Somatic Cell Counts in Dairy Marketing: Quantile Regression for Count Data

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Abstract: We study the determinants of somatic cell count (SCC) for fluid milk among U.S. dairies. We synthesize much of the work that has been done to model SCC economically in order to identify the potential impacts of buyer-imposed penalties and incentives within the supply chain. Additionally we estimate quantile regression for count data to measure impacts specifically for those operations with the highest SCC and to account for the statistical properties of the data. Premiums in particular have the potential to reduce SCC considerably where it is currently the highest. We draw implications for profitability in relation to SCC reduction.

Introduction

The quality of agricultural commodities in the United States, broadly defined, has wide-ranging economic implications. Quality drives prices received by producers as well as those ultimately paid by consumers in the retail sector. Consumers and all agents of the post-farm gate food supply chain increasingly demand food that is safe and traceable, factors tied directly to quality. The quality of U.S. agricultural output, relative to that of other nations, shapes the dynamics of international supply, demand, and trade. We develop an economic model to understand the quality determinants of fluid milk, as measured by somatic cell count (SCC), which shares a well-established, inverse relationship with quality.[1] In doing so, we provide implications for both producers and buyers towards increasing fluid milk quality via reductions in SCC. A growing body of international evidence (e.g. Bennett, 2003) suggests that reductions in SCC in the U.S. dairy industry can mitigate the economic costs of diminished yields or infectious diseases that have been linked to elevated SCC and related bovine health issues.

Fluid milk is one of the United States' most important agricultural commodities. The factors most important in shaping fluid milk quality are relevant to welfare considerations throughout the dairy industry and for consumers, as a factor shaping retail food prices, and to the competitiveness of U.S. agriculture in the global market. Dairy products rank third among all agricultural commodities in terms of total receipts (Economic Research Service, 2013) and 12th according to the total value of exports (Economic Research Service, 2011). With respect to global agriculture, it has been argued that comparatively lax federal regulations regarding allowable SCC in fluid milk leaves the U.S. dairy industry at a competitive disadvantage relative to other major exporters (Dong, et al., 2012)[2]. Several states have begun imposing stricter SCC

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[1] Blowey and Edmondson (2010) provide a thorough review of the scientific literature on SCC.
[2] Fluid milk itself is not a major U.S. export, but SCC is a determinant of both milk yield and quality, as discussed in

limits, and one of the primary objectives of this study is to investigate how incentives or

penalties, which can be imposed without high fixed costs on the part of dairies (as compared to

adjustments in capital or technology) within the dairy industry may be exploited to significantly

reduce SCC.

We also investigate important potential linkages between SCC and producer profitability.

According to the Agriculture Resource Management Survey (ARMS), the majority of dairy

producers in the U.S. are not profitable, in that they do not have positive net returns. There

appears to be an important connection between average SCC levels and the probability of being

profitable. Meeting certain SCC thresholds, set lower than the federally regulated maximum,

may be reasonably attainable for a range of operations according to our results and can

considerably increase the likelihood of dairy producers establishing profitability.

The Economics of SCC and the Dairy Industry

Fluid milk in the United States is marketed according to a grading system. The federal

government has set standards to determine quality as being of Grade A or Grade B, the standards

for the former being more stringent. Only Grade A milk can be marketed for fluid consumption,

while Grade B milk is used for the production of cheese, butter, and other products. Over 90

percent of all milk produced in the U.S. is Grade A (Agricultural Marketing Service, 2013).[3]

Somatic cell count is one of the two measures used nationally to assess quality and to distinguish

Grade A from Grade B milk.[4] The premium commanded by Grade A milk and its suitability for a

wider range of commercial uses have generated interest among economists regarding how dairy

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detail below. Therefore SCC has direct implications for the processed dairy industry, for which fluid milk is the major input. Processed dairy includes major exports such as cheese.

[3] Grade B milk is often referred to as "manufacturing grade" milk within the dairy industry.

[4] The other is standard plate count, a measure of bacteria in fluid milk, and it is not an aspect of this study.

producers may be incentivized to reduce SCC and obtain Grade A-status for their output (Balagtas, et al., 2007).

The majority of economic research related to SCC, however, has focused on the direct and indirect costs associated with bovine diseases and other issues attributable to high SCC. These costs, broadly defined, stem from multiple sources. Increased SCC in raw milk is associated with reduced shelf life for pasteurized milk (Barbano, et al., 2006) as well as reduced yields from dairy cows (Green, et al., 2006, Howard, et al., 1991). The price commanded by fluid milk likely bears an inverse relationship with SCC, ceteris paribus. Atsbeha et al. (2012) estimated a hedonic pricing function for bulk-tank fluid milk and found it to decrease nearly linearly with SCC. Dekkers et al. (1996) estimated the pecuniary benefits dairy producers may achieve, per cow, by reducing SCC below various threshold levels. The benefits were drawn mostly from the increased yields and higher milk prices that would result from lower SCC.

High SCC is strongly associated with the incidence of bovine disease mastitis, which is one of the most significant and quantifiable sources of the costs arising from high SCC levels.[5] It is the single most costly disease to dairy producers (Bennett and IJpelaar, 2005, Rodenburg, 2012). Recently economists have come to recognize that the capacity to control outcomes such as mastitis may be enhanced from insights gleaned through modeling techniques and empirical approaches commonly used in the field (McInerney, 2008). Huijps et al. (2008) found that dairy producers are likely to underestimate considerably the costs associated with bovine mastitis, suggesting that further research and education on the economic impacts of the disease as well as an improved incentive structure towards reducing SCC are likely motivated. To that end, Huijps et al. (2010) demonstrated penalties to be more effective than bonuses in reducing SCC and

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[5] Dairy cows afflicted with mastitis are unable to produce milk, at least temporarily. The mammary gland may cease production entirely and the udder sac becomes inflamed and firm. Rodenburg (2012) provides additional background on the disease.

mitigating mastitis. As demand for organic foods continues to expand in the U.S. and organic production grows concomitantly, it remains unclear as to whether there is a systematic difference in SCC or the incidence of mastitis between organic and conventional operations and, if so, the direction of the difference (Dong, et al., 2012, Richards, et al., 2002).

