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**Meat Slaughter and Processing Plants' Traceability
Levels: Evidence From Iowa**

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Title: Meat Slaughter and Processing Plants' Traceability Levels: Evidence From Iowa

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Meat Slaughter and Processing Plants' Traceability Levels: Evidence From Iowa

Abstract

Based on an econometric analysis of the data obtained from a survey of meat plants ($n = 53$) in Iowa in summer 2007, this paper identifies the factors impacting the meat plants' voluntary adoption of forward and backward traceability activities. The results suggest that the ownership type (corporate versus independent) and operations type (slaughtering versus not) matter rather than the size and meat type produced (beef, pork, or poultry) as suggested in the previous surveys. Furthermore, food safety activities appear to be complementary to traceability activities. The findings may assist ongoing regulatory efforts in implementing traceability in U.S. in the near future.

Key Words: country of origin labeling, food safety, multiple imputation method, national animal identification system, ordered logistic regression, quality assurances, traceability

JEL Classifications: Q13, Q18, C21, C35

1. Introduction

The incidences of bovine spongiform encephalopathy (BSE) and possible introduction of contagious diseases such as foot and mouth disease in livestock, the bioterrorism threat, recent high profile food scares and recalls due to *Escherichia coli* 0157:H7 (E. Coli) and *Salmonella* increased interest in traceability in the United States (U.S.). The basic idea of traceability is to create and maintain an “information trail” that follows to a certain extent the path taken by a given physical product in its entire production process. There is no commonly accepted and one-type-fits-all definition for traceability. In this paper, the word “traceability” is used in a broad sense as the ability to trace and track the flow of product or product attributes through the supply chain.

Despite increased calls from consumer groups and other stakeholders, the U.S. is lagging behind E.U. and other competitors in adopting a traceability system. There is no uniform traceability regulation across the U.S. food sector, which is supervised by two agencies the Food and Drug Administration (FDA) and U.S. Department of Agriculture

(USDA). FDA implemented one-step back and one-step forward traceability over the industries under its jurisdiction, which covers nearly 80% of food products including grain, animal feed, vegetables and pet food. USDA, which oversees red meat, poultry and egg production, requires some record keeping as part of food safety regulation. Particularly, a two-part-system has developed in the meat supply chain; live animal traceability and meat traceability with slaughter and processing plants in between.

There are ongoing regulatory efforts to improve meat and live animal traceability. For live animal tracking, the National Animal Identification System (NAIS) originally scheduled to be fully implemented in 2009, is now a voluntary program and includes three components; premise registration, animal identification and animal tracing. According to the USDA, as of January 22, 2008, over 30% of eligible premises had been registered nationwide. A somewhat related mandate is country of origin labeling (COOL); a 2002 Farm Bill provision; which requires appropriate labeling as to the country of origin of product at the retail counter, but specifically blocked the Secretary of Agriculture from requiring national animal identification to implement COOL. The implementation of mandatory COOL for all covered commodities (beef, pork, lamb, etc.) except wild and farm raised fish and shellfish was postponed twice and is now due to begin in September 2008.

Amid these regulatory trends, towards connecting the meat and live animal traceability and establishing full chain traceability, meat slaughter and processing plants will play critical role, yet their traceability activities have not been studied in a straightforward and coherent manner. Previous studies have rather focused on the meat plants' adoption of Hazard Analysis and Critical Control Points (HACCP) plans and food

safety investments (Hooker, Nayga, and Siebert 1999; Ollinger, Moore, and Chandran, 2004; Muth, et al., 2005a; Cates, et al. 2006; Ollinger and Moore, 2007). The current information and evidence on U.S. meat plant's adoption of traceability activities is limited to the reporting of the responses to a few questions included in food safety surveys (Hooker, Nayga, and Siebert 1999; Cates, et al. 2006). The latter study further performs Chi-square tests (independence tests) regarding the size factor vis-à-vis forward and backward traceability activities in the subsamples of red meat and poultry plants.

The objective of this study is to fill the gap in the literature by empirically examining the factors affecting the meat plants' decisions to adopt traceability practices in a multivariate econometric model. To this end, a survey including 43 questions which characterize meat plants' traceability level, production process, products, and plant type was prepared. The survey was sent to the licensee plants of Iowa Department of Agriculture and Land Stewardship, which covers 194 meat plants including those with national brands and mostly small or very small plants in summer 2007. The response rate to the survey was 27.5% (53 plants).

Based on the survey responses, an indirect (categorical) measure of traceability and appropriate explanatory variables are constructed (see Table 1 for their descriptions). Using these variables, ordered logit equations for forward and backward traceability are estimated. The economic factors impacting plants' decision to voluntarily adopt more stringent traceability practices are identified as the ownership type (corporate versus independent) and operations type (slaughtering versus not) rather than the size and meat type produced (beef, pork, or poultry) as suggested in the aforementioned studies. Furthermore, food safety activities appear to be complementary to traceability activities.

The findings may help better targeting of ongoing regulatory efforts and limited regulatory resources in implementing traceability in U.S. in the near future.

2. Data Sources

Our target sample included 194 Iowa based (117 federally and 77 state inspected) meat plants. They were listed as licensees in the website of Iowa Department of Agriculture and Land Stewardship (IDALS) Meat and Poultry Bureau in the fiscal year 2007.¹ A profile of meat plants in Iowa is provided in the Economic Census of U.S. Census Bureau in Iowa in 2002; 92 plants have animal (except poultry) slaughtering operations. Of these slaughtering plants, 27 plants have at least 20 employees. 44 plants process meat from carcasses. Of these meat processing plants, 25 plants have at least 20 employees. Nine plants process poultry. Of these poultry processing plants, six have at least 20 employees (U.S. Department of Commerce, 2004).

The survey was carried-out in June and July 2007. Plants' contact information in IDALS' website was verified and supplemented with the information in Yellow Book's website (www.yellowbook.com). Nine plants were excluded from the initial sample for reasons such as being a university research unit, repeated facility, change of business, and missing address. Self-administered surveys with pre-paid envelopes were mailed out. If no response was received within two weeks, a post-card was sent as a reminder. In the end, 53 plants responded to the survey, the response rate became 27.5%. Of these respondent plants, 28 had federally inspected and the remaining 25 had state inspected plant status. Hence, both federal and state inspected plants are fairly represented in the

¹ For more information on a sample of plants, see <http://www.kellysolutions.com/ia/MeatPoultry/>.

data.

