crop acreage.[7] $\vartheta_{ct,t}$ and τ_{ct} are choice variables that represent the percentage of acreage in county ct planted according to the proportions observed in year t or in the synthetic acreage estimate. Constraint (5) forces a convex combination of previously observed and synthetic planted acreages.

In the second stage, crop harvest delay and water treatment decisions are modeled according to the proposed FSMA and LGMA regulations, respectively. First- and second-stage acreage decisions are linked in equation (6), where a'' is second-stage acreage that varies across states of nature, (n), length of harvest delay (d), and water treatment (tr). On the other hand, first-stage acreage decisions do not vary across states of nature, delay in harvest, or water treatment. First-stage acreage decisions are made irrespective of states of nature, while second-stage water treatment and harvest delay decisions vary across states of nature. Acreage planted in the first stage limits the second-stage acreage choices. LGMA does not include harvest delay as a remediation option. Hence, for the LGMA scenarios,

[4]This parameter is zero in the baseline model and is used to examine the effects of greater water scarcity and irrigation costs.

[5]To limit dimensionality, Arizona's smallest producing counties are combined into one district. To allow for greater heterogeneity of water quality and to utilize available USGS water quality data, large counties including Yuma and Fresno are disaggregated into 9 and 7 districts, respectively.

[6]LGMA is the baseline standard, while FSMA rule new. Therefore, we are interested in cost-effectiveness of FSMA and do not consider costs of implementing LGMA.

[7]Synthetic crop mix is used for greater model planting flexibility than what would be implied by the historical crop mix. The synthetic planted acreage is estimated following the methodology presented in Chen and Onal (2012).

we assume that if water quality does not meet the standard, the remedial action will be to treat water (*tr*) with no delay in harvest (*d0*).

$$\sum_{d,tr} a''_{n,i,f,ct,ws,g,d,tr,r} = a'_{i,f,ct,ws,g,r} \qquad \forall n, i, f, ct, ws, g, r \tag{6}$$

Supply of crop i in state of nature n is constrained by the aggregate production, as a product of yield ($y_{i,ct,g,d,r}$) and acreage $a''_{n,i,f,ct,ws,g,d,tr,r}$ where ex_i represents net export for crop i.

$$x^s_{n,i} = \sum_{f,ct,ws,g,d,tr,r} a''_{n,i,f,ct,ws,g,d,tr,r} * y_{i,ct,g,d,r} - ex_i \forall n, i \tag{7}$$

Following the FSMA guidelines, equation (8) uses the GM and STV criteria to impose a delay in harvest of up to four days based on a 0.5 log per day microbial die-off (FDA 2014).

$$a'_{i,f,ct,ws,g,r} = \begin{cases} a''_{n,i,f,ct,ws,g,d_0,tr_0,r} & if \begin{cases} GM_{n,i,f,ct,ws,r} * 10^0 \leq \theta_{GM} \leq max \\ and \\ STV_{n,i,f,ct,ws,r} * 10^0 \leq \theta_{STV} \leq max \end{cases} \\ a''_{n,i,f,ct,ws,g,d_1,tr_0,r} + a''_{n,i,f,ct,ws,g,d0,tr_1,r} & if \begin{cases} GM_{n,i,f,ct,ws,r} * 10^{(-0.5)} \leq \theta_{GM} \leq GM_{n,i,f,ct,ws,r} * 10^0 \\ and \\ STV_{n,i,f,ct,ws,r} * 10^{(-0.5)} \leq \theta_{STV} \leq STV_{n,i,f,ct,ws,r} * 10^0 \end{cases} \\ a''_{n,i,f,ct,ws,g,d_2,tr_0,r} + a''_{n,i,f,ct,ws,g,d0,tr_1,r} & if \begin{cases} GM_{n,i,f,ct,ws,r} * 10^{(-1.0)} \leq \theta_{GM} \leq GM_{n,i,f,ct,ws,r} * 10^{(-0.5)} \\ and \\ STV_{n,i,f,ct,ws,r} * 10^{(-1.0)} \leq \theta_{STV} \leq STV_{n,i,f,ct,ws,r} * 10^{(-0.5)} \end{cases} \\ a''_{n,i,f,ct,ws,g,d_3,tr_0 r} + a''_{n,i,f,ct,ws,g,d0,tr_1,r} & if \begin{cases} GM_{n,i,f,ct,ws,r} * 10^{(-1.5)} \leq \theta_{GM} \leq GM_{n,i,f,ct,ws,r} * 10^{(-1.0)} \\ and \\ STV_{n,i,f,ct,ws,r} * 10^{(-1.5)} \leq \theta_{STV} \leq STV_{n,i,f,ct,ws,r} * 10^{(-1.0)} \end{cases} \\ a''_{n,i,f,ct,ws,g,d_4,tr_0,r} + a''_{n,i,f,ct,ws,g,d0,tr_1,r} & if \begin{cases} GM_{n,i,f,ct,ws,r} * 10^{(-2.0)} \leq \theta_{GM} \leq GM_{n,i,f,ct,ws,r} * 10^{(-1.5)} \\ and \\ STV_{n,i,f,ct,ws,r} * 10^{(-2.0)} \leq \theta_{STV} \leq STV_{n,i,f,ct,ws,r} * 10^{(-1.5)} \end{cases} \\ a''_{n,i,f,ct,ws,g,d_5,tr_0,r} + a''_{n,i,f,ct,ws,g,d0,tr_1,r} & if \begin{cases} \theta_{GM} \leq GM_{n,i,f,ct,ws,r} * 10^{(-2.0)} \\ and \\ \theta_{STV} \leq STV_{n,i,f,ct,ws,r} * 10^{(-2.0)} \end{cases} \end{cases}$$

$$\forall i, f, ct, ws, g, r \tag{8}$$

The FSMA regulatory standard (equation 8) requires: (1) θ_{GM} of 126 or less CFU per 100 ml of water, and (2) θ_{STV} of 410 or less CFU (FDA 2014). If either criterion is violated, farmers must cease irrigating from the contaminated source, delay harvest to allow for microbial die-off, or treat irrigation water (FDA 2014). According to the FSMA guidelines, harvest can be delayed for up to four days. Produce that is not in compliance even after four additional days of microbial die-off, based on the 0.5 log rate reduction of CFUs per day, is to be discarded. The optimal solutions are obtained by iteratively varying standard stringency, θ_{GM} and θ_{STV}, proportionally. This approach is used in place of solving the model for θ_{GM} and θ_{TV} as endogenously determined variables to minimize nonlinearity of the model and reduce computational complexity.

Following LGMA guidelines, equation (8') uses the CFUs of water quality samples to impose water treatment.

$$a'_{i,f,ct,ws,g,r} = \begin{cases} a''_{n,i,f,ct,ws,g,d0,tr_0,r} & if \quad GM'_{n,i,f,ct,ws,g,r} \leq \theta' \leq max \\ a''_{n,i,f,ct,ws,g,d0,tr_1,r} & if \quad GM'_{n,i,f,ct,ws,g,r} \geq \theta' \end{cases} \quad \forall i, f, ct, ws, g, r. \tag{8}$$

where θ' is the LGMA water quality standard, 126 CFU/100 ml of irrigation water (California Leafy-Greens Marketing Agreements 2020). $GM'_{n,i,f,ct,wsg,r}$ is the irrigation-event-specific geometric mean (California Leafy-Greens Marketing Agreements 2020).