Several studies have attempted to estimate the total economic costs associated with increases in or high levels of SCC. The identification of costs associated with SCC is difficult due to the large number mechanisms by which SCC can generate economic loss as well as the multitude of agents, including consumers, tied to fluid milk output and quality. Bulk-tank SCC spiked in the U.S. in 1996 and a large number of studies attempted to estimate the related economic impacts. In a survey of this literature, Losinger (2005) estimated that this short-term increase in average SCC levels resulted in a net loss of approximately $810 million to the U.S. economy. Bennett (2003) found that mastitis alone is responsible for a net loss of 57 to 185 million pounds to the U.K. economy annually. It is not an objective of this paper to refine the estimation of the economic costs of SCC, but rather to improve our understanding of the determinants of SCC, including economic incentives, given the potential for improvement in the U.S. dairy industry and the myriad related costs of excessive SCC.

Econometric Model

Our study is not the first to examine empirically the determinants of SCC or closely-related bovine diseases, such as mastitis. Somatic cell count has been modeled in many different ways, oftentimes as the basis of a case study, and almost uniformly for European countries. Our empirical approach can be thought of as a synthesis of different approaches to the problem, applied to the United States and with a data set that stands out in the extant literature for its depth and richness, namely the ARMS.

Broadly speaking, models of SCC to date have focused primarily on production practices and managerial factors. Production practices that have been studied, which are often tied to SCC via biological mechanisms, include the adoption of organic status (Haskell, et al., 2009, Richards, et al., 2002) or the method of milking (Green, et al., 2006, Sauer and Zilberman, 2012). Relevant managerial factors include attributes of managers such as location or capital intensity as well as linkages to the buyers and the supply chain (Dong, et al., 2012, Howard, et al., 1991, Huijps, et al., 2010). In this latter category, some studies have focused specifically on the roles of premiums or penalties imposed by buyers (Hand, et al., 2012, Nightingale, et al., 2008).

To be sure, there is often some degree of overlap among these studies, particularly since production practices and managerial factors are typically interrelated. However, owing largely to data limitations and small sample sizes, few studies have incorporated key elements from both categories. Dong et al. (2012), who use the same data utilized in our study, are an exception to this although they do not examine the importance of incentives within the dairy supply chain, generated through the buyer-producer relationship, that can be so important to shaping milk quality. We argue that it is these factors, endemic to the terms established between buyers and dairy producers, that provide fertile ground for the identification of cost-effective and logistically practical means by which to reduce SCC in the U.S. dairy industry. This is a contention strongly supported by the work of Huijps et al. (2010). Drawing on the implications of previous research on SCC and mastitis, we model milk quality among dairy producers as:

(1)   *Milk Quality = f(Buyer Terms, Production Practices, Managerial Factors) + error*,

where *Buyer Terms* serves as an umbrella term for the quality-based requirements imposed upon producers by milk buyers and any related penalties or bonuses. Model (1) is designed to control

for key determinants of SCC as evidenced by the existing literature on the topic in order to flesh

out the potential role of buyer requirements or standards. The econometric specification is

therefore

$$SCC_{i,t} = \beta_1 + \beta_2 SCCPremium_{i,t} + \beta_3 VolumePremium_{i,t} + \beta_4 TestPenalty_{i,t} + \beta_5 PricePenalty_{i,t}$$
$$+ \beta_6 SecurityGuidelines_{i,t} + \beta_7 MGMTPractices_{i,t} + \beta_8 HerdSize_{i,t} + \beta_9 HerdSizeSq_{i,t} +$$
$$(2) \quad \beta_{10} CowAge_{i,t} + \beta_{11} HousingAge_{i,t} + \beta_{12} Organic_{i,t} + \beta'\textbf{\textit{Location}}_i + \varepsilon_{i,t}$$

The data used in the empirical analysis are drawn from the USDA's 2005 ARMS Phase

III, administered jointly by the USDA's Economic Research Service and National Agricultural

Statistics Service (NASS). The ARMS Dairy Costs and Returns Report provides detailed data on

a large and varied sample of dairy farms. The underlying survey is part of a larger data collection

endeavor by the USDA and responses are obtained through a sequence of in-depth structured

interviews with producers. The survey is conducted approximately every five years, but the most

recent 2010 survey does not include information on SCC. All variables are drawn directly from

ARMS. The survey targeted dairy operations in twenty four states that account for more than

90% of national milk production and covered all major production areas (McBride and Greene,

2009). Survey data had a total of 1,814 observations.

The complete list of variables used in the analysis, including brief definitions and

summary statistics, is available in table 1. The dependent variable, SCC, gives the annual

average bulk tank somatic cell count for dairy producer i in year t. For the purpose of ARMS

data collection, SCC is reported in thousands, suggesting the importance of accounting for the

statistical properties of count data. We revisit this point in detail below.

Table 1 here.