The survey includes 43 questions in total, which characterize meat plants' traceability level, production process, products, and plant type. The questions were reviewed by the IDALS bureau and several industry contacts for feedback purposes without any implication of endorsement or responsibility. The raw data for select variables are presented in Table 2 Parts 1, 4 and 5. A missing data problem is apparent from responses; the average percentage of missing observations for 40 variables in Parts 1, 4, and 5 is 17% with the standard deviation of 17%, the minimum of 0% (fully observed variables in Part 1), and the maximum of 58.5% for the variable *QAS Supplier*.² The following section provides information on how this issue is handled.

3. Imputation Strategy

The missing data problem is dealt by using a Bayesian method of multiple imputations (MI), which is extensively discussed in Schafer and Graham (2002) and chapter 27 in Cameron and Trivedi (2005). The following discussion closely follows their expositions. MI creates multiple data sets for incomplete multivariate data by drawing from a conditional distribution. The information in incomplete cases is utilized rather than lost as in ad-hoc methods such as list-wise deletion. Actually list-wise deletion of the observations with missing values would leave few observations for the analysis, whereas MI provides the advantage of proceeding with complete data methods and software. Furthermore, because MI predicts more than one value for each missing value, the uncertainty in imputation process can be incorporated into estimated standard errors and

² The variable *Non-Slaughtering* in Table 2 Part 1 is not included in these calculations because it is constructed from other operation type variables in the same table.

p-values.

MI method assumes that the probability an observation is missing depends on the observed values of variables but not on the unobserved values (missing at random (MAR) assumption). This is weaker assumption than the independence assumption between complete and incomplete values (missing at completely random (MCAR) assumption), which is implicitly made in list-wise deletion method. In our data set, it appears that missing data are mostly associated with the state inspected very small plants, which favors the MAR assumption. In any case, the departures from MAR have minor impact on estimates and standard errors under the MI method. Furthermore, the MI method assumes that the variables in the data are jointly distributed as normal. Even though some of the variables are discrete and all variables are non-negative in our dataset, MI is shown to be quite robust to the deviations from multivariate normal distribution, and rounding off the imputed values are deemed to be plausible.

We used the procedure PROC MI in SAS (SAS Institute, 2003) which implements the MI method. Even though five imputations are often considered enough, we conservatively set the number of imputations to 10 as the variables do not confirm to normal distribution. The variables with the full number of observations in the original dataset (except the variable *Non-Slaughtering* see footnote 2), which are presented in Table 2 Part 1, are used to impute the variables with missing observations. This process does not assume a causal relationship between imputer and imputed variables.

Furthermore, we chose the Multiple Markov Chain Monte Carlo (MCMC) mechanism in imputation under PROC MI. MCMC mechanism includes initial prior selection step followed by imputation and posterior steps which are repeated over a

number of times. Given parameters (mean vector and covariance matrix) from prior, the imputation step draws values for the missing values of a vector of variables for each observation from its conditional distribution on the fully observed variables for that observation. This is independently done for each observation. Once the data set is complete, the posterior step simulates the posterior distribution of the mean and covariance matrix. The new parameter values obtained from this step are then used in the following imputation step and so on. If these steps are iterated long enough, the parameters and missing values form a Markov Chain which converges to a stationary distribution, which yields the desired estimates.

In the prior selection stage, we chose an informative prior by using the estimated mean and covariance matrix from initial data. We used separate chains for each imputation, set the number of burning iterations before the first imputation and the number of iterations between imputations to 1000. As initial values, the MCMC method used the values obtained from posterior Expectation Maximization (EM) algorithm. EM algorithm yields the parameter estimates which maximize the observed data posterior. SAS reported that EM algorithm converged. Regarding the convergence of the MCMC algorithm, using TIMEPLOT and ACFPLOT options in PROC MI, we verified that there is no serial dependency in time series and autocorrelation function plots of estimated parameters against the iteration number. At the imputation stage the values are rounded up to one digit. The restrictions on minimum and maximum values are imposed once the incomplete data is imputed. For example, if a value of a variable as a percentage is imputed to be higher than 100, then it is set to 100 or if it is imputed as negative, it is set to zero.

The data summary of the imputed data is presented in Table 3 Parts 1 and 2. Comparing that with the data summary in Table 2 Parts 4 and 5 shows that imputation process generated predictions which are consistent with the original data.

4. Econometric Modeling

We define ordered logit equations where probability to adopt a forward or backward traceability level is modeled as a function of plant's characteristics. This is in line with the following studies: Hassan, Green and Herath (2006) analyzes the food safety and quality activities of Canadian meat processors using a ordered logistic regression equation. Souza-Monteiro and Caswell (2006) uses a binomial logit model to explain the adoption of traceability at the farm level in the Portuguese pear industry, where the choice is over EurepGAP (European Retailers for Good Agricultural Practices) standards versus the mandatory E.U. level.

The relationship between level of adoption for backward or forward traceability and plant characteristics is written in separate equations as

$$(1) \quad T^i = \beta_0^i + \sum_{j=1}^{K^i} X_j^i \beta_j^i + \varepsilon^i$$

where $i = \{B, F\}$ indexes the traceability equations (B for backward; F for forward) and equation specific variables and parameters, $j = 1, \dots, K^i$ indexes the explanatory variables,

T^i is the unobservable dependent variable, β_0^i is the intercept parameter, X_j^i are

explanatory variables, β_j^i are the corresponding parameters, K^i is the number of explanatory variables, and ε^i is the disturbance term.

Equation (1) can be seen as a reduced form of a structure which is based on the traceability level decision of a profit maximizing firm. Such a modeling approach is taken in Souza-Monteiro and Caswell (2006). Furthermore, Souza-Monteiro and Caswell (2005) consider a decision problem within a principal agent framework where the customer is principal and the plant is agent. Other structures may include hedonic pricing approach within a competitive market equilibrium framework. This route is taken for the food safety variable in Antle (2000). We concentrate our efforts on the specification of equation (1) without adhering to a particular structure.