Each day of delay in harvest is assumed to reduce yield by a fixed share (π) until the fifth day, when produce is discarded.[8] Hence, the per acre yield is expressed as follows (equation 9) where d is days of delay in harvest (e.g., d_0 indicates no delay, d_1 represents 1 day of delay, etc.), and $\breve{y}_{i,ct,g}$ is average observed yield of crop i in county ct with no delay.

$$\begin{cases} y_{i,c,g,d,r} = \breve{y}_{i,ct,g} * (1 - \pi d) & if\ d = d_0,\ d_1,\ d_2, d_3,\ d_4 \\ y_{i,ct,g,d,r} = 0 & if\ d =\ d_5 \end{cases} \quad \forall i, ct, g, r \tag{9}$$

Equations (10) and (11) estimate the GM and STV values across production districts and farm types in each state of nature (Bihn et al. 2017).

$$GM_{n,i,f,ct,ws,r} = 10^{\left\{ \begin{array}{c} \{\sum_{t'} \log\left(CP_{n,i,f,ct,ws,t',r}\right) \\ + \\ \sum_{g' \leq g} test_{i,f,ct,ws,g,g',r} * \log\left(C_{n,i,f,ct,ws,g',r}\right)\}/\Lambda(ws) \end{array} \right\}} \quad \forall n, i, f, ct, ws, r \tag{10}$$

$$STV_{n,i,f,ct,ws,r} = 10^{\left(GM_{n,i,f,ct,ws,r} + 1.282 * STD_{n,i,f,ct,ws,r}\right)} \quad \forall n, i, f, ct, ws, r \tag{11}$$

where $C_{n,i,f,ct,ws,g,r}$ is *E. coli* CFU per 100 ml of irrigation water, and $CP_{n,i,ct,f,ws,t',r}$ is *E. coli* CFU per 100 ml from irrigation in the months prior to the last month of the growing season (t')[9] as part of the Microbial Water Quality Profile (MWQP). $STD_{n,i,f,ct,ws,r}$ is the combined standard deviation of $\log\left(C_{n,i,f,ct,ws,g',r}\right)$ and $\log\left(CP_{n,i,f,ct,ws,t',r}\right)$. g' refers to the preceding and current irrigation events.[10] GM and STV are estimated based on the aggregate CFUs of generic *E. coli* across irrigation events. $\Lambda(ws)$ is the number of surface and groundwater samples. The initial MWQP is to be based on at least twenty surface water samples and at least four groundwater samples. In subsequent years, five (one) samples of surface (ground) water in the last month of irrigation are required to update MWQP (FDA 2020).

E. coli content of irrigation water ($CO_{n,i,f,ct,ws,g,r}$) is stochastic:

$$CO_{n,i,f,ct,ws,g,r} = Max\{(0, \Omega(k_1,\ k_2))\} \forall n, i, f, ct, ws, g, r \tag{12}$$

where Ω is the Lognormal or Weibull distribution and (k_1, k_2) are the scale and shape parameters.

E. coli O157:H7 transmits from irrigation water to crops according to equation (13), where CFUs from all irrigation events are aggregated and adjusted to reflect die-off including from delays in harvest in FSMA scenarios. LGMA recognizes several methods for water

[8]Lettuce planting, harvest, transportation, and retail are on strict and predetermined schedules according contracted by buyers and producers due to the perishable nature of lettuce. Delays in either of these steps can lead to significant spoilage losses (Drost 2020). We explore the significance of this parameter in the sensitivity analysis.

[9]We focus on irrigation in the last growing month because *E. coli* from irrigation prior to the last month dies off before the harvest. We and assume that crops are irrigated every 6 days (Smith et al. 2011).

[10]For instance, for the third irrigation event, g' includes first, second, and third irrigation events.

treatment including physical devices such as heat sterilization and ultraviolet light (UV) and chemicals like chlorine dioxide or peroxyacetic acid (Rock 2020). Following Krishnan et al. (2021), we assume that applying chlorine to water is the most common agricultural water treatment method. According to the CDC (2022a) adding 0.5 mg/l free chlorine to water for less than 30 minutes reduces the concentration of *E. coli* by 99.99%. Crop irrigation water consumption is determined by irrigation efficiency (λ) (evapotranspiration divided by applied water per acre). Hence, the amount of *E. coli* in lettuce after irrigation is proportional to consumptive use (Solomon et al. 2002).[11] Irrigation efficiency varies across irrigation methods. California and Arizona lettuce producers mostly use pressurized furrow irrigation technology (FDA 2016).

$$CN_{n,i,f,ct,ws,g,d,tr,r} = \sum\nolimits_{g' \le g} \left(\frac{CO_{n,i,f,ct,ws,g',r}}{100} \right) * \lambda * R * 0.96 * e^{-\frac{l(g')^{\zeta}}{\varepsilon}} * 10^{-0.5*d} * 10^{-4\{tr-1\}} * \eta \; \forall n, i, f, ct, ws, g, d, tr, r \tag{13}$$

An exponential microbial die-off function ($e^{-\frac{l(g')^{\zeta}}{\varepsilon}}$) (Brouwer et al. 2017) quantifies the decay of *E. coli* CFUs from irrigation events to harvest. $l(g')$ represents the number of days between each irrigation event and the final irrigation before harvest.

E. coli O157:H7 is the primary *E. coli* strain that causes foodborne illness outbreaks (CDC 2020). Therefore, based on the availability of O157:H7 prevalence data relative to *Generic E. coli*, in the baseline scenario, we focus on *E. coli* O157:H7 (Muniesa et al. 2006; Ottoson et al. 2011; Pang et al. 2017). However, foodborne illnesses can also be caused by other pathogens such as *E. coli* O26, O45, O103, O111, O121, and O145 (Bertoldi et al. 2018). We vary (R) in the sensitivity analysis to examine how water pathogenicity affects optimal water quality standard.

Following Pang et al. (2017), it is assumed that fresh lettuce remains in storage and transportation for 4 days after harvest before consumption, with associated microbial die-off.[12] The microbial die-off during storage, transportation, and retail is modeled using an exponential form (Pang et al. 2017):

$$CNS_{n,i,f,ct,ws,g,d,tr,r} = CN_{n,i,f,ct,ws,g,d,tr,r} * e^{-(U*4*24)} \qquad \forall n, i, f, ct, ws, g, tr, r \tag{14}$$

where $CNS_{n,i,f,ct,ws,g,d,tr,r}$ is CFUs of *E. coli* in crop after transportation, storage, and retail and before consumption. U is the average hourly die-off rate per CFU of *E. coli*.

The dose–response formulation is adopted from Pang et al. (2017). Serving size (ϱ_i) and pathogen quantity per gram of produce after the delay in harvest are used to estimate *E. coli* dose ($D_{n,i,f,ct,ws,g,d,tr,r}$) per contaminated serving (equation 15). A dose–response relation (16) estimates the probability ($p_{n,i,f,ct,ws,g,d,tr,r}$) of illness per contaminated serving, where ρ and ω are dose–response parameters (Pang et al. 2017). Illnesses are calculated based on the probability of illness per contaminated serving (17).[13]

In equation (16), α is the impact of distributors, retailers, and consumers' prevention efforts. Formulation in equation (16) implies substitution between prevention efforts and regulatory stringency ($S_{\theta\alpha}$<0). An alternative formulation

[11]In the baseline scenario, 70% of *Generic E. coli* in irrigation water is delivered to the field ($\eta = 0.7$).

[12]Harvesting tools, shredders, flume tanks, conveyor belts, centrifuges, and shakers used during washing and shredding can lead to lettuce contamination after harvest (Pang et al. 2017). We do not model these factors in this study.

[13]Since yield is expressed in hundredweights, number of illnesses per state of nature is obtained using 50,802.3 (grams/CWT).

$p_{n,i,f,ct,ws,g,d,tr,r} = 1 - \left(1 + \frac{D_{n,i,f,ct,ws,g,d,tr,r}}{\alpha * \omega}\right)^{-\rho}$ can be used for complementarity ($S_{\theta\alpha} > 0$), which is unlikely in our case.

$$D_{n,i,f,ct,ws,g,d,tr,r} = CNS_{n,i,f,ct,ws,g,d,tr,r} * \varrho_i \forall n, i, f, ct, ws, g, d, tr, r \tag{15}$$

$$p_{n,i,f,ct,ws,g,d,tr,r} = \left[1 - \left(1 + \frac{D_{n,i,f,ct,ws,g,d,tr,r}}{\omega}\right)^{-\rho}\right] * \left(\frac{1}{\alpha}\right) \forall n, i, f, ct, ws, g, d, tr, r \tag{16}$$

$$ill_n = \sum_{i,f,ct,ws,g,d,t,r} p_{n,i,f,ct,ws,g,d,tr,tr,r} * a''_{n,i,f,ct,ws,g,d,tr,r} * y_{i,ct,g,d,r} * \frac{50,802.3}{\varrho_i} \forall n \tag{17}$$

We assume that foodborne outbreaks result in negative demand shocks. The demand response is assumed to be a function of the number of foodborne illnesses (equation 18). $\aleph$ is the median reduction in demand per illness in each state of nature and is obtained according to Bovay and Sumner (2017) and Arnade et al. (2009) (see Appendix B).

$$\varpi_n = \aleph * ill_n \forall n \tag{18}$$

Data

The empirical analysis focuses on the microbial irrigation water quality in lettuce production. Lettuce is of particular interest for food safety because all lettuce is consumed fresh without further processing. Also, unlike other fresh vegetables, lettuce is highly perishable, limiting the opportunity for storage and microbial die-off before consumption. Forty-three counties in California and Arizona produce nearly all U.S. Head and Leaf-Romaine lettuce (U.S. Department of Agriculture 2018). In 2017, Head and Leaf-Romaine lettuce were planted on approximately 18,194 and 48,964 acres in California and Arizona, respectively.