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We examine two variables representing bonuses or rewards. *SCCPremium* reports the value of the premium, in dollars per cwt, offered by the buyer in return for yielding SCC levels below an agreed-upon threshold.[6] Over 59 percent of dairies were offered an SCC premium with the premium averaging about 24¢ per cwt. A preliminary investigation revealed that operations which dealt with buyers offering a premium had lower average SCC levels (244 thousand cells per ml.) compared with the dairies that had no premium structure in place (294 thousand cells per ml.) We sorted the dairies in the observed sample retained for the model into quartiles by the reported SCC. The average premium paid for dairies in the lowest quartile of SCC was $0.36 per cwt, dropping to $0.12 per cwt for dairies in the highest quartile of SCC. The empirical regularity is that higher premium payments are associated with lower SCC values or higher quality milk from the dairy producer. *VolPremium* is a dummy variable equal to one if the producer was offered a premium for meeting an annual volume threshold, also agreed upon between the buyer and seller. Over 43 percent of the surveyed operations were offered a volume premium for their milk production. The proportion of operations receiving a volume premium increases with size. For the smallest dairies (1-49 milk cows) only 18 percent receive a premium while premiums are reported by over 60 percent of dairies in the largest size class (over 500 cows). The potential impact of this premium on SCC is unclear because it incentivizes quantity at the potential expense of quality, but higher overall milk yield is typically associated with lower SCC (Green et al., 2006).

We also focus on two variables representing penalties imposed by buyers for failing to meet imposed standards. Respondents to ARMS are presented with a series of eight requirements that are commonly set by buyers and asked to indicate how many requirements are imposed to

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[6] This variable can take the value of zero. This variable represents the combination of responses to two questions in ARMS. One question asks if a SCC premium is offered at all, and the follow-up question asks the value of the premium if one is offered.

them and, if imposed, the respective ramifications of failure. *TestPenalty* reports the number of these standards for which the penalty of failure is a retesting of milk quality, specifically SCC levels, by the buyer. *PricePenalty* reports the number of questions for which the penalty is a potential reduction or renegotiation of the milk selling price. The full details behind the construction of these variables are available in Appendix B.

The next of variables address managerial factors, which largely describe dairy operations in an effort to control for key SCC determinants as shown by the literature. Most of these are relatively time-invariant or very costly to adjust, though exhibit a large degree of cross–sectional variation. *HerdSize* and *HerdSizeSq* are linear and quadratric, respectively, counts of dairy cows in the operation, in 1000s. Allore et al. (1997) and Oleggini et al. (2001) found larger herds to be associated with lower bulk talk SCC. Several studies on the dairy industry have uncovered systematic differences in performance, profitability, quality, and yields by geographic region. MacDonald et al. (2007) surveyed the dairy industry using ARMS data and organized dairy-producing states into traditional, western, southern, and "other" categories. We use this classification to construct a vector of geographical dummies *Location*.[7] *CowAge* is the average age of the cows in the milking herd, as Harmon (1994) and Dong et al. (2012) showed the age of dairy cattle to be a small but significant factor driving up SCC.[8] *HousingAge* is the average age of the housing units used for dairy cows. Following Dong et al. (2012), we include this as a measurement of the extent to which housing facilities are modern and equipped to contain or reduce SCC.

The final set of variables focuses on production practices, which are related to managerial factors but more closely determined according to operators' choices and typically more elastic

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[7] The complete classification of states is found in table 1.
[8] Harmon (1994) found that the impact of age is marginal for healthy cows but age greatly exacerbates SCC levels in cows afflicted by mastitis.

over time. *SecurityGuidelines* is an index that reports the extent to which operators abide by a

series of common biosecurity measures, categorized within ARMS. *MgmtPractices* is also an

index, showing the extent to which operators engage in a series of practices listed in ARMS that

involve the use of modern milking or testing methods, digital technology, and marketing

techniques.[9,10] Finally, *Organic* is a dummy equal to one for certified organic operations. The

expected relationship between SCC and organic status is not clear. Richards et al. (2002) note

that organically-produced milk may have higher SCC due to the increased incidence of

infections among cattle on these operations, but that organic producers typically hold their milk

with the highest SCC back from the market in order to achieve average SCC levels below certain

thresholds.[11]

Estimation Issues

The ultimate objective of this study is to identify means by which dairy operations can feasibly

reduce SCC in order to meet lower thresholds, or higher quality standards. Naturally, this

exercise has the strongest implications for those producers exhibiting the highest SCC.

Estimating (2) with ordinary least squares (OLS) or any approach that imposes the requirement

that the conditional probability distribution must be approximated by a few moments of a

parametric distribution limits our interpretation of coefficients to estimated impacts on mean

SCC. As Dong et al. (2012) argued, quantile regression is a potentially valuable tool for this

research question as it allows for the estimation of effects on SCC specific to operators with

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[9] The complete details behind the construction of *SecurityGuidelines* and *MgmtPractices* are available in Appendix A.

[10] We considered separating out the marketing techniques from this measure, as their potential relationships with SCC are not as clear as those linking technological enhancements or modernization in general. The practices in question are forward purchasing and price discounts, both of which are defined fully in appendix A. However the proportion of farms surveyed that utilize these approaches is very small and either removing both or treating them as a separate index does not change the findings.

[11] Richards et al. (2002) also note that there may be reason to expect SCC to increase with cow age more rapidly on organic operations, as compared to conventional. We experimented with interacting *CowAge* with *Organic* to investigate this possibility and found no evidence to support this.

different levels of SCC, most importantly those with the highest and greatest need for improvement.