The dependent variables in equation (1) (*Backward* and *Forward*) are constructed as an indirect measure for backward and forward traceability levels based on the responses to the survey question on the plants' frequency for mock forward and backward traceability trials, respectively. As presented in Table 2 Parts 3 and 4, for either traceability variable, routine once or twice in a year mock traceability activity is considered as high level (level 3), whereas no traceability activity in a year is considered as low (basic) level (level 1) of traceability. Occasional or rare traceability activity is taken as middle ground (level 2). Then, the relationship between indirect measure of traceability (T^i) and unobservable traceability level variable (T^{i*}) is written as

$$(2) \quad T^i = \begin{cases} 1 & \text{if } -\infty \leq T^i < \mu_1^i, \\ 2 & \text{if } \mu_1^i \leq T^i < \mu_2^i, \\ 3 & \text{if } \mu_2^i \leq T^i < \infty, \end{cases}$$

where the bounds μ_1^i and μ_2^i are parameters to be estimated for $i = \{B, F\}$. Plugging T_i^* from (1) into (2) yields the following in terms of probabilities of adopting a particular level in forward or backward traceability

$$(3) \quad \begin{aligned} P(T^i = 1 | \mathbf{X}^i) &= \Lambda(\mu_1^i - \mathbf{X}^i \beta^i) \\ P(T^i = 2 | \mathbf{X}^i) &= \Lambda(\mu_2^i - \mathbf{X}^i \beta^i) - \Lambda(\mu_1^i - \mathbf{X}^i \beta^i), \\ P(T^i = 3 | \mathbf{X}^i) &= 1 - \Lambda(\mu_2^i - \mathbf{X}^i \beta^i) \end{aligned}$$

where $\Lambda = \frac{e^z}{1+e^z}$ is the cumulative probability function for logistic distribution with a generic variable z and \mathbf{X}^i is the matrix of explanatory variables for $i = \{B, F\}$.

Table 1 provides the descriptions for the dependent variables (T^F and T^B) and explanatory variables (X_1, X_2, \dots, X_{23}) constructed from the survey responses and used in the estimations. Based on the findings of previous literature, the following factors are of particular interest (see Bulut and Lawrence, 2007 for a more detailed discussion); meat type (beef, poultry or pork), the share of meat products with credence attributes in plant's sales, the percentage of branded as opposed to commodity meat products in plant's sales, if a plant exports its products, plant's specialization in cooked versus fresh products, the degree of reliance to contracting relative to spot-market in supplier and/or customer base,

ownership type (corporate versus independent plants), extra (over and above what is required in HACCP rule) testing of meat products and environment, the presence of a quality assurance system (such as ISO 9001, 2000; quality assurance systems, QAS), size of plant, capital intensity of plants, and operations type (slaughtering versus not).

5. Estimation Results

Meat plants' probability of adopting a higher order of traceability level in equation (3) is estimated for each of 10 imputed data sets using the procedure PROC LOGISTIC in SAS (SAS Institute, 2003). Then, the results from these 10 regression estimations are combined and reported using the procedure PROC MIANALYZE in SAS (SAS Institute, 2003) which incorporates the additional uncertainty from multiple imputations in the final report of standard errors and p-values. Tables 4 and 5 present the final results from the estimation of three models for each type of traceability (forward and backward, respectively). In the following, unless a particular table is specified, Model 1 refers to both Model 1 in Table 4 and Model 1 in Table 5. The same applies in referring to Model 2 and Model 3.

The first model under the column Model 1 includes meat type and size variables. These factors are found to be significant in Cates, et al. (2006). Particularly, they report that poultry plants adopt more backward and forward traceability than red meat (beef or pork) plants. As the size of plants increase, they adopt more forward traceability both in poultry and red meat plants. In backward traceability, size is a factor in the overall sample of poultry plants, and in the sub-samples of non-very small (large or small) versus

very small poultry plants but not anywhere in red meat plants. Both red meat and poultry plants appear to adopt more forward than backward traceability.

Although meat type factor is not found significant, the size factor is initially significant at the conventional levels under the column Model 1. However, some other variables are also identified as significant under the column Model 2: *Corporate* and *Non-Slaughtering* for both types of traceability; *Insurance* and *Contracting Supplier* for forward traceability; *Extra Testing of Products* and *Branded* for backward traceability. Once all the variables in columns Models 1 and 2 are included together under the column Model 3, size variables are no longer significant, meat type variables are still insignificant, whereas other variables remain significant. Using the TEST statement in PROC MIANALYZE, the size and meat type variables are not even jointly significant together (with p-values of 0.53 in forward and 0.69 in backward traceability equations, respectively).

Dropping the highly insignificant size and meat type variables from Model 3 yields back Model 2. Similarly, the remaining explanatory factors listed in Table 1 (referring to all variables except $(X_1, X_2, X_3, X_{11}, X_{12}, X_{17})$ for forward and $(X_1, X_2, X_3, X_{10}, X_{11}, X_{15})$ for backward traceability equations) are added one by one to Model 2 and tested for significance at the conventional levels. However, none of these variables turned out to be significant at the conventional levels once the variables in Model 2 are controlled for.³ Because no other significant variable can be added to Model

³ The variables with the lowest p-values turn out to be $X_{12} = \textit{Contracting Supplier}$ with p-value of 0.18 in the backward traceability equation and $X_5 = (\textit{Medium Capital}, \textit{High Capital})$ with p-value of 0.24 (based on the joint test of significance of categories in X_5) in the forward traceability equation. Further details can be requested from the authors.

2 for both types of traceability, it will be the final model and is reviewed in the following.

The finding of insignificant size can be attributed to the advantages and disadvantages to various sizes of plants in adopting traceability. The larger and the more complicated the operations are, the costlier traceability is to satisfy a given safety or quality assurance standard as the total variable cost of traceability increases with the size. On the other hand, average fixed cost of implementing traceability decreases with the units of inputs processed. Large firms may have a disadvantage over small and mid-size firms in implementing a traceability system because the individual suppliers of inputs can not fill the big scale operations. This necessitates the mixing of inputs from different sources, which increases the cost of tracking (Bailey, Robb, and Checketts, 2005).

Regarding the meat type factor, poultry plants are known to be more vertically integrated and have more automated production process compared to red meat plants (Hennessy, Miranowski and Babcock, 2004). However, a possible impact these organizational differences across meat types on the voluntary traceability adoption is not accentuated through meat type variables in our results.