The cost burden of FSMA regulations falls disproportionately on small farms due to economies of scale (Lichtenberg and Page 2016; Bovay and Sumner 2017; Adalja and Lichtenberg 2018; Bovay et al. 2018). Therefore, farms are categorized into small, gross income less than $250,000, and large, gross income greater than $250,000 (U.S. Department of Agriculture 2017) to account for scale economies. The costs of implementing the water quality standards based on GM and STV criteria are obtained from the FDA (2015b) and include water sampling, testing, and recordkeeping costs. Similarly, water treatment costs in LGMA and FSMA are estimated using FDA (2015b). In particular, the baseline water treatment costs are estimated at $24.76 and $2.48 per acre for small and large lettuce producing farms, respectively. Calvin et al. (2017) also provide estimates of direct irrigation water treatment costs. However, their estimated costs are presented per firm rather than per acre. Hence, we rely on the FDA's cost estimates. Production, consumption, planted acreage, prices, import, export, and applied irrigation water data for lettuce are obtained from U.S. Department of Agriculture (USDA) ERS and NASS.

The FDA estimates that the microbial irrigation water quality standard implementation for domestic farms costs $50 million annually (FDA 2015b). This estimate includes water sampling, testing, and recordkeeping costs. Adjusting this estimate based on the share of harvested lettuce acreage relative to all fresh fruits and vegetables acres, the cost for the lettuce industry is approximately $3 million annually.

Costs per foodborne illness vary depending on the severity of the disease and estimation methodology. USDA (2019) uses $8,500 per illness caused by *E. coli* O157:H7. Hammitt and Haninger (2007) estimates willingness to pay (WTP) to avoid foodborne illness between ten and twenty thousand dollars. We use $8,500, following USDA as a baseline value, but rely on Hammitt and Haninger (2007) values in the sensitivity analysis.

Own-price elasticity of demand (Okrent and Alston 2012),[14] cross-price elasticities of demand (Ferrier et al. 2016), and own-price elasticity of supply (Lohr and Park 1992) are provided in the appendix (Table B.3). The average of the cross-price elasticities between Head and Leaf and Head and Romaine is used as the proxy for the cross-price elasticity between Head lettuce and the combined Leaf-Romaine lettuce. A similar assumption applies to the Leaf-Romaine and Head lettuce cross-price elasticity.

Spatial microbial water quality data for *Generic E. coli* are obtained from the National Water Quality Monitoring Council (USGS-EPA 2020).[15] The reported *Generic E. coli* water quality ranges from 32 CFU per 100 ml in San Joaquin county to 5,931 in Ventura county. Density plots, Q-Q plots, P-P plots, and Akaike Information Criteria (AIC) are used to select the best distribution function for each county using the data from NWIS and STORET Databases. *E. coli* content in groundwater is only available for three counties for which we use Weibull distribution functions. For the rest of the counties, the corresponding surface water distribution functions are shifted to the left to obtain groundwater quality distribution. The shift parameter is the average ratio of the means of surface and groundwater distributions in the counties where the data are available for both sources. *Generic E. coli* data are absent for 17 smaller counties in California. Data for these counties are obtained from the neighboring counties. The same density functions are used to obtain random draws for production districts located within a county. Five hundred random draws in each production district are used per model solution for microbial water quality data. Mean values of *E. coli* CFU/100 ml across counties are provided in Appendix Figure B.1.

Results

The empirical model is validated by reproducing observed prices and quantities in the past under baseline conditions. Annual results from 2008 to 2017 are reproduced using county crop acreage data from the corresponding years. Model solutions produce lettuce quantities and prices within 1% and 5% of the observed data in the corresponding year (Table B.4). These validation results provide a solid foundation for FSMA scenario analysis. The policy analyses are based on the supply and demand functions calibrated to the prices and quantities observed in 2016. Planted acreage is subject to synthetic and observed crop mix data from all available years. Hence, the model solutions represent a long-run market equilibrium.

Table 1 shows results from two scenarios corresponding to baseline and high water treatment costs. Each of these cases includes four subscenarios corresponding to FSMA-mandated, optimal FSMA, LGMA-mandated, and optimal LGMA standards. The FSMA mandate scenario uses fixed water quality threshold values (θ_{GM} and θ_{STV}) as required by the FDA rule (126 CFU/100 ml for GM and 410 CFU/100 ml for STV). Similarly, the LGMA mandate scenario has the same GM threshold. The optimal FSMA and LGMA scenarios provide solutions with endogenously determined thresholds for microbial water quality standards that generate the greatest objective function value.

[14]Okrent and Alston (2012) estimated the elasticity for lettuce in general and not for specific varieties of lettuce. We assume that Head and Leaf-Romaine have the same elasticity according to Okrent and Alston (2012).

[15]Available at www.waterqualitydata.us and includes data from the USGS National Water Information System (NWIS), the EPA STOrage and RETrieval (STORET), and the USDA ARS Sustaining the Earth's Watersheds-Agricultural Research Database System (STEWARDS).

Table 1. Regulatory standard, welfare, illnesses, and lettuce prices

Scenario		Regulatory Standard (CFU/100 ml) FSMA GM	STV	LGMA	Price of Lettuce ($ per CWT) Head	Leaf-Romaine	Consumer and Producer Surplus ($ Billion)	Social Welfare ($ Billion)	Symptomatic Illnesses
Baseline Cost of Water Treatment	FSMA	126	410	–	25.37	16.76	2.574	2.559	1,568
	Optimal FSMA Standard	0	0	–	24.50	14.74	2.593	2.587	0
	LGMA Regulation	–	–	126	24.57	16.77	2.574	2.562	1,323
	Optimal LGMA Regulation	–	–	0	24.50	14.74	2.593	2.587	0
High Cost of Water Treatment	FSMA	126	410	–	25.91	17.19	2.564	2.532	3,727
	Optimal FSMA Standard	252	820	–	25.51	17.00	2.570	2.533	4,276
	LGMA Regulation	–	–	126	27.91	18.28	2.523	2.293	1,193
	Optimal LGMA Regulation	–	–	882	25.78	17.16	2.566	2.503	2,719

Notes: FSMA and LGMA stand for Food Safety Modernization Act and Leafy-Greens Marketing Agreement, respectively.

There are three reasons for including the high treatment cost scenario in this study. First, the baseline cost of water treatment in the FDA (2015b) includes only labor and material costs. However, the use of chemicals such as chlorine for treating irrigation water can increase plant phytotoxicity and create toxic by-products, e.g., haloacetic acid and trihalomethanes (Raudales et al. 2014; Dery et al. 2020). These by-products can be harmful for human health (Deborde and von Gunten 2008; Raudales et al. 2014) and to environment. Second, treatment chemicals can degrade lettuce quality as excess cholerine can accumulate in crop tissues, resulting in crop leaves with a burned or scorched appearance (University of Maryland Extension 2022). Third, only two estimates of irrigation water treatment costs are available (FDA 2015b; Calvin et al. 2017), which suggests uncertainty about the costs of water treatment. We iteratively increase the water treatment costs until the LGMA treatment is no longer cost effective. The results show that the baseline water treatment costs have to increase 500 times for water treatment to be inferior to harvest delay.

In the low water treatment cost scenario, FSMA regulation produces slightly lower benefits than the LGMA program. The difference is attributed to a greater number of illnesses under FSMA than under LGMA. In the FSMA scenario, small farmers choose to delay harvest rather than treat water when water is contaminated. However, treating water is more effective for preventing illnesses than delaying harvest, which reduces microbial contamination but does not eliminate it. Therefore, the number of symptomatic cases under LGMA is lower than under FSMA. However, even in the LGMA scenario, there are some illnesses because water is treated only if microbial water is worse than the standard of 126 CFUs per 100 ml.

The results show small welfare variation across the scenarios in Table 1. Hence, FSMA regulation does not improve welfare relative to the existing LGMA program. This result is not surprising given a small number of annual lettuce-related foodborne illnesses and associated monetary losses, relative to the value of the lettuce market in terms of aggregate consumer and producer surplus.

In the low-cost water treatment scenario (baseline), the optimal water quality standard is significantly more stringent than the standard mandated under the FSMA and LGMA. This result is expected for the low water treatment cost scenarios because water treatment prevents foodborne illness without sacrificing consumer and producer surplus. If treatment costs are low, then treating water is justified to prevent illness costs. Although water treatment is expensive for small farms even in the low-cost scenario, the benefits of a strict threshold, which prevents more illnesses, outweigh the treatment costs for small farms.