Additionally, while SCC is measured in 1000s, it may not be appropriate to model this variable as being continuous. The variable includes no information past 1000, therefore as an example, an actual SCC between 55,000 and 56,000 is recorded in ARMS as 55. We therefore argue that it is more appropriate to model SCC as count data, given that it consists of discrete, nonnegative integers. Ordinary least squares relies on the assumption of normality, which is typically violated by the highly skewed nature of count data, and can lead to biased estimates (Cameron and Trivedi, 1998). Taking these factors into account, we subject (2) to a generalized Poisson estimation, which is widely considered appropriate for use with count data, as well as quantile regression for count data. Via the latter approach, we examine how quantiles of the conditional distribution of a response variable recorded in discrete units (1000s of SCC) depend on a set of explanatory variables.

In addition to modeling the entire distribution of SCC, the quantile regression approach relaxes important restrictions in the parametric specifications of count data models. When using more common count data approaches, such as the generalized Poisson or negative binomial, the relationships between explanatory variables and response variables are determined explicitly by a few moments of the parametric distribution (Winkelmann, 2006). In our context, these restrictions would ensure that SCC increases yield only a single switch between positive and negative marginal effects. The quantile model for count data relaxes these restrictions and allows for a richer determination of the relative magnitudes of marginal effects.

The quantile regression for count data approach was developed by Machado and Santos Silva (2005). The methodology is based on a smoothing algorithm that constructs a continuous

variable with conditional quantiles that have a one-to-one relationship with the conditional

quantiles of the counts. The discrete count response, y_i, is replaced with a smooth, continuous

transformation so that linear quantile regression methods can be applied. An auxiliary variable is

created such that $z_i = y_i + U_i [0,1)$, where U_i is a uniform random variable in the interval $[0,1)$.

Any continuous distribution that has support on $[0,1)$ can be used in the transformation and

standard quantile techniques can be applied to a monotonic transformation of the auxiliary

variable z_i. The estimated quantiles of z_i are non-negative and the transformed quantile function

is linear in the parameters when a monotonic transformation is used.

Let $Q_y(\tau|X)$ and $Q_z(\tau|X)$ denote the τth quantiles $(0 \leq \tau \leq 1)$ of the conditional distribution

of y_i and z_i and define

$$Q_z(\tau|X) = \tau + \exp[X\beta(\tau)].$$

The set of explanatory variables is denoted by X and β represents the estimated parameters. The

predictive equation includes the additive term τ because $Q_z(\tau|X)$ is bounded from below by τ due

to the additive random variable U $[0,1)$. The model can be estimated in a linear form using the

following logarithmic transformation of z

$$\text{Log}(z-\tau) \qquad \text{if } z_i > \tau$$

$$\text{Log} (\varsigma) \qquad \text{if } z_i \leq \tau$$

and regressing these values on X. The ς term represents a suitably small positive number. The

transformation back to the y_i counts uses the ceiling function

$$Q_y(\tau|X) = [Q_y(\tau|X)-1]$$

where $[\alpha]$ returns the smallest integer greater than or equal to α. The estimated quantile functions

for z_i (denoted as the jittered y_i) provide a smooth linear interpolation among the step functions

for y_i. The y_i are described as "jittered" to signify that uniformly distributed random noise is

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added to the original data. The result is that $Q_y(\tau|X)$ can be recovered from information on $Q_z(\tau|X)$. The quantile function is not everywhere differentiable because the distribution function has corners. But when the explanatory variables in the model include at least one continuous variable the corner points have measure zero. Moreover, Machado and Santos Silva (2008) demonstrated that the estimator is consistent and asymptotically normal.

To further motivate the approach, figure 1 plots SCC as a function of number of milk cows per operation. The sample of dairy farmers was split into quartiles by herd size and then the SCC was computed for each dairy size quartile. The medians of the SCC for each dairy size are represented by the horizontal lines with the edges of the boxes revealing the 25th percentile and 75th percentile (the lower and upper quartiles), respectively. Particularly among the three largest quartiles, it is clear that both median SCC as well as variability across farms decrease with herd size. These observations conform with the findings of Allore et al. (1997) and Oleggini et al. (2001) and also serve to suggest that SCC likely exhibits structural differences across dairy farms of varying characteristics. While boxplots and related statistical tools are limited to examining the distribution of SCC with respect to a single variable, the quantile regression method offers a powerful framework with which to estimate models for the conditional median function along with the full range of other conditional quantile functions, each as a function of a set of explanatory variables.

Figure 1 here.

One final concern in estimating (2) is the possibility that *SCCPremium* is endogenous. If dairy operators select buyers based on characteristics such as incentives offered, then it is conceivable that dairies with relatively low SCCs seek out buyers offering premiums in order to reap benefits. In that case, then the estimated coefficient on *SCCPremium* would only partially

capture the effects of such offers on SCC, and would also include the effects of dairy self-selection. Given that formal statistical testing for endogeneity in a quantile regression for count data setting is not possible, we put forth two arguments for why we do not consider endogeneity to be in issue in our estimation.

Firstly, in an investigation of market power in the dairy industry, Sumner and Ahn (2008) make two important observations on the market for fluid milk. One is that the bulk of the economic evidence on the dairy industry indicates that dairy operations are competitive and are therefore price takers. Additionally, raw milk is expensive to transport and the market for most fluid milk is local. These notions, taken in tandem, suggest that it is unlikely that milk producers have the ability to shop among buyers based on a menu of characteristics or prices offered.

Second, the incidence of SCC premiums is highly dependent on geography in the data. The share of producers offered an SCC premium is 72 percent in the "other" states, 64 percent in the traditional states, 60 percent in the western states, and 22 percent in the southern states.[12] Therefore in each region, either the large majority of producers are offered a premium for SCC levels or very few are. Practically, this corroborates Sumner and Ahn (2008) in that the possibilities for producers to select among buyers based on characteristics such as premiums are limited. Statistically, it means that any systematic differences in the effect of premiums on SCC levels is captured by the regional dummies and is therefore not in the error term and not a concern for endogeneity.