Non-slaughtering plants are found to be more likely to adopt both forward and backward traceability activities. The odds of having more stringent forward traceability are 5.9 times, and more stringent backward traceability are 7.5 times higher for non-slaughtering plants.⁴ By their nature, traceability might be more adoptable in non-slaughtering (processing and/or distribution) than slaughtering operations. The former

⁴ The estimated coefficients can be converted into odds ratios by taking their exponential transformation which is $e^{\hat{\beta}}$ for an estimated parameter $\hat{\beta}$ for dummy variables. For continuous variables one uses $100(e^{\hat{\beta}} - 1)$ for an estimated parameter $\hat{\beta}$ which yields the percentage change in odds ratio as a result of one unit change in the explanatory variable.

typically involves regrouping of given lots of meat inputs into new lots of meat products, whereas the latter involves first disassembling of a given lots of animals into meat cuts and then remixing and resorting these cuts into outgoing lots.

Furthermore, it could be more difficult to establish liability against slaughtering plants than non-slaughtering plants. Slaughter plants are less visible and may rely on the fact that they sell meat which has the stamp of a USDA inspection for wholesomeness.⁵ This can particularly apply for enteric bacteria such as E-coli and Salmonella which emanate from feces in cattle intestines. These are more likely to originate from slaughter plants' operations because non-slaughtering plants do not work with hides covered with manure. The raw meat arrives at the processing plant in packages bearing USDA's mark of inspection. If a meat product is tested positive for enteric bacteria in a non-slaughtering facility, it is no longer the responsibility of source slaughter plant (Kramer, Coto, and Weidner, 2005).

In addition, corporate plants are found to be more likely to adopt more stringent traceability both forward and backward, than independent plants. Specifically, the odds of having more stringent forward traceability are 16.5 times and more stringent backward traceability are 6 times higher for corporate plants. This finding can be attributed to corporate policies against reputation loss and liability costs, which are considered to be strong drivers of traceability (Pouliot and Sumner, 2008). Note that in our data set, nearly half of corporate plants are small, which indicates that small plants are fairly represented

⁵ In slaughtering plants, inspectors are present during operations. Unless a violation of federal safety rules is detected, the products are shipped out bearing the USDA's mark on raw meat products for wholesomeness. However, this mark does not mean a certified assurance of safety to eat and can be misinterpreted by consumers even though they report higher valuation for federal inspection vis-à-vis COOL and traceability in Loureiro and Umberger (2007).

among corporate plants. Moreover, the majority of corporate plants do not have slaughtering operations, whereas the majority of independent plants have slaughtering operations.

Furthermore, food safety and traceability efforts appear to be complementary. Particularly, those that adopt extra testing of products are 4.4 times more likely to adopt backward traceability and those that carry insurance against food recalls are 4.2 times more likely to adopt a higher level of forward traceability. This finding provides evidence on the association between food safety and traceability, which is explored in theoretical papers such as Starbird and Amanor-Boadu (2006) and Pouliot and Sumner (2008).

Plants that sell branded products have a statistically significant negative coefficient in backward traceability equation. Particularly, a 1% increase in the share of branded products in a given plant's sales decreases the odds of that plant's adopting voluntary traceability practices by 1.8%. Despite some loss in industry reputation as a result of food safety recalls, so long as a firm does not have recall experience for a given product, its branding for that product may provide a shield against reputation loss because the problems can be externalized to other brands (Thomsen, Shiptsova, and Hamm, 2006).^{6,7} Possible higher incentives for quality control to consistently preserve the reputation of the brand could make traceability more desirable in that regard. However, plants may rely on other instruments for quality purposes such as testing, inspection, and process control (Antle, 2001).

⁶ Following pet food poisoning recalls in March 2007, FDA and American Medical Association initially urged consumers to switch brands (Associated Press, 2007).

⁷ Absent branding, Pouliot and Sumner (2007) study how traceability can protect the broad reputation of industry by making recalls more effective during food safety outbreaks.

Finally, we find a statistically significant negative association between contract use in supplier base and forward traceability adoption. Particularly, 1% increase in the use of contracting in supplier base decreases the odds of adopting forward traceability activities by 2.2%. This might suggest that the use of contracting decreases the need for adopting more stringent traceability activities. One of the reasons reported in Muth, et al. (2005b) for higher reliance on alternative marketing arrangements (contracting in particular) relative to cash (spot) market in purchase or sales is that these arrangements facilitate product traceability by allowing necessary exchange of information.

6. Conclusion

This paper studies the traceability levels of meat slaughter and processing plants based on the estimation of an ordered logistic model using the data collected from a survey of meat plants in Iowa in June and July 2007. The initial problem of missing data is handled by applying the multiple imputation method, which is (to our knowledge) the first application of this method to meat plants' survey data and can be adopted by other researchers in future. The information obtained from this study sheds light on plant level solutions in adopting traceability activities as response to economic incentives and environment, which may help better targeting of limited regulatory resources to implement traceability in the U.S. meat supply chain in the near future.

Among many that are initially considered, this study identifies a few factors that are critical in adoption of traceability activities. These variables are a type of operation *Non-Slaughtering* (processing and/or distributing but not slaughtering), and a type of ownership *Corporate* (part of a corporate company) for both forward and backward

traceability. Contrary to previous survey findings on traceability, it turns out that adoption of traceability is independent of size of plants and the type of meat they produce once these variables are considered along with the other relevant factors in a multivariate regression framework.

Furthermore, traceability activities appear to be complementary to food safety efforts; particularly carrying insurance against recalls and extra testing of meat products are positively associated with forward and backward traceability, respectively. Ensuring that a plant's traceability system is functional could be part of its recall plans if these plans are tested through mock scenarios (Kramer, Coto, and Weidner, 2005). Moreover, plants with branded products show less likelihood of adopting traceability, which may suggest that these plants may rely on branding rather than traceability in isolating themselves from recalls and outbreaks occurring in other plants.

Among the economic arguments of adopting traceability in resolving information asymmetry in supply chain as suggested in Hobbs (2004), the ex-post cost reduction and liability functions of traceability are supported in our study but not the ex ante quality verification function (includes verifying credence claims). Particularly, no evidence is found regarding possible synergies with quality assurance efforts (represented by the variables *QAS Plant* and *QAS Supplier*) and the adoption of traceability activities. Furthermore, regarding organizational factors, a negative association is found between the level of contracting use in supplier base and the adoption of forward traceability practices. Nevertheless, there was no statistical difference across meat types in adopting either type of traceability activities as these industries are known to differ in terms of degree of vertical integration.