On the other hand, the optimal water quality standard is less stringent than the FSMA and LGMA requirements in the high-water treatment cost scenario. In this case, delaying harvest under FSMA is preferred to treatment. However, harvest delays are costly due to consumer and producer surplus losses. Therefore, the optimal FSMA standard is less stringent than the FSMA rule.

In the high treatment cost scenario, the LGMA objective function value is 9.4% (2.293/2.532) lower than the FSMA value. Similarly, the optimal LGMA objective function is 1.2% (2.503/2.533) lower than the optimal FSMA value. The dominance of FSMA relative to LGMA is not surprising since the high treatment cost scenario is designed to increase treatment costs until treating water is no longer optimal relative to harvest delay. Therefore, the addition of harvest delay as an option under FSMA can improve efficiency relative to LGMA if water treatment costs are substantially (at least 500 times) higher than in the baseline scenario. However, the difference in social welfare between corresponding FSMA and LGMA scenarios is still small.

FDA estimated $310 million in annual benefits of FSMA irrigation water quality standards from avoided foodborne illnesses (2015b). Our baseline estimates suggest that FSMA water quality regulation decreases welfare by $34 ($61) million in a low (high) water treatment cost scenario. The results differ because our estimates a) account for changes in consumer and producer surplus from production and planting decisions and b) are benchmarked against the LGMA program.

As expected, there is an inverse relationship between water quality standard stringency and the number of foodborne illnesses in both treatment cost scenarios. In the high treatment cost scenario, doubling the microbial quality limit in the FSMA, which implies less stringent regulation, produces 14.7% more illnesses in the optimal FSMA scenario (4,276/3,727). Similarly, in the LGMA standard, higher microbial water quality limit increases illnesses. However, since the cost of water treatment is prohibitively expensive, the social welfare improves relative to the mandated requirement under FSMA despite the increase in the number of symptomatic illnesses.

In the baseline treatment cost scenario, FSMA results in 3.3% higher Head (25.37/24.57) and 0.1% lower Leaf-Romaine (16.76/16.77) lettuce prices, respectively, relative to LGMA outcomes. The changes in prices are due to a) long run acreage adjustment in response to the regulatory requirements and b) supply losses due to harvest delays in the FSMA scenario. As expected, prices do not change across FSMA and LGMA scenarios with optimized microbial water quantity threshold. In the high treatment cost

Table 2. FSMA impacts on small and large farms as well as ground and surface water using farms

Scenario	Farm/ Water Source Type	Cost of Implementing FSMA ($ Million)		Total Supply (10,000 CWT)			Revenue ($ Million)		
		No FSMA	FSMA	No FSMA	FSMA	Change in Supply (%)	No FSMA	FSMA	Change in Revenue (%)
Baseline Cost of Water Treatment	Small Farm	0	1.88	8,012.1	7,416.5	−7.43	1581.8	1588.4	0.42
	Large Farm	0	0.02	890.2	824.1	−7.43	175.8	176.5	0.42
High Cost of Water Treatment	Small Farm	0	1.79	8,012.1	7,246.5	−9.56	1581.8	1589.6	0.49
	Large Farm	0	0.79	890.2	810.9	−8.91	175.8	177.9	1.19
Baseline Cost of Water Treatment	Surface Water	0	0.42	4,272.9	3,624.9	−15.17	840.8	774.2	−7.92
	Ground Water	0	0.49	4,629.4	4,615.7	−0.30	916.7	990.7	8.07
High Cost of Water Treatment	Surface Water	0	0.41	4,272.9	3,421.7	−19.92	840.8	748.6	−10.97
	Ground Water	0	0.49	4,629.4	4,635.7	0.14	916.7	1,018.8	11.14

scenario, prices are lower in the FSMA than in the LGMA solutions. Higher prices in the LGMA scenario are due to the decrease in the long run crop acreage in response to expensive and mandatory water treatment.

Foodborne illness estimates include all incidents that range from mild discomfort to life-threatening cases. Our illness estimates are comparable to Pang et al. (2017), who estimate 2,160 to 9,320 annual foodborne illnesses on average from contaminated lettuce via irrigation water. The CDC's reports indicate that 167 people were ill due to *E. coli* lettuce contamination in 2019 (CDC 2021). However, the CDC shows only the reported cases, while our estimates include total symptomatic cases, some of which are mild and most are unreported. In practice, only 1 in 26 symptomatic cases is reported (Scallan et al. 2011; Scharff et al. 2016). Accounting for underreporting in CDC records, our estimates are consistent with the reported illness data in 2019.

We evaluate the distribution of FSMA impacts on small versus large lettuce producing farms and on farms that rely on the surface versus groundwater. The results in Table 2 show that in the baseline treatment cost scenario, large and small farms decrease supply by 7.43%, and their revenues increase by 0.42%.[16] The increase in producer revenue is due to the increase in lettuce prices under FSMA scenario. A qualitatively similar positive effect on revenues is observed in the high water treatment cost scenario, where small and large

[16]Our formulation does not include explicit farm level production cost. Instead, the objective function includes an industry scale supply curve, constrained by acreage and yield (equation 7). Therefore, we report total revenue rather than profit impacts.

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Table 3. Effects of changes in irrigation costs, distributor and consumer preventive efforts, and cost of implementing the FSMA standard in the high water treatment cost environment

Scenario	Lettuce Type	Additional cost of Irrigation Water ($/acre- irrigation)		Distributor and Consumer Preventive Effort	Marginal Cost of Implementing FSMA ($ per acre)		Water Use Relative to the Base Scenario (%)	Production Relative to the Base Scenario (%)	Price Relative to the Base Scenario (%)	Change in Optimal Standard Relative to the Proposed Standards in FSMA (%)
		Small Farm	Large Farm		Small Farm	Large Farm				
Baseline Optimal Regulation	Head	0	0	1	283	80	100.0	100.0	100.0	+100
	Leaf-Romaine						100.0	100.0	100.0	
Scenario 1: Irrigation Water Cost	Head	80	120	1	283	80	89.5	94.0	107.0	+110
	Leaf-Romaine						97.7	99.2	100.7	
Scenario 2: Distributor and Consumer Preventive Effort	Head	0	0	5	283	80	101.7	102.0	97.5	+540
	Leaf-Romaine						102.8	103.7	97.1	
Scenario 3: Cost of Implementing FSMA	Head	0	0	1	849	240	96.8	98.8	101.4	+720
	Leaf-Romaine						97.8	98.4	101.2	

Notes: Scenario (1) shows the results of an increase in irrigation cost relative to the baseline scenario. Scenarios (2) and (3) show the impacts of an increase in distributor and consumer preventive efforts and cost of implementing the FSMA standard on optimal water quality standard, production, price, and water use.

farms decrease production by 9.56% and 8.91%, while their revenues increase by 0.49% and 1.19%. The results show a relative disadvantage of small farms, which is similar to Bovay and Sumner (2017), who show that FSMA increases (decreases) revenues of large (small) farms by 7%–9% (8%–29%).

A comparison of impacts on farms that use surface versus groundwater reveals that, as expected, FSMA affects surface water producers more than groundwater producers (Table 2). In the baseline treatment cost scenario, surface (ground) water farms' supply decreases by 15.17% (0.3%), with a corresponding 7.92% decrease (8.07% increase) in total revenue. In the high treatment cost scenario, surface (ground) water farms decrease (increase) production by 19.92% (0.14%), which results in a 10.97% (11.14%) decrease (increase) in revenues. The asymmetric effect of FSMA is expected because groundwater is less contaminated and is less stringently regulated. As a result, some production shifts from surface to groundwater irrigation.

We empirically examine the effect of irrigation water cost (proposition a), contamination prevention efforts by consumers and producers (proposition b), and FSMA compliance cost (proposition c) on optimal water quality standard and water use in the high water treatment cost scenario. According to proposition a), more costly irrigation is expected to reduce irrigation and stringency of microbial water quality standard. Irrigation costs decrease production, which increases the marginal value of output. Also, lower production results in fewer illnesses. Hence, optimal standard stringency decreases. We examine this effect empirically by varying the cost of irrigation water. In the baseline scenario (Table 3), water-related costs are included in the per acre marginal production costs. In scenario 1, the additional irrigation costs are increased to \$80 and \$120 for small and large farms, respectively, per irrigation event per acre.[17] Although irrigation is price inelastic (Scheierling et al. 2006), with a sufficiently large increase in irrigation costs, water use decreases, and so does the stringency of optimal water quality standard. A twenty-fold increase in irrigation costs to \$80 and \$120 for small and large farms reduces water use by 10.5% and 2.3% in Head and Leaf-Romaine lettuce production, respectively. As a result, the production of Head and Leaf-Romaine lettuce decreases by 6% and 0.8%, respectively. With less irrigation and lower output, *E. coli* contamination decreases, which results in fewer cases of foodborne illnesses. Consequently, with smaller expected damages from foodborne illnesses, the stringency of water quality standard decreases. Relative to the baseline scenario, regulatory stringency in scenario 1 decreases by 10%.