Results and Discussion

In our approach, we estimate (2) for five quantiles, $\vartheta = 0.05, 0.25, 0.50, 0.75,$ and 0.95. In doing so, we aim to yield estimates of the relationships between key producer and buyer characteristics

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[12] To investigate the geographic differences in SCC premium in greater depth, we estimate a first stage regression on SCC Premium using ordinary least squares. In this setting, regional and even state effects are highly significant but most of the other components in (2) are not.

and the major quartiles of SCC as well as the extremes of the distribution. The 0.95, for example, is intended to provide insights into the factors most important in driving variation in the 95th percentile of the SCC distribution. Ergo, the significant factors of the 0.95 quantile regression have the strongest implications for those dairies with the highest average SCC. Table 2 shows the regression results for both the generalized Poisson (GPoisson) regression and the quantile regressions.

Table 2 here.

A striking feature of the results is the extent to which the GPoisson results can differ from the quantile regression results. For example, according to the GPoisson results, management practices have a positive and significant impact on SCC, meaning that they reduce average milk quality. However, this index is negatively and significantly associated with the 0.95 quantile for SCC among dairy farms and is insignificant for the rest. This suggests important differences in efficacy between the two approaches.

To investigate this further, we examine predicted SCC versus actual. We predict SCC for a conventional (non-organic) dairy located in a traditional dairy producing state that receives a volume premium. The continuous explanatory variables from the model are set at their mean values.[13] Figure 2 plots the hit rate for both the quantile regression and GPoisson results, by SCC quantile. Our hit rate methodology is drawn from Benoit and Van den Poel (2009), whereby a prediction is considered accurate if the observed SCC meets or exceeds the prediction. At the 70th percentile the quantile regression for count model successfully predicts 32 percent of the dairies with SCC levels at least that level, well above the two percent hit rate of the GPoisson. In fact, the GPoisson has no predictive power for the highest levels of SCC, which translate for our

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[13] We experimented with a number of different possibilities for conditioning the predicted SCC based on the variables in (2). The percentage of accurate predictions using count regression can change somewhat, but for high levels of SCC the GPoisson estimation robustly gets zero percent of predictions correct.

estimation purposes to the 0.75 and 0.95 quantiles. We focus the remainder of our discussion on

the richer and more flexible quantile regression results.[14]

Figure 2 here.

The factors shown to be important in shaping SCC at the 0.75 and 0.95 quantile are of the

highest salience in understanding the means by which bulk tank SCC in the U.S. may be reduced

via cost-effective means. And in general, the number of statistically significant explanatory

variables grows with quantile size. No component of (2) is significant for the 0.05 quantile,

suggesting that these operations are structurally oriented towards low SCC and high milk quality,

likely owing to long-term investments in capital and established relationships with buyers.[15]

Alternatively, nine of the regressors are significant for the 0.95 quantile of SCC. Dong et al.

(2012) found similar lack of statistically significance explanatory factors for the 0.05 quantile,

except for buyer requirements for testing. They found that requirements for testing for

pasteurization incubation and for standard plate count, were associated with lower SCC levels for

the 0.05 quantile.

Several factors, some of which are comparatively easy to adjust on a per-farm basis, are

shown to significantly impact SCC at the highest quantiles. The aforementioned management

practices are negatively and significantly associated with SCC at the 0.95 quantile. Each of the

included practices are used by relatively few operations, meaning that the wide-scale adoption of

forward purchasing or individual cow production records could lead to economically significant

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[14] One interesting insight gleaned from the GPoisson results is that the conditional delta indicates that *SCC* is overdispersed. Initial plotting of the data as well as the summary statistics reported in table 1 showed *SCC* to be underdispersed, with the sample mean considerably larger than the sample standard deviation. The observed underdispersion was one factor in initially choosing GPoisson over other possibilities such as the negative binomial. Conditional on all of the factors included in (1), this is no longer the case.

[15] Summary statistics, by SCC quartile, help to illustrate these structural differences. Of the dairy operations in the lowest SCC quartile, 77% are located in either the western or traditional dairy states. They have an average herd size of 350. Of those in the highest quartile, 57% are located in the western or traditional states and the average herd size is 290. Hence the farms with the lowest SCCs are far more likely to be larger and located in states with older dairy operations than those with the highest, reflecting characteristics that exhibit little or no variability over time.

SCC reductions. Organic certification is associated with reduced SCC for the 0.50, 0.75, and 0.95 quantiles. Taking this finding into account, the overall impact of organic production on SCC and milk quality remains unclear, particularly in a dynamic setting, given that the results do not inform as to the long- or short-run effects of obtaining certification on SCC. But it is evident that it is associated with improvement among the operations with the highest SCC levels.

There is ample evidence that penalty and reward schemes, as constructed within buyer-producer relationships, have the potential to reduce SCC where it is the highest. Premiums based on achieving SCC below agreed-upon thresholds effectively reduce SCC for the 0.50 and 0.75 quantiles. Volume premiums are significant in lowering SCC for the three largest quantiles. This finding may be capturing, in part, increased efforts on the part of producers to increase yields, which have been inversely linked to SCC. In this respect we observe another case where the quantile-based results differ importantly from those of the GPoisson, which measures a small but positive and significant impact on SCC. Increased milk testing is shown to reduce modestly SCC for the 0.75 and 0.95 quantiles.