In terms of policy implications, a policy change mandating more stringent traceability across all segments in meat supply chain may not work to the disadvantage of small or very small firms. This is in contrast with the negative impact of HACCP Rule on small or very small processors reported in the literature (Siebert, Nayga and Hooker, 2001; Antle, 2001; Boland, Peterson-Hoffman and Fox, 2001). Furthermore, the impact of such a uniform policy change will mainly be on slaughtering plants and independent plants as non-slaughtering plants and corporate plants are more likely to voluntarily adopt traceability activities. In other words, instead of such a uniform policy, regulatory efforts for implementing traceability can concentrate on the plants with less likelihood of voluntarily adopting traceability such as slaughtering and independent plants.

The findings of this study also have implications for ongoing regulatory proposals. If NAIS is implemented in the near future, the traceability at the live animal stage will improve. For a complete traceability along the meat supply chain, this must be matched by slaughter and meat processor plants. The possibility of implementation of mandatory COOL in September 2008, which requires record keeping and verification as to the origin of meat products, could induce meat plants to adopt traceability activities as part of their preparation for the regulation. However, our findings indicate that this hypothesis appear to hold true for non-slaughtering plants but not for slaughtering plants. Amid ongoing discussion and the surrounding uncertainty on the implementation of NAIS and COOL, slaughtering plants appear to be unmotivated and may remain unprepared.

It has been more than a decade since U.S. meat plants have been mandated to adopt the HACCP rule. Meanwhile, according to 2006 data, after a period of decline, the

incidences of infection for E. coli and Salmonella are returning to earlier levels compared to the base year of 1996 to 1998 (Centers for Disease Control, 2007). Recent increases in the frequency and scale of the incidences for these infections have raised many questions on the effectiveness of inspection policy and pointed out significant hurdles in tracing meat products backward and forward in supply chain.⁸ As a result, Food Safety and Inspection Service (FSIS) at USDA reassessed some of the testing and inspection practices (USDA, 2007). Nevertheless, for a durable solution, food safety outbreaks must be viewed and approached as system-wide problems and the accountability in all segments of supply chain must be established. Towards that direction, some changes in FSIS's rules for requiring and handling of source information in the event of a recall are reported (Scherer, 2008). In addition to our study, further evidence on meat plants' traceability adaptation from other states and ideally at the national level in future studies can help intensify such regulatory efforts and is warranted.

⁸ By the time this paper has been written, the largest beef recall in U.S. meat industry was underway. The recall was due to violations federal safety rules (torturing cattle and processing 'downer' cattle intended for human consumption) and exposed not by inspection but rather an undercover videotape. It involved 143 million pounds (65 million kilograms) of beef (thought to feed more than 2.2 million U.S. citizens for a year) that was shipped out from a California meatpacker since February 2006. Most of the meat had probably been consumed and no related health incidents have been reported (Blinch and Doering, 2008; Zhang, 2008).

References

- Antle, J.M. 2000. "No Such Thing as a Free Safe Lunch: The Cost of Food Safety Regulation in the Meat Industry." *American Journal of Agricultural Economics* 82(2): 310-22.
- Antle, J.M. 2001. "Economic Analysis of Food Safety." Gardner, B.L. and R.C. Gordon, eds. *Handbook of agricultural economics*. Volume 1B. Marketing, distribution and consumers. *Handbooks in Economics*, vol. 18. Amsterdam; London and New York: Elsevier Science, North-Holland: 1083-1136.
- Bailey, D., J. Robb, and L. Checketts. 2005. "Perspectives on Traceability and BSE Testing in the U. S. Beef Industry." *Choices* 20(4): 4th Quarter.
- Blinch, R. and C. Doering, 2008. "Record U.S. Beef Recall a Wake-Up Call". Reuters, February 20. Internet site: <http://www.reuters.com/article/newsOne/idUSN2038194520080220> . Last Accessed on February 26, 2008.
- Boland, M., D. P. Hoffman, and J.A. Fox. 2001. "Post-implementation Costs of HACCP and SSOP's in Great Plains Meat Plants." *Journal of Food Safety* 21(3): 195-204
- Bulut, H. and J.D. Lawrence. 2007. "Meat Slaughter and Processing Plants' Traceability Levels." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL. Available at the internet site: http://www.farmdoc.uiuc.edu/nccc134/conf_2007/pdf/confp20-07.pdf .
- Cameron, A.C. and P.K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. Cambridge University Press, New York, NY, USA.
- Cates, S.C., Karns, S., Viator, C., & Muth, M.K. 2006. "Food Safety Practices and Technologies Used by U.S. Meat Slaughter Plants: Results of a National Mail Survey." 93rd Annual International Association for Food Protection Meeting, Calgary, Alberta, Canada, August 13–16.
- Centers for Disease Control and Prevention, 2007. "New Report Highlights Growing Foodborne Illness Challenges E. coli O157, Salmonella and Vibrio among Notable Concern," April 12. Internet site: http://www.cdc.gov/od/oc/media/pressrel/2007/r070412.htm?s_cid=mediarel_r070412_x. Accessed in February 20, 2008.
- Associated Press. 2007. "Some Pet Owners Turn to Making Own Pet Food After Contamination Scare." Internet site: <http://www.foxnews.com/story/0,2933,263941,00.html>. Last accessed on Feb 20, 2007.