Proposition b) says that distributor and consumer prevention efforts have an ambiguous effect on the optimal water quality standard and irrigation when regulatory stringency and prevention efforts are substitutes. Substitution may arise when distributor and consumer efforts decrease the effectiveness of the quality standard and vice versa. For example, under strict food safety standards, consumers may be less inclined to wash fresh produce before eating. Our empirical results (Table 3, scenario 2) show that a five-fold decrease in the probability of illness due to greater distributor or consumer prevention efforts results in less stringent water quality standard, greater irrigation, increase in production by 2–3.7%, and a decrease in prices of Head and Leaf Romain lettuce by 2.5 and 2.9%, respectively. When consumers or distributors exert more effort to prevent foodborne outbreaks, the probability and the number of foodborne illnesses decrease. As a result, production expands, and the optimal stringency of water quality standard declines.

We empirically examine proposition c) using the high and low costs of FSMA implementation. In scenario 3 (Table 3), costs of FSMA implementation are three times greater

[17]According to USDA (2013), cost per irrigation per acre is \$4 and \$6 for small and large farms. Larger farms rely on costlier groundwater, while smaller farms mostly use less expensive surface water.

Table 4. Sensitivity analysis for key parameter values

Scenarios	Parameter Values for Sensitivity Analysis				Results: Ratios of Optimal and the FDA Water Quality Standards			
	δ	η	π	***R***	δ	η	π	***R***
1	5,000	0.5	0.05	0.100	6.6	2.5	0.2	0.6
2	7,000	0.6	0.10	0.060	2.1	2.0	1.0	1.7
3 (baseline)	8,500	0.7	0.15	0.014	2.0	2.0	2.0	2.0
4	10,000	0.8	0.19	0.007	2.0	2.0	2.1	7.0
5	12,000	0.9	0.22	0.004	1.7	2.0	2.3	7.4

Notes: δ refers to the economic losses per case of illness; η is the proportion of *E. coli* in the water source that is delivered to the crop; π is the productivity loss as a result of the delay in harvest by a day; *R* is the ratio of harmful pathogen presence per CFU of *Generic E. coli* in irrigation water.

than in the baseline. Confirming proposition c), an increase in the standard's operational costs reduces the standard's optimal stringency by 720% relative to the optimal regulation scenario with baseline costs. Less stringent standard reduces harvest delay and increases foodborne illnesses. As a result of more foodborne illnesses and associated demand response, production decreases until the marginal cost of additional illness equals marginal benefit of additional lettuce supply in terms of consumer and producer surplus. In our example, Head and Leaf-Romaine lettuce production decreases by approximately 1.2% and 1.6% and prices increase by 1.4% and 1.2%, respectively.

The sensitivity to the key parameters is examined by varying one parameter value at a time, holding others at baseline values. The parameters in the sensitivity analysis and the respective values are provided in the first four columns of Table 4, including the monetary value of foodborne illness damages (δ), the transmission of pathogens from source water to lettuce via irrigation (η), yield loss due to each additional day of delay in harvest (π), and the ratio of harmful pathogens including *E. coli* O157:H7 to *Generic E. coli (R)*. Scenario 3 is the baseline case in the sensitivity analysis. Sensitivity analysis results are presented in terms of the ratio of the optimal and FDA mandated (GM=126 and STV=410) standard stringencies in the last four columns. A ratio that is greater (less) than 1 suggests less (more) stringent regulation than what is articulated in the FDA rule.

The results show that the severity of foodborne illness (δ) and stringency of water quality standard are positively related. In the baseline scenario, the ratio of optimal and FSMA-mandated standard stringency is 2. If the average cost per illness is \$5,000 (\$7,000) rather than the baseline \$8,500, then the optimal microbial water quality threshold is 6.6 (2.1) times greater than the FSMA regulation. Hence, the greater the cost of foodborne illness, the greater the ex-post damages of water contamination. Therefore, the stringency of water quality standard increases in response to costlier illness to reduce the ex-post damages. Similarly, the greater transmission of pathogens from source water to crop (η) results in a more stringent standard. If the transmission of pathogens from irrigation water to crops decreases from 70% to 50%, then the standard is 2.5 rather than 2 times less stringent than the FDA standard.

We also observe that the magnitude of output loss due to harvest delay influences the optimal standard stringency. For example, if yield loss from the delay in harvest (π)

decreases from 15% to 5%, the ratio of the optimal microbial threshold to the FSMA rule threshold changes from 2 to 0.2. Hence, with a 5% yield loss, the optimal water quality standard is more stringent than the FSMA rule. Greater yield loss results in producer and consumer surplus loss due to lower supply and higher prices when the harvest is delayed, which indirectly increases the costs of water quality standard and affects long run planting decisions.[18]

The results are also sensitive to the pathogenicity of irrigation water per CFU of *Generic E. coli*. The increase in the ratio (R) represents a greater presence of pathogens, including *E. coli* O157:H7, per CFU of *Generic E. coli*. The results show that the stringency of water quality standard increases as the prevalence of pathogens increases. For instance, a ten-fold increase in R increases the stringency of the optimal standard relative to the FDA's standard.

The sensitivity analysis demonstrates that the FDA water quality standard is not optimal in most scenarios. Eighteen out of twenty scenarios produce less stringent optimal standards than the FDA-mandate. Hence, in most cases, the FDA rule is not economically efficient.

Conclusions

The FDA standards regulate irrigation water quality based on mandatory water sampling and harvest delays. Following a theoretical analysis of the regulation, we examine the FDA standard empirically using the lettuce market as a case study. We evaluate FSMA guidelines relative to the existing LGMA. To our knowledge, this paper is the first attempt to examine the food safety-related irrigation water quality regulatory standard as proposed by the FDA using an economic framework that explicitly includes consumer and producer surplus measures with detailed pathogen exposure and dose–response formulations. The empirical analysis uses a stochastic two-stage price endogenous partial equilibrium model with recourse. The economically efficient design of the food safety regulation, including microbial irrigation water quality standard, requires balancing marginal losses from illnesses and marginal impacts on consumer and producer welfare. We extend the FDA's (2015a) irrigation water quality regulation analysis by explicitly considering consumer and producer welfare impacts.

The results are provided for baseline and high water treatment cost scenarios. The baseline cost of water treatment, obtained from (2015b), excludes the negative externalities of using chemicals in water treatment. Therefore, we estimate the lower bound for the increase in contaminated water treatment costs relative to the baseline scenario such that treating contaminated water becomes suboptimal relative to harvest delays in FSMA. The results suggest that delaying harvest according to FSMA rule becomes preferred relative to the treatment of contaminated water if costs of water treatment are five hundred times greater than in the baseline.

In most high treatment cost scenarios, the FDA's irrigation water quality standard is excessively stringent. The optimal FSMA regulatory standard is 100% less stringent than the FDA standard in terms of the threshold for acceptable microbial quality of irrigation water. However, the microbial water quality rule can be cost effective under sufficiently high costs per foodborne illness or pathogenicity of irrigation water per CFU of *Generic E. coli*.

[18]Yield loss can have a positive or negative effect on producer surplus depending on the elasticities of supply and demand curves. However, the combined consumer and producer surplus declines due to yield loss.

This study is limited in terms of the considered pathogens. *E. coli* O157:H7 causes severe illness and is the most prevalent strain *E. coli* in North America (FDA 2012). Therefore, we mostly focus on O157:H7. However, other pathogens, such as *E. coli* O26, O45, O103, O111, O121, and O145 can also cause foodborne illnesses. We address this limitation in the sensitivity analysis, where we obtain solutions assuming a greater presence of pathogens per CFU of *Generic E. coli* as an indicator organism.