Rounding out the significant findings, larger herd sizes are associated with decreased SCC at the 0.95 quantile. The quadratic herd size term is positive and significant, conforming to expectations and indicating that herd size shares a "u-shaped" relationship with SCC among those farms with lowest milk quality. Among the highest quantiles, SCC is lower in both the western states and the traditional dairy states, as compared to the remaining states in the survey. Dong et al. (2012) found a relatively consistent and positive effect on SCC levels across the quantiles for states in the southeastern region (Tennessee, Kentucky, Florida and Georgia). The average age of the dairy herd significantly contributes to SCC for the 0.50 and 0.95 quantiles, a finding similar to that of Dong et al. (2012), who measured herd age in the same fashion. We

find little to no effects on SCC for housing age, biosecurity guidelines, or buyer-imposed

penalties related to the potential price decreases.

Conditional SCC Predictions and Marginal Effects

The interpretation of coefficients in quantile regression for count data is not entirely intuitive.

Following Miranda (2008), we calculate the predicted SCC and marginal effects for all

explanatory variables, by quantile. The marginal effect of a change in x_j from x_j^o to x_j^1 is given

by

(3) $$\Delta_j = Q_{SCC}(\alpha \mid x_j^1, X) - Q_{SCC}(\alpha \mid x_j^0, X)$$

where Q_{SCC} is the value of the conditional quantile of SCC, α is the quantile itself (0.05, 0.25,

0.50, 0.75, 0.95), and X is still the vector of remaining explanatory variables, with continuous

variables held at their means and dummy variables at their modes. The marginal effects can be

interpreted as the predicted impact of an incremental change in the variable of interest on SCC.

As Miranda (2008) notes, this procedure is important in the quantile regression setting because a

significant regression coefficient does not necessarily mean that the marginal impact is also

statistically significant. The results are reported in table 3.

Table 3 here.

Once again it is evident that many factors have the strong potential to impact SCC at the

highest quantiles, particularly 0.95. For those farms in the highest quantile in terms of SCC, each

additional management practice leads to a reduction in SCC of 10,600. The implementation of

additional practices such as those listed in appendix B certainly requires case-by-case

consideration, but as noted, each individual practice was only in place at a small minority of

operations as of 2005. Organic certification is associated with a marginal reduction of 41,000 for

the 0.75 quantile and 87,000 for the 0.95 quantile. The SCC-based premium can lead to a marginal decrease of 75,000-80,000 for farms in the upper half of average SCC, though the effect is not significant for the 0.95 quantile. The volume-based premium has significant marginal effects for the three largest quantiles which grow in magnitude with average SCC. It has a marginal impact of 64,000 for farms in the 0.95 quantile.

The marginal effects for many of the remaining variables are in line with the signs and statistical significance of the estimated coefficients in table 2. Given that larger operations tend to have lower SCC, an increase of 100 head of dairy cattle is associated with 5,600 marginal reduction in SCC for the 0.95 quantile. Large marginal impacts persist across quantiles for operating in western or traditional dairy states. Each additional year in average age of the dairy herd has a marginal increase of 11,000 for the operations with the highest SCC.

It is interesting to note that, among those dairies in the 0.75 and 0.95 quantiles, several of the controls that are capital-intensive or involving high fixed costs have small or insignificant marginal effects on SCC. While more work, ideally with a longitudinal data set, is called for to estimate dynamic impacts of the imposition of premiums or penalties, the results demonstrate that such factors alone have the potential to significantly reduce SCC in the dairy industry. Given that each marginal effect is calculated holding all others constant, we have evidence that the role of incentives is distinct from that of investment, as premiums are associated with large decreases in SCC without important changes in factors such as housing age, herd size, or biosecurity measures. Organic certification is costly for U.S. dairy producers (Greene, et al., 2009) but given our findings and the potential benefits in terms of SCC reduction, there is reason to evaluate the costs associated with certification in comparison to those associated with capital investments

aimed at SCC reduction. The observed benefits of organic production on SCC also have policy implications, for example potential certification cost sharing.

The differences in predicted SCC across quantiles are vast. Those operations in the 0.05 quantile have a conditional, predicted SCC of 65,000. As points of comparison, the allowable SCC limit for market grade milk in the U.S. is 750,000 cells/mL, meaning these operations are producing milk of a much higher quality than is required for Grade A status. However the predicted SCC for those farms in the highest quantile is 440,000, which is higher than the 400,000 cells/mL limit of the European Union as well as those imposed by several other nations, including New Zealand and Australia (Steevens and Poock, 2010). The predicted SCC for the median quantile is 250,000, which is above the threshold typically indicative of mastitis of some form (Smith, 1997).

Predicted SCC and Dairy Operation Profitability

Many of the economic studies on SCC, mastitis, and related issues have conducted measurements of economic loss, much of which is due to lost revenues or profits on the part of dairy producers. Recall that SCC is inversely related to both yields and prices for fluid milk. Following MacDonald et al. (2007), we define net returns as the difference between the gross value of production and total costs. Positive net returns indicate that the dairy is able to cover all costs, including costs of capital recovery. Henceforth, we describe operations having positive net returns as being profitable.[16]

By this definition, only 29 percent of the dairy operations in ARMS were profitable as of 2005, as shown in Table 4. The average net return across the entire survey is -$6.96 per cwt. However the incidence of dairy farm profitability can differ importantly by SCC levels. The 75th

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[16] The gross value of production for the dairy enterprise includes payments from milk production, from sales of dairy animals, and from other sources. Payments received from other sources includes dairy co-op patronage dividends, leasing of animals or space, or the value of manure produced.

percentile (P75) of SCC in our sample, or 275,000, is one convenient threshold to use as an example. Thirty two percent of operations with SCC below P75 are profitable, while 22 percent of those above this threshold are profitable. Hence those below this threshold are 10 percentage points, or nearly 50 percent more likely to be profitable. Additionally, P75 is in between the predicted SCC levels for the 0.50 and 0.75 quantiles in table 3. Since so many marginal effects are significant for dairies in the 0.75 quantile, it is straightforward to observe the means by which predicted SCC levels below the P75 threshold can be attained.