- Hassan Z., R. Green, and D. Herath. 2006. "An Empirical Analysis of the Adoption of Food Safety and Quality Practices in the Canadian Food Processing Industry." Available at the internet site: <http://www.bepress.com/sjohnson/>.
- Hennessy D., J. A. Miranowski, and B. Babcock. 2004. "Genetic Information in Agricultural Productivity and Product Development." *American Journal of Agricultural Economics* 86 (1): 73-87.
- Hooker, N., R.M. Nayga, Jr., and J. Siebert. 1999 "Preserving and Communicating Food Safety Gains." *American Journal of Agricultural Economics* 81:1102-1106.
- Hobbs, J.E. 2004. "Information Asymmetry and the Role of Traceability Systems." *Agribusiness* 20(4): 397-415.
- Kramer, M.N., D. Coto, J.D. Weidner. 2005. "The Science of Recalls." *Meat Science* 71: 158-163.
- Loureiro, L.M. and W.J. Umberger. 2007. "A Choice Experiment Model for Beef: What U.S. Consumer Responses Tell Us About Relative Preferences for Food Safety, Country-of-Origin Labeling and Traceability." *Food Policy* (32): 496-514.
- Muth, M. K., R. Beach, S. Karns, C. Viator. 2005a. "Economic Impact Analysis: BSE Rulemaking." Report prepared for the U.S. Department of Agriculture, Food Safety and Inspection Service, March. Available at the internet site: <http://www.aamp.com/foodsafety/documents/BSE-EconomicImpactAnalysis-2005.pdf> . Last Accessed on February 28, 2008.
- Muth, M.K., Brester, G., Del Roccili, J., Koontz, S., Martin, B., N. Piggott, J. Taylor, T. Vukina, and M. Wohlgenant. 2005b. "Spot and Alternative Marketing Arrangements in the Livestock and Meat Industries: Interim Report." July. Interim Report prepared for the U.S. Department of Agriculture, Grain Inspection, Packers and Stockyards Administration.
- Ollinger, M., D. Moore, and R. Chandran. 2004. "Meat and Poultry Plants' Food Safety Investments: Survey Findings." U.S. Department of Agriculture, Economic Research Service, Technical Bulletin 1911.
- Ollinger, M. and D. Moore. 2007. "Market Forces, Plant Technology, and Food Safety Technology Use". Paper based on the poster presentation at the Annual Meeting of American Agricultural Economics Association, Portland, OR, July 29-August 1.
- Pouliot, S. and D.A. Sumner. 2007. "Traceability, Recalls, and Industry Reputation." Paper presented at the 2007 Annual Meeting of the American Agricultural Economics Association, Portland, OR, July 29-August 1.

- Pouliot, S. and D.A. Sumner. 2008. "Traceability, Liability, and Incentives for Food Safety and Quality." *American Journal of Agricultural Economics*. 90 (1): 15-27
- SAS Institute. SAS™ under Windows. Version 9.1. SAS Institute Inc., Cary, NC, 2003.
- Schafer, J.L. and J.W. Graham. 2002. "Missing Data: Our View of the State of the Art." *Psychological Methods* 7: 147-177.
- Scherer, M. 2008. "The Feds are Still Looking For the E. Coli" Internet site: http://www.salon.com/news/feature/2007/05/01/e_coli/ .
- Siebert J.W., R. M. Nayga Jr. and N. Hooker. 2000. "Dimensions of Food Safety Risk Mitigation Strategies Adopted by Meat Processors: The Case of HACCP". World Food and Agribusiness Forum International Food and Agribusiness Management Association.
- Souza-Monteiro, D. M. and J. A. Caswell. 2005. "The Economics of Traceability for Multi-Ingredient Products: A Network Approach." Paper presented at the Annual Meeting of the American Agricultural Economics Association, Providence, RI, July 24-27.
- Souza-Monteiro, D. M. and J. A. Caswell. 2006. "Traceability Adoption at the Farm Level: An Empirical Analysis of the Portuguese Pear Industry." Paper presented at 2006 Annual Meeting of American Agricultural Economics Association, July 23-26, Long Beach, California. Available at the internet site <http://agecon.lib.umn.edu/cgi-bin/index.pl> .
- Starbird, A. and V. Amanor-Boadu. 2006. "Do Inspection and Traceability Provide Incentives for Food Safety?" *Journal of Agricultural and Resource Economics* 31(1): 14-26.
- Thomsen M. R., R. Shiptsova, and S. J. Hamm. 2006. "Sales Responses to Recalls for *Listeria monocytogenes*: Evidence from Branded Ready-to-Eat Meats." *Review of Agricultural Economics* 28(4), 482-493, Winter.
- U.S. Department of Agriculture, Food Safety and Inspection Service. 2007. "Notice of Reassessment for *Escherichia Coli* O157:H7 Control and Completion of a Checklist for All Beef Operations." Notice 65-07, October 12, Washington, DC. Available at the internet site <http://www.fsis.usda.gov/OPPDE/rdad/FSISNotices/65-07.pdf> . Accessed on February 20, 2008.
- U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau. 2004. 2002 Economic Census. Washington, DC, December.

Zhang, J. 2008. "Tracing Beef Supply is Hurdle for U.S." The Wall Street Journal, March 5, 2008, Leading the News Section.

Table 1. Part 1: Description of variables constructed from responses to the traceability survey.

Variables	Description
$T^F = \text{Forward}$	Categorical variable which take the value one for low level, two for medium level, and three for high level of forward traceability.
$T^B = \text{Backward}$	Categorical variable which take the value one for low level, two for medium level, and three for high level of backward traceability.
$X_1 = \text{Non-Slaughtering}$	Dummy variables which takes the value of one for the plant has the operations such as processing or distribution but not slaughtering and zero otherwise. Base is plants with their operations including slaughtering. Other constructed variables for operation types, used in the imputations stage, are <i>Slaughter Only</i> , <i>Processor Only</i> , <i>Distributor Only</i> , <i>Slaughter & Processor</i> , and <i>Processor & Distributor</i> which take value of one for the corresponding operation type and zero otherwise.
$X_2 = (\text{Beef}, \text{Poultry})$	Continuous variables which show the percentages of the meat types of beef and poultry within the plant's total annual production, respectively. Poultry include chicken, turkey and other poultry. Base is <i>Pork</i> which is defined for pork meat type similar to <i>Beef</i> and <i>Poultry</i> . <i>Pork</i> also includes a very small share of red meat other than beef and pork.
$X_3 = (\text{Large}, \text{Small})$	Dummy variables which indicate the size of plant. They take value of one if the number of employees exceeds 100, if the number of employee exceed 10 but less than or equal to 100, respectively and zero otherwise. Base is <i>Very Small</i> takes value of one if the plant has at most 10 employees.
$X_4 = (\text{Young Age}, \text{Medium Age}, \text{Old Age})$	Dummy variables which indicate the age of plant. They take the value of one, if the plant has at least 5 but less than 10 years of operations, if the plant has at least 10 but less than 20 years of operations, and if the plant has at least 20 years of operations, respectively, and zero otherwise. Base is <i>Very Young Age</i> if the plant has less than 5 years of operations.
$X_5 = (\text{Medium Capital}, \text{High Capital})$	Dummy variables which indicate the capital level of plant. They take the value of one if the value of capital is at least \$500,000 and but less than \$5 million, and if the value of capital is at least \$5 million, respectively and zero otherwise. Base is <i>Low Capital</i> takes value of 1 if the value of capital is less than \$500,000 and zero otherwise.