Another caveat of the study is that we do not address contamination between harvest and consumption. Pathogens can be introduced all along the supply chain, including packaging, processing, distribution, storage, restaurant, and retail. Precautionary measures can also be taken at various steps allowing the supply chain to prevent foodborne illnesses. In this study, we focus specifically on irrigation water quality rule according to the FDA's regulation. However, we consider the effects of prevention measures by consumers and distributors on water quality regulation. Future studies should consider downstream supply chain factors more explicitly.

Also, we abstract away from hydrological factors and do not model joint distribution of *E. coli* content in water. A more advanced modeling of joint water quality distribution would require fuller water quality data than what we use in this study. Future studies may include the joint distribution of *E. coli* in different water sources and consider spatial hydrologic interdependencies.

Finally, due to the dimensionality and complexity of the model, we only focus on lettuce. Therefore, the analysis in this study is not to be interpreted as an overall assessment of FSMA. Instead, this analysis examines the benefits of FSMA exclusively in the lettuce market. Because the FDA's standards cover all fresh fruits and vegetables, a more comprehensive analysis that includes other fruits and vegetables will be useful.

The results have important policy implications. The FDA's irrigation water quality regulation should balance consumer and producer welfare impacts, costs of water treatment, and foodborne illness damages from contaminated irrigation water in choosing the stringency of microbial irrigation water quality standards. Our baseline results show that in lettuce industry FSMA irrigation rules do not provide improved economic outcomes relative to the LGMA program. However, we find that the conclusion can be sensitive to assumed parameter values, and in some circumstances, benefits of FSMA can exceed costs.

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Appendix A Theoretical model, equations, and proofs

Table A.1. Summary of variables and parameters used in the theoretical model

Symbol	Variable/Parameter
SW	Expected value of social welfare
θ	Water quality standard
w	Irrigation water
$P(X(w), \theta)$	The inverse demand function
c	Cost of irrigation water.
α	Consumer, producers, and distributors prevention efforts
$S(\mu, X(w); \alpha)$	The monetary value of damages from foodborne illnesses
β	Cost shift parameter
$R(\theta; \beta)$	Cost of implementing the water quality standard
μ	The quality of irrigation water
$f(\mu)$	Probability distribution of microbial water quality

Less stringent irrigation water quality standard and greater use of irrigation water is assumed to increase social damages from contamination at an increasing rate, $\frac{\partial s}{\partial \theta} > 0$, $\frac{\partial s}{\partial w} > 0$, $\frac{\partial^2 S}{\partial \theta^2} > 0$, and $\frac{\partial^2 S}{\partial w^2} > 0$. Damages are increasing in w because more irrigation implies greater potential contamination, foodborne illness and associated damages. An increase in preventative efforts of consumers and distributors is assumed to decrease marginal damages from additional water use, $\frac{\partial^2 S}{\partial \alpha \partial w} < 0$. Also, $\frac{\partial^2 S}{\partial w \partial \theta} > 0$, i.e., less stringent water quality standard leads to greater marginal damages from additional water use. Also, $\frac{\partial R}{\partial \theta} < 0$ and $\frac{\partial^2 R}{\partial \theta^2} \geq 0$, i.e., costs of implementing the standard increase at an increasing rate. A decrease in the stringency of water quality standard is assumed to have a nonpositive effect on demand (i.e., $\frac{\partial P}{\partial \theta} \leq 0$) with a decreasing rate ($\frac{\partial^2 P}{\partial \theta^2} \leq 0$). Increase in θ implies a less stringent standard, which is not likely to increase demand. The production function is assumed to be concave (i.e., $\frac{\partial X}{\partial w} \geq 0, \frac{\partial^2 X}{\partial w^2} < 0$). The first-order conditions with respect to θ and w are

$$\frac{\partial SW}{\partial \theta} = \int_0^X \frac{\partial P}{\partial \theta} dX + \frac{\partial S}{\partial \theta} \int_z^\theta f(\mu) d\mu - \frac{\partial R}{\partial \theta} = 0 \tag{A.1}$$

$$\frac{\partial SW}{\partial w} = P[X(w), \theta] \frac{dX}{dw} - c - \int_k^\theta \frac{\partial S}{\partial w} f(\mu) d\mu + \frac{\partial S}{\partial w} \int_z^\theta f(\mu) d\mu = 0 \tag{A.2}$$

Propositions a, b, and c are obtained from the first-order conditions in equations (A.1) and (A.2) and the following second-order derivatives with respect to θ and w.

$$H_{11} = \frac{\partial^2 SW}{\partial \theta^2} = \int_0^X \frac{\partial^2 P}{\partial \theta^2} dX + \frac{\partial^2 S}{\partial \theta^2} \int_z^\theta f(\mu) d\mu + \frac{\partial S}{\partial \theta} f(\theta) - \frac{\partial^2 R}{\partial \theta^2} \leq 0 \tag{A.3}$$

$$H_{22} = \frac{\partial^2 SW}{\partial w^2} = \frac{\partial P}{\partial X} \left(\frac{dX}{dw} \right)^2 + P \frac{d^2 X}{dw^2} - \int_0^\theta \frac{\partial^2 S}{\partial w^2} f(\mu) d\mu + \frac{\partial^2 S}{\partial w^2} \int_z^\theta f(\mu) d\mu \leq 0 \tag{A.4}$$

$$H_{12} = \frac{\partial}{\partial w} \left(\frac{\partial SW}{\partial \theta} \right) = \frac{\partial}{\partial w} \left(\frac{\partial S}{\partial \theta} \right) \int_z^\theta f(\mu) d\mu + \frac{dX}{dw} \frac{\partial P}{\partial \theta} \leq 0 \tag{A.5}$$

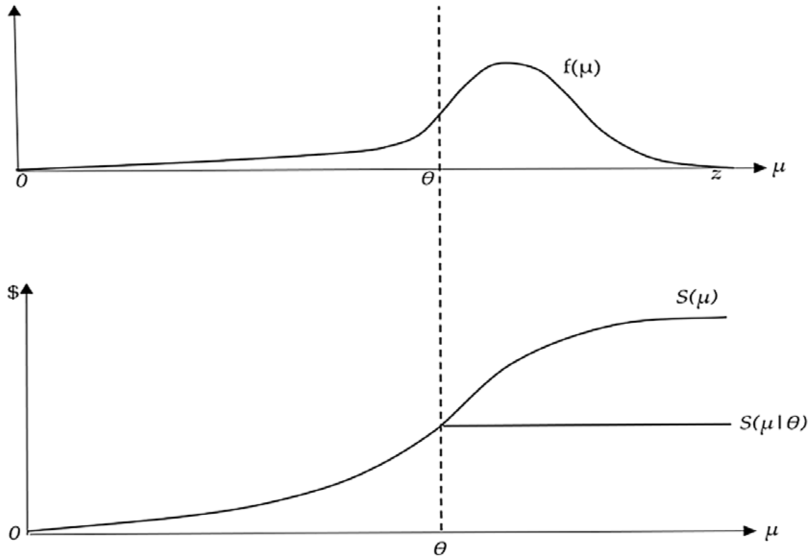

Figure A.1. Distribution of microbial water quality (top panel) and damages from foodborne illnesses (bottom panel).

$$H_{21} = \frac{\partial}{\partial\theta}\left(\frac{\partial SW}{\partial w}\right) = \frac{\partial}{\partial\theta}\left(\frac{\partial S}{\partial w}\right)\int_z^\theta f(\mu)d\mu + \frac{dP}{d\theta}\frac{dX}{dw} \leq 0 \tag{A.6}$$

Comparative static results provide the following expressions for the impacts of the parameters of interest on the optimal water quality standard and optimal irrigation.