Via the marginal effects reported in table 3, we are able to visualize a number of means by which dairy operations with SCC levels above P75 can slip below that threshold and improve the likelihood of profitability. Naturally, effective and cost-effective SCC reduction is a process that, in practice, needs to be evaluated and carried out on a per-operation basis. However let us assume for this exercise that each operation in the 0.75 quantile has the predicted SCC of 320,000. For those operations whose buyers do not offer an SCC premium, implementing one is predicted to lower SCC by 75,000, thereby reducing SCC to beneath P75. There are paths to P75 even for those operations in the 0.95 quantile. For example, switching to organic production, the addition of a volume premium, and a reduction in the average age of the dairy herd by two years can achieve predicted SCC of below P75.

The P75 threshold is of course illustrative and arbitrary. More importantly, the dairy operations in ARMS illustrate an important economic relationship between SCC levels and profitability. Table 4 reports average net returns and percentage of profitable operations by SCC decile. The relationship is not perfectly inverse, as the decile with the highest share of profitable operations is the fifth. However the highest SCC decile has the lowest share of profitable operations, at 18 percent. The eighth, ninth, and tenth SCC deciles have three of the four lowest

average net returns. For reasons unknown, the first decile has relatively poor net returns and only a profitability rate of only 23 percent. Leaving that decile for future research, the pattern in terms of average SCC and net returns or profitability is much clearer. The differences in SCC across deciles can be modest in many cases, while the differences in net returns can be substantial. Our results indicate that there are numerous strategies that dairy operations as well as buyers can undertake to reduce SCC such that expected net returns and the likelihood of dairy profitability can increase in economically significant numbers. Therefore the incentives are in place, at the firm level, to reduce SCC domestically.

Table 4 here.

While it is not a goal of this paper to analyze or predict dairy farm returns or profitability, there are certainly more factors at play in determining profitability in the U.S. dairy industry alone. Several of these are likely to be confounding factors, shaping net returns and SCC jointly. MacDonald et al. (2007) suggests that dairy size is likely to be an important example of such considerations. To that end, we also break down profitability by SCC decile for only those operations with herds larger than 500 cows. It is immediately apparent that larger dairies are far more likely to be profitable, as 68 percent of these 284 large operations have positive net returns and the average for the group is $1.43 per cwt. But also importantly, the link between SCC and profitability is not at all obvious among these larger operations. Figure 1 demonstrated that the variability in SCC was the smallest among this group of the largest dairies, and indeed variation decreases with herd size for most of the variables included in (2).

Conclusions

We synthesize much of the work that has been done on measuring the biological, managerial, and economic determinants of SCC in fluid milk. We develop and estimate a model of SCC that

draws upon several key factors, with the intent of highlighting incentive-based means by which SCC may be reduced among U.S. dairy operations. Importantly, we apply quantile regression to count data to account for the statistical properties of the ARMS dairy data and to measure directly the impacts on dairy producers with the highest SCC levels, as these are the operations standing to benefit most from novel approaches to SCC reduction. Our results indicate that many managerial factors and production practices have the potential to reduce significantly SCC for those operations with the highest average levels. Possibilities include volume-based premiums and increased testing requirements on the part of buyers, organic certification, and the utilization and maintenance of younger dairy herds.

We also uncover a potentially important link between SCC and dairy profitability and discuss several means by which the results indicate that dairy farms and reduce their SCC in order to increase their potential net returns substantially. There appear to be economically important differences across SCC levels in terms of the likelihood of positive net returns. However it's important to note that these implications do not necessarily pertain to the largest dairy operations in the U.S., which are the most profitable and do not exhibit a clear relationship between returns and SCC.

In terms of policy implications, our work suggests that for many dairy operations, SCC can be reduced substantially through cost-effective means. One efficient approach may be through efforts to forge closer relationships between dairy producers and their buyers, as relationships involving more detailed reward and punishment schemes seem to have great potential to reduce SCC among those producers with the highest levels. We demonstrate that organic production is associated with significantly lower SCC among dairies with high levels, suggesting that policies to subsidize or streamline the often costly organic certification process

may have benefits in this respect. Efforts to target SCC reductions may be less effective among the largest dairies, those with greater than 500 cows, but this is not to say they should be ignored.

There are several limitations and cautions to the findings reported in this paper. The results are preliminary and several aspects of the analysis remain for further investigation. The SCC level is reported as an annual average level. This value smooths considerable variation that may occur during the year. We find that the level of SCC premium received is associated with state level indicators. This suggests aspects of the buyer-dairy market may be important. Although this market environment may be captured in part by the regional binary variables, there may be other buyer practices that are not fully controlled for by our regional variables.

Our results leave much room for future work. One strongly motivated avenue is an improved understanding of the determinants of net returns, or profitability, in the dairy industry. Such research must account for SCC, given the large number of potential confounding factors involved. But increases in our understanding of profitability would greatly enrich this story, and likely provide insights into how SCC may be effectively reduced even among the largest dairies in the United States.