Table 1. Part 2: Description of variables constructed from responses to the traceability survey continues.

Variables	Description
$X_6 = (Interstate, Exports)$	Continuous variables which indicate the percentage of interstate and exports market within plant's total sales. Base is the percentage of intrastate sales.
$X_7 = (Mid\ Supplier\ Concentration, High\ Supplier\ Concentration)$	Dummy variables indicating the concentration of the top three suppliers in plant's total dollar value of inputs (animal/fresh meat). They take the value of 1 if the share of top three suppliers is less than 25%, at least 25% but less than 75%, and at least 75%, respectively and zero otherwise. Base is <i>Low Supplier Concentration</i> .
$X_8 = (Mid\ Customer\ Concentration, High\ Customer\ Concentration)$	Dummy variables indicating the concentration of the share of top three customers in plant's total sales revenue. They take the value of 1 if the share of top three customers is less than 25%, at least 25% but less than 75%, and at least 75%, respectively and zero otherwise. Base is <i>Low Customer Concentration</i> .
$X_9 = Credence$	Continuous variable indicating the percentage of products with credence claims (characteristics which are not perceivable to users when the product is purchased or consumed, and which users can not personally and directly assess) within plant's total annual sales.
$X_{10} = Branded$	Continuous variable indicating the percentage of branded products within plant's total annual sales.
$X_{11} = Corporate$	Dummy variables for plant ownership. Corporate takes value of 1 if plant is a branch of corporate company and zero otherwise. Base is independently owned and operated plants.
$X_{12} = Contracting\ Supplier$	Continuous variable indicating the percentage of inputs (live animal/fresh meat) procured using forward contracting or marketing agreements versus cash/spot market.
$X_{13} = Contracting\ Customer$	Continuous variable indicating the percentage of sales made using forward contracting or marketing agreements versus cash/spot market.
$X_{14} = (Customer\ Type\ Restaurant, Customer\ Type\ Retailers, Customer\ Type\ Exporters)$	Continuous variables indicating the percentage of sales coming from restaurants, retailers, exporters, respectively. Base is plants' other customer types.

Table 1. Part 3. Description of variables constructed from responses to the traceability survey continues.

Variable	Description
$X_{15} = \textit{Extra Product Testing}$	Dummy variable which takes value of one if plant does test its products over and above that which is required in Pathogen Reduction/HACCP Rule.
$X_{16} = \textit{Extra Environment Testing}$	Dummy variable which takes value of one if plant does tests the environmental cleanliness in the production area or production equipment, respectively, over and above that which is required in Pathogen Reduction/HACCP Rule.
$X_{17} = \textit{Insurance}$	Dummy variable which takes value of one if plant carries insurance against product recalls and zero otherwise.
$X_{18} = \textit{Fresh}$	Continuous variable indicating the percentage of fresh meat products in total annual production.
$X_{19} = \textit{Supplier Incentive}$	Dummy variable which takes value of one if plant provides incentives in the form of premiums or discounts based on certain quality characteristics to its suppliers and zero otherwise.
$X_{20} = \textit{QAS Plant}$	Dummy variable which takes value of one if plant has a quality assurance system (such as QSA, PVP, ISO 9000, etc.) in place and zero otherwise.
$X_{21} = \textit{QAS Supplier}$	Dummy variable which takes value of one if plant's suppliers have a quality assurance system (such as QSA, PVP, ISO 9000, etc.) in place and zero otherwise.
$X_{22} = \textit{Computer Use}$	Dummy variable indicating the plant's method to keep track of its business operations and transactions. It takes value of one if plant indicated use of computer in keeping records and zero otherwise. Base is plants indicated that their record keeping is paper-based only.
$X_{23} = \textit{Recall}$	Dummy variable which takes value of one if plant indicated that it had been subject to a product recall due to food safety problem in the last 3 years and zero otherwise.

Table 2. Part 1. Data summary of fully observed variables ($n = 53$)

Variables	Frequency	Percentage
<i>Processor & Distributor</i>	7	13.2
<i>Processor Only</i>	19	35.8
<i>Distributor Only</i>	1	1.9
<i>Slaughter Only</i>	3	5.7
<i>Slaughter & Processor</i>	17	32.1
<i>Non-Slaughtering</i>	27	50.9
<i>Small</i>	20	37.7
<i>Large</i>	9	17.0
<i>Extra Product Testing</i>	40	75.5
<i>Extra Environment Testing</i>	37	69.8
<i>Recall</i>	3	5.7
<i>Computer Use</i>	35	66

n : Number of observations.

Table 2. Part 2. Data summary for the construction of the variable *Forward* (forward traceability level)

Levels	Mock Traceability trials	Frequency of trials	Frequency of the corresponding level
Level 3 = High	Routinely twice in a year	7	14
	Routinely once in a year	7	
Level 2 = Medium	Occasionally	5	7
	Rare	2	
Level 1 = Low (Basis)	Never	9	9
Missing data	Don't Know	12	23
	No response	11	

Table 2. Part 3. Data summary for the construction of the variable *Backward* (backward traceability level)

Levels	Mock Traceability trials	Frequency of trials	Frequency of the corresponding level
Level 3 = High	Routinely twice in a year	3	17
	Routinely once in a year	14	
Level 2 = Medium	Occasionally	6	8
	Rare	2	
Level 1 = Low (Basis)	Never	13	13
Missing data	Don't Know	12	15
	No response	3	