(1) *The effect of water cost (c)*

$$\begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}\begin{bmatrix} \frac{\partial\theta}{\partial c} \\ \frac{\partial w}{\partial c} \end{bmatrix} = \begin{bmatrix} -\frac{\partial}{\partial c}\left(\frac{\partial SW}{\partial\theta}\right) \\ -\frac{\partial}{\partial c}\left(\frac{\partial SW}{\partial w}\right) \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{A.7}$$

$$\frac{\partial\theta}{\partial c} = \frac{\begin{vmatrix} 0 & H_{12} \\ 1 & H_{22} \end{vmatrix}}{H_{11}H_{22} - H_{12}H_{21}} = \frac{-H_{12}}{H_{11}H_{22} - H_{12}H_{21}} \geq 0 \tag{A.8}$$

$$\frac{\partial w}{\partial c} = \frac{\begin{vmatrix} H_{11} & 0 \\ H_{21} & 1 \end{vmatrix}}{H_{11}H_{22} - H_{12}H_{21}} = \frac{H_{11}}{H_{11}H_{22} - H_{12}H_{21}} \leq 0 \tag{A.9}$$

(2) *The effect of cost of implementation of FSMA* (β)

$$\begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}\begin{bmatrix} \frac{\partial\theta}{\partial\beta} \\ \frac{\partial w}{\partial\beta} \end{bmatrix} = \begin{bmatrix} -\frac{\partial}{\partial\beta}\left(\frac{\partial SW}{\partial\theta}\right) \\ -\frac{\partial}{\partial\beta}\left(\frac{\partial SW}{\partial w}\right) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial\beta}\left(\frac{\partial R}{\partial\theta}\right) \\ 0 \end{bmatrix} \tag{A.10}$$

$$\frac{\partial\theta}{\partial\beta} = \frac{\begin{vmatrix} \frac{\partial}{\partial\beta}\left(\frac{\partial R}{\partial\theta}\right) & H_{12} \\ 0 & H_{22} \end{vmatrix}}{H_{11}H_{22} - H_{12}H_{21}} = \frac{\frac{\partial}{\partial\beta}\left(\frac{\partial R}{\partial\theta}\right)H_{22}}{H_{11}H_{22} - H_{12}H_{21}} \geq 0 \tag{A.11}$$

$$\frac{\partial w}{\partial \beta} = \frac{\begin{vmatrix} H_{11} & \frac{\partial}{\partial \beta}\left(\frac{\partial R}{\partial \theta}\right) \\ H_{21} & 0 \end{vmatrix}}{H_{11}H_{22} - H_{12}H_{21}} = \frac{-\frac{\partial}{\partial \beta}\left(\frac{\partial R}{\partial \theta}\right)H_{21}}{H_{11}H_{22} - H_{12}H_{21}} \leq 0 \tag{A.12}$$

(3) *The effect of consumer and distributor efforts* (α)

$$\begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}\begin{bmatrix} \frac{\partial \theta}{\partial \alpha} \\ \frac{\partial W}{\partial \alpha} \end{bmatrix} = \begin{bmatrix} -\frac{\partial}{\partial \alpha}\left(\frac{\partial SW}{\partial \theta}\right) \\ -\frac{\partial}{\partial \alpha}\left(\frac{\partial SW}{\partial w}\right) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right)\int_\theta^z f(\mu)d\mu \\ \int_0^\theta \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)f(\mu)d\mu + \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)\int_\theta^z f(\mu)d\mu \end{bmatrix} \tag{A.13}$$

$$\begin{aligned} \frac{\partial \theta}{\partial \alpha} &= \frac{\begin{vmatrix} \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right)\int_\theta^z f(\mu)d\mu & H_{12} \\ \int_0^\theta \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)f(\mu)d\mu + \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)\int_\theta^z f(\mu)d\mu & H_{22} \end{vmatrix}}{H_{11}H_{22} - H_{12}H_{21}} \\ &= \frac{H_{22}\frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right)\int_\theta^z f(\mu)d\mu - H_{12}\left[\int_0^\theta \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)f(\mu)d\mu + \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)\int_\theta^z f(\mu)d\mu\right]}{H_{11}H_{22} - H_{12}H_{21}} \end{aligned} \tag{A.14}$$

Depending on the sign of $S_{\alpha\theta}$, the first term on the right-hand side in the numerator can be negative or positive while the second term is positive (assuming that $\frac{\partial}{\partial \alpha}\left(\frac{\partial SW}{\partial w}\right) > 0$, i.e., an increase in consumer and distributor prevention efforts increases the marginal benefit of water use). This indicates that the impact of consumer and distributor effort on optimal water quality standard is positive or negative depending on the sign of $S_{\alpha\theta}$.

$$\frac{\partial \theta}{\partial \alpha}\begin{cases} = ? & , \text{if } \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right) < 0 \\ \leq 0 & , \text{if } \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right) > 0 \end{cases} \tag{A.15}$$

$$\begin{aligned} \frac{\partial w}{\partial \alpha} &= \frac{\begin{vmatrix} H_{11} & \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right)\int_\theta^z f(\mu)d\mu \\ H_{21} & \int_0^\theta \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)f(\mu)d\mu + \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)\int_\theta^z f(\mu)d\mu \end{vmatrix}}{H_{11}H_{22} - H_{12}H_{21}} \\ &= \frac{\left[\int_0^\theta \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)f(\mu)d\mu + \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial w}\right)\int_\theta^z f(\mu)d\mu\right]H_{11} - H_{21}\frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right)\int_\theta^z f(\mu)d\mu}{H_{11}H_{22} - H_{12}H_{21}} \end{aligned} \tag{A.16}$$

Similarly, the first term on the right-hand side in the numerator is positive, while the second term can be positive or negative (depending on the sign of $S_{\alpha\theta}$). This indicates that the sign of $S_{\alpha\theta}$ determines whether the impact of consumer and distributor effort on optimal water use is positive or negative.

$$\frac{\partial w}{\partial \alpha}\begin{cases} = ? & , \text{if } \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right) < 0 \\ \geq 0 & , \text{if } \frac{\partial}{\partial \alpha}\left(\frac{\partial S}{\partial \theta}\right) > 0 \end{cases} \tag{A.17}$$

Appendix B Empirical model: demand response, FSMA cost, additional tables and figures

Demand response

Bovay and Sumner (2017) and Arnade et al. (2009) estimate that demand declines by 6.9% following an outbreak. This demand change corresponds to 204 cases of foodborne illnesses (Arnade et al. 2009). We use these estimates to obtain the reduction in demand per case of foodborne illness (0.034%). Shuval et al. (1997) estimate that the ratio of clinical illnesses caused by *E. coli* to the total number of infections is 1 to 100. Also, according to Scharff et al. (2016) and Scallan et al. (2011), only one in 26 symptomatic cases is reported in practice. We divide the demand shift parameter by 26*100 to obtain the demand response ($\aleph$) per reported clinical case, which is multiplied by the number of illnesses to obtain a demand response in each state of nature (ϖ_n) (equation 18).

FSMA costs

Cost of implementing FSMA is expressed as a downward sloping linear function of standard stringency (θ). The intuition is that the implementation cost is greatest when $\theta=0$, which corresponds to the situation where any amount of *E. coli* results in producers having to take remediation measures. As the standard is relaxed (θ increases), the cost of implementing FSMA decreases.

To obtain the values of slopes ($\xi_{f,GM}$ *and* $\xi_{f,STV}$) and intercepts ($M_{f,GM}$ *and* $M_{f,STV}$), we linearly approximate the implementation cost function between two points, A and B. We rely on FDA (2015b) to obtain costs of implementing FSMA, \$27.5 and \$21.1 million for small and large farms, respectively. We assume that these costs correspond to the water quality standard as proposed by the FDA (GM should not exceed 126 CFU per 100 ml of water and STV should not exceeds 410). This gives us point A. To linearly approximate the FSMA implementation cost function, we obtain the second point (B) using sufficiently high values of θ_{GM} and θ_{STV} (1,200 CFU/100 ml for GM and 3,900 CFU/100 ml for STV) so that FSMA regulatory constraint (equation 8) produces no delays in any state of nature across all random draws for irrigation water quality. In other words, smallest θ_{GM} and θ_{STV} values are identified such that equation (8) is never bunding across any state of nature. This corresponds to no FSMA regulation and no costs are incurred. This represents point B. We use these two points to derive a linear cost function for GM and STV. In the next step, we divide the intercepts and slopes by the acreages of farms as reported by the FDA (2015b) to obtain the per acre cost. Finally, we adjust these estimates by the percentages of lettuce acreage relative to total vegetable acreage from USDA (2017).