Table 2. Part 4. Data summary of incomplete continuous explanatory variables

Variables	N	Mean	Standard Deviation	Min	Max
<i>Forward</i>	38	2.1	0.9	1	3
<i>Backward</i>	30	2.2	0.9	1	3
<i>Beef</i>	45	40.0	31.5	0	100
<i>Poultry</i>	45	5.2	8.5	0	42
<i>Branded</i>	28	58.6	45.8	0	100
<i>Credence</i>	31	12.2	30.7	0	100
<i>Interstate</i>	47	31.3	41.9	0	100
<i>Exports</i>	47	7.4	20.8	0	100
<i>Fresh</i>	48	59.2	40.7	0	100
<i>Contracting Customer</i>	32	18.0	34.2	0	100
<i>Contracting Supplier</i>	36	15.4	31.4	0	100
<i>Customer Type Exporters</i>	41	9.6	25.5	0	100
<i>Customer Type Restaurants</i>	41	12.6	24.3	0	100
<i>Customer Type Retailers</i>	41	14.4	23.2	0	90

Table 2. Part 5. Data summary of incomplete categorical explanatory variables

Variables	N ^b	Frequency ^b	Percentage ^b
<i>Corporate</i>	52	15	28.8
<i>Insurance</i>	39	25	64.1
<i>Mid Supplier Concentration</i>	36	15	41.7
<i>High Supplier Concentration</i>	36	17	47.2
<i>Mid Customer Concentration</i>	34	11	32.4
<i>High Customer Concentration</i>	34	8	23.5
<i>QAS Plant</i>	32	20	62.5
<i>QAS Supplier</i>	22	16	72.7
<i>Supplier Incentive</i>	47	17	36.2
<i>Medium Capital</i>	43	14	32.6
<i>High Capital</i>	43	9	20.9
<i>Young Age</i>	52	12	23.1
<i>Medium Age</i>	52	10	19.2
<i>Old Age</i>	52	21	40.4

Table 3. Part 1. Data Summary for Imputed Continuous Variables ^a $m \times n = 10 \times 53$

Variables	Mean	Standard Deviation	Min	Max
<i>Forward</i>	2.0	0.8	1	3
<i>Backward</i>	2.1	0.8	1	3
<i>Beef</i>	40.9	30.3	0	100
<i>Poultry</i>	4.9	7.9	0	42
<i>Branded</i>	53.7	41.4	0	100
<i>Credence</i>	14.5	27.8	0	100
<i>Interstate</i>	33.0	40.8	0	100
<i>Exports</i>	8.6	20.4	0	100
<i>Fresh</i>	59.0	39.5	0	100
<i>Contracting Customer</i>	21.1	30.9	0	100
<i>Contracting Supplier</i>	19.0	29.1	0	100
<i>Customer Type Exporters</i>	11.1	24.1	0	100
<i>Customer Type Restaurants</i>	12.2	22.0	0	100
<i>Customer Type Retailers</i>	15.3	21.6	0	90

m : Number imputations, n : Number of observations.

Table 3. Part 2. Data Summary for Imputed Categorical Variables ^a $m \times n = 10 \times 53$

Variables	Frequency ^b	Percentage ^b
<i>Corporate</i>	15.2	28.7
<i>Insurance</i>	34.4	64.9
<i>Mid Supplier Concentration</i>	24.1	45.5
<i>High Supplier Concentration</i>	24.2	45.7
<i>Mid Customer Concentration</i>	15.3	28.9
<i>High Customer Concentration</i>	11.4	21.5
<i>QAS Plant</i>	32.1	60.6
<i>QAS Supplier</i>	37.9	71.5
<i>Supplier Incentive</i>	9.9	18.7
<i>Medium Capital</i>	17.3	32.6
<i>High Capital</i>	11.0	20.8
<i>Young Age</i>	12.0	22.6
<i>Medium Age</i>	10.3	19.4
<i>Old Age</i>	21.6	40.8

^a m : Number imputations, n : Number of observations.

^b Averaged over 10 imputed samples

Table 4. Part 1. Forward Traceability Multiple Imputation Parameter Estimates:
 Dependent Variable: Probability of having a higher forward traceability level.
 $m \times n = 10 \times 53$

Parameter	Model 1	Model 2	Model 3
μ_1	-0.272 (-0.36)	-0.503 (-0.82)	-1.105 (-1.04)
μ_2	-2.136 ** (-2.53)	-2.907 *** (-3.73)	-3.627 *** (-2.95)
<i>Beef</i>	0.014 (1.18)	...	0.011 (0.7)
<i>Poultry</i>	0.033 (0.9)	...	0.030 (0.69)
<i>Large</i>	2.632 ** (2.4)	...	0.785 (0.52)
<i>Small</i>	0.859 (1.32)	...	-0.250 (-0.25)
<i>Corporate</i>	...	2.806 *** (2.94)	2.958 *** (2.77)
<i>Non-Slaughtering</i>	...	1.779 ** (2.58)	1.733 ** (2.02)
<i>Insurance</i>	...	1.444 ** (2.06)	1.366 * (1.86)
<i>Contracting Supplier</i>	...	-0.022 * (-1.81)	-0.017 (-1.19)

Notes: m : Number imputations, n : Number of observations; t-values are in the parentheses;
 ***, **, * indicate significance at 1%, 5%, and 10%, respectively, based on the t-statistics.

Table 5. Backward Traceability Multiple Imputation Parameter Estimates: Dependent Variable: Probability of having a higher backward traceability level.

$m \times n = 10 \times 53^a$

Parameter	Model 1	Model 2	Model 3
μ_1	-0.810 (-0.85)	-0.664 (-0.69)	-1.753 (-1.06)
μ_2	-2.196 ** (-2.46)	-2.401 ** (-2.37)	-3.570 ** (-2.21)
<i>Beef</i>	0.015 (1.27)	...	0.020 (1.11)
<i>Poultry</i>	0.00009 (0)	...	0.026 (0.63)
<i>Large</i>	2.573 ** (2.47)	...	1.104 (0.83)
<i>Small</i>	1.510 ** (2.03)	...	0.598 (0.58)
<i>Corporate</i>	...	1.799 ** (2.34)	2.056 ** (2.03)
<i>Non-Slaughtering</i>	...	2.013 *** (2.62)	1.803 ** (2.1)
<i>Extra Testing of Products</i>	...	1.487 * (1.75)	1.483 * (1.66)
<i>Branded</i>	...	-0.018* (-1.87)	-0.021 * (-1.94)

Notes: m : Number imputations, n : Number of observations; t-values are in the parentheses; ***, **, * indicate significance at 1%, 5%, and 10%, respectively, based on the t-statistics.