Additional figures and tables

Table B.1. Summary of variables

Symbol	Variable	Unit
SW	Expected value of social welfare	$
$p^d_{n,i}\left(\varpi_n * x^d_{n,i}\right)$	Inverse demand function	–
ϖ_n	Demand response to foodborne outbreaks	–
$p^s_{n,i}\left(x^s_{n,i}\right)$	Inverse supply function	–
$x^d_{n,i}$	Quantity demanded of crop *i*	CWT
$x^s_{n,i}$	Quantity supplied of crop *i*	CWT
ill_n	Number of illness cases	–
$a'_{i,f,ct,ws,g,r}$	Ex-ante planted acreage	Acres
$a''_{n,i,f,ct,ws,g,d,tr,r}$	Ex-post planted acreage	Acres
$cmix_{i,ct,t}$	Historical percentage of planted acreage of crop *i*	Acres
$\vartheta_{ct,t}$	Convex hull choice variable	–
$smix_{i,ct}$	The synthetic crop acreage pattern	Acres
τ_{ct}	Convex hull choice variable	–
$y_{i,ct,g,d,r}$	Yield of crop *i*	CWT
$CN_{n,i,f,ct,ws,g,tr,r}$	Concentration of *E. coli* in crop after delay in harvesting	CFU/ml
$CNS_{n,i,f,ct,ws,g,tr,r}$	Concentration of *E. coli* in crop during storage, transportation, and retail and before consumption	CFU/ml
$D_{n,i,f,ct,ws,g,d,tr,r}$	Dose per contaminated serving	CFU/serving
$p_{n,i,f,ct,ws,g,d,tr,r}$	Probability of illness per serving	Probability/serving

Table B.2. Summary of parameters

Symbol	Parameter	Baseline Values	Unit	Source
N	Number of states of nature	500	–	Authors assumption
δ	Economic losses per illness	8,500	\$	USDA (2019)
ς	Cost of irrigation water	Small farm: 4.0 Large farm: 6.0	\$/Acre/ irrigation	USDA (2013)
$\xi_{f,GM}$	Marginal cost of implementing FSMA based on GM	Small farm: 0.0034 Large farm: 0.0003	\$/Acre	Authors calculations based on FDA (2015b)
$M_{f,GM}$	Costs such that any amount of *E. coli* requires discarding the irrigated produce based on GM	Small farm: 4.12 Large farm: 0.35	\$/Acre	Authors calculations based on FDA (2015b)
$\xi_{f,STV}$	Marginal cost of implementation of FSMA based on STV	Small farm: 0.0011 Large farm: 0.0001	\$/Acre	Authors calculations based on FDA (2015b)
$M_{f,STV}$	Costs such that any amount of *E. coli* requires discarding the irrigated produce based on STV	Small farm: 4.12 Large farm:0.35	\$/Acre	Authors calculations based on FDA (2015b)
θ	Water quality standard	GM:126 STV:410	CFU/ 100 ml	FDA (2016) FDA (2016)
MT_f	Per acre cost of water treatment	Small farm: 24.76 Large farm: 2.48	\$/Acre	Authors calculations based on FDA (2015b)
ex_i	Net export of lettuce	Head: -262,796 Leaf-Romaine: 2,409,853	CWT	USDA (2018)
$GM_{n,i,f,ct,ws,r}$	Geometric mean for FSMA	–	CFU/ 100 ml	Model estimation
$GM'_{n,i,f,ct,ws,g,r}$	Geometric mean for LGMA		CFU/ 100 ml	Model estimation
$STV_{n,i,f,ct,ws,r}$	Statistical threshold value	–	CFU/ 100 ml	Model estimation
π	Rate of change in yield due to additional days of delay	0.15	–	Authors assumption
$\check{y}_{i,ct,g}$	Average observed yield	Various	CWT	USDA (Various years)
$CP_{n,i,f,ct,ws,t',r}$	Concertation of *Generic E. coli* in water in the previous months	–	CFU/ 100 ml	USGS-EPA (2020)
$C_{n,i,f,ct,ws,g,r}$	Concertation of *Generic E. coli* in water	–	CFU/ 100 ml	USGS-EPA (2020)
Λ(ws)	Number of water samples	Surface water: 20 Ground water: 4	–	Authors assumption

(Continued)

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Table B.2. (*Continued*)

Symbol	Parameter	Baseline Values	Unit	Source
$CO_{n,i,f,ct,ws,g,r}$	*E. coli* content of irrigation water	–	–	Generated by the model
λ	Irrigation efficiency	0.7	–	USDA (2013)
R	Ratio of *E. coli* O157:H7 to *Generic E. coli*	$10^{-1.9}$	–	Pang et al. (2017); Ottoson et al. (2011)
ϵ	Die-off function parameter	0.59	–	Brouwer et al. (2017)
$l(g)$	Number of days between irrigation events	6	Days	Smith et al. (2011)
ζ	Die-off function parameter	2.1	–	Brouwer et al. (2017)
η	Proportion of *E. coli* in water source that remains in applied irrigation water	0.7	–	Authors assumption
Ʊ	Average hourly die-off rate during retail, storage, and transportation per CFU of *E. coli*.	0.013	CFU/ hour	Pang et al. (2017)
ϱ_i	Serving size of crop i	Head: 85	Gram	FDA (2015b)
		Leaf-Romaine: 85		
ω	Dose–response function parameter	229.3	–	Pang et al. (2017)
α	Consumer and distributor effort	1	–	Authors assumption
ρ	Dose–response function parameter	0.267	–	Pang et al. (2017)
$\aleph$	Demand shift per number of reported and clinically diseased individuals	1.3e-7	–	Bovay and Sumner (2017); Arande et al. (2009); Shuval et al. (1997)

Table B.3. Own and cross elasticities of demand and own-price elasticity of supply of Head and Leaf-Romaine lettuce

Elasticity	Lettuce Type	Head	Leaf-Romaine
Elasticity of demand	Head	−0.84	0.035
	Leaf-Romaine	0.015	−0.84
Elasticity of supply	Head	0.56	–
	Leaf-Romaine	–	0.56

Note: Own-price elasticities of demand are obtained from Okrent and Alston (2012), cross-price elasticities of demand are derived from Ferrier et al. (2016), and own-price elasticities of supply are obtained from Lohr and Park (1992).

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Table B.4. Comparison of simulation results and the observed data for Head and Leaf-Romaine lettuce

		Year										
	Lettuce Type	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Baseline
a) Observed Data												
Quantity (10,000 CWT)	Head	5,136	4,952	4,933	4,928	5,011	4,459	4,593	4,353	4,591	4,291	4,591
	Leaf-Romaine	3,172	3,073	3,720	3,660	3,748	3,614	3,441	3,535	4,096	4,084	4,096
Price ($/CWT)	Head	20.25	22.40	20.85	22.29	16.83	24.97	22.45	26.51	24.5	32.17	24.5
	Leaf-Romaine	25.24	31.33	28.26	31.42	25.15	13.63	13.88	22.95	14.74	17.21	14.74
b) Model Solution												
Quantity (10,000 CWT)	Head	5,136	4,952	4,933	4,931	5,010	4,459	4,593	4,338	4,591	4,273	4,592
	Leaf-Romaine	3,172	3,073	3,720	3,660	3,748	3,614	3,441	3,535	4,096	4,084	4,096
Price ($/CWT)	Head	19.54	21.61	20.57	21.98	16.59	24.18	23.44	27.61	23.63	33.57	24.32
	Leaf-Romaine	24.36	30.23	27.32	30.45	24.36	13.21	13.39	22.14	14.58	16.98	14.57
c) Percentage Difference Between Model Solution and Observed Data												
Quantity (%)	Head	0.00	0.00	0.00	0.08	0.00	0.00	0.00	−0.33	0.00	−0.41	0.02
	Leaf-Romaine	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.00
Price (%)	Head	−3.51	−3.53	−1.34	−1.39	−1.43	−3.16	4.41	4.15	−3.55	4.35	−0.73
	Leaf-Romaine	−3.49	−3.51	−3.33	−3.09	−3.14	−3.08	−3.53	−3.53	−1.09	−1.34	−1.15

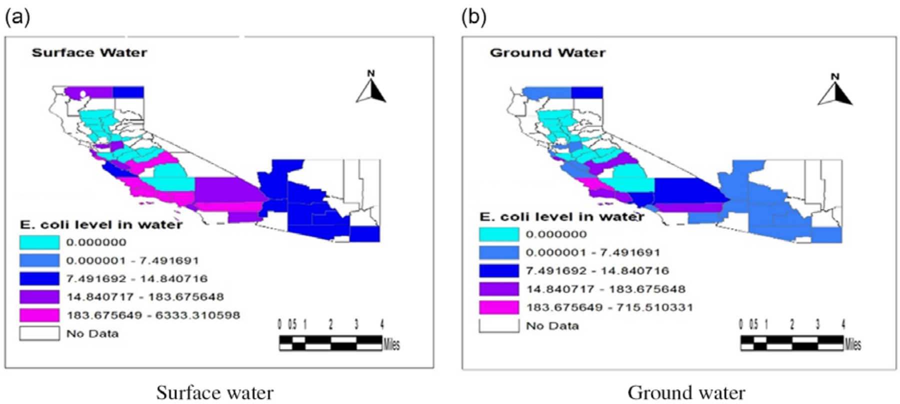

Figure B.1. Average *E. coli* CFU per 100 ml of surface water and ground water in Arizona and California counties.

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