Table 1: Variable Descriptions and Summary Statistics (N = 1,553)

Name	Description	Mean	St. Dev.
SCC	Somatic cell count (SCC) (in 1,000s)	257.58	114.92
SCCPremium	Average premium paid based on somatic cell count (in dollars per cwt.)	0.24	0.49
VolPremium	Binary =1 if operation received a premium based on the annual production volume	0.43	0.50
TestPenalty	Index reporting the number of questions asked by buyers for which the operation's response may warrant more frequent milk testing	0.11	0.70
PricePenalty	Index reporting the number of questions asked by buyers for which the operation's response may warrant a reduction in milk price[c]	0.73	1.50
HerdSize	Dairy cow herd size (1000s)	0.36	0.69
HerdSizeSq	Dairy cow herd size squared (quadratic term)	6.00	34.31
SecurityGuidelines	Score based on the adherence to biosecurity guidelines[a]	1.22	1.33
MgmtPractices	Score based on management practices utilized	5.18	2.61
WesternState	Binary =1 if farm is located in a western dairy state[b]	0.22	0.42
TraditionalState	Binary =1 if farm is located in a traditional dairy state	0.49	0.50
OtherState	Binary =1 if farm is located in an other state	0.29	0.45
CowAge	Average age of cows in milking herd (years)	4.53	1.08
Organic	Binary =1 if operation was certified organic	0.20	0.40
HousingAge	Average age of the housing units used for dairy cattle (decades)	1.93	1.35

a: The applicable biosecurity guidelines, as well as management practices, are drawn directly from the ARMS survey and are listed in appendix A.
b: The state classifications follow MacDonald et al. (2007) and are as follows. Western states: AZ, CA, CO, ID, MT, NV, NM, OR, TX, UT, WA, and WY. Traditional dairy States: CT, DE, IA, IL, IN, MA, MD, ME, MI, MN, MO, NH, NJ, NY, PA, OH, RI, VT, and WI.
Other States: AK, AL, AR, GA, FL, HI, KS, KY, LA, MS, NC, ND, NE, OK, SC, SD, TN, VA, and WV.
c. The complete details of *TestPenalty* and *PricePenalty*, including both the relevant questions and the actions that may be taken as a result of producer responses, are found in appendix B.

Table 2: Regression Results for Equation (2), the Determinants of *SCC*

	Quantile					Generalized Poisson
	0.05	0.25	0.50	0.75	0.95	
HerdSize	0.254	0.041	-0.023	0.044	-0.128***	-0.188***
	(0.20)	(0.41)	(0.68)	(0.27)	(3.72)	(3.89)
HerdSizeSq	-0.033	-0.001	0.002	0.001	0.003***	0.002**
	(0.85)	(0.78)	(0.80)	(0.57)	(5.37)	(2.02)
Security Guidelines	-0.029	-0.015	-0.013	-0.016	0.013	-0.016
	(0.22)	(0.51)	(1.58)	(0.86)	(1.57)	(1.30)
Mgmt Practices	0.110	3.4e-5	-0.010	-0.014	-0.024***	0.043***
	(0.51)	(0.00)	(1.54)	(1.18)	(5.34)	(6.38)
WesternState	-0.036	-0.201	-0.235***	-0.208***	-0.123*	-0.083**
	(0.07)	(0.62)	(8.30)	(3.03)	(1.86)	(2.03)
Traditional State	-0.075	-0.100**	-0.105***	-0.123	-0.060***	-0.053*
	(0.12)	(2.52)	(4.64)	(2.95)	(2.74)	(1.62)
CowAge	0.067	0.015	0.025***	0.024	0.025*	0.031**
	(0.20)	(0.54)	(4.64)	(0.87)	(1.67)	(2.30)
Organic	0.502	0.061	-0.104**	-0.137***	-0.211***	0.038
	(0.52)	(1.00)	(2.56)	(2.69)	(2.73)	(0.98)
HousingAge	-0.003	-0.002	-0.001	-0.002**	0.001	-0.003***
	(0.14)	(0.74)	(0.85)	(2.25)	(0.45)	(2.66)
SCCPremium	-0.181	-0.537***	-0.351***	-0.253***	-0.132	-0.156***
	(0.26)	(6.08)	(6.38)	(6.62)	(0.92)	(3.70)
VolPremium	0.325	-0.044	-0.089***	-0.097*	-0.147***	0.050*
	(0.67)	(0.79)	(3.50)	(1.88)	(6.67)	(1.65)
TestPenalty	-0.678	-0.020**	-0.037	-0.047***	-0.014***	-0.064***
	(0.91)	(2.54)	(0.73)	(6.24)	(2.89)	(2.83)
PricePenalty	0.052	0.007	-0.001	-0.002	0.009	0.018**
	(0.21)	(0.36)	(0.06)	(0.26)	(1.35)	(1.98)
Intercept	3.376	5.433***	5.750***	6.024***	6.272***	5.355***
	(0.88)	(43.06)	(100.27)	(42.84)	(71.76)	(66.52)
Delta (δ)[a]						0.905***
N	1,552	1,552	1,552	1,552	1,552	1,552

***: Coefficient is significant at the 0.01 level. **: At the 0.05 level. *: At the 0.10 level.
Absolute values of z-scores in parentheses.
a: Delta in this setting reports the dispersion of the SCC count data, conditional on controlling for the full set of covariates in (1).

Table 3: Predicted Values of *SCC* and Marginal Effects for Covariates, by Quantile

	$Q_z(0.05|\mathbf{x})$	$Q_z(0.25|\mathbf{x})$	$Q_z(0.50|\mathbf{x})$	$Q_z(0.75|\mathbf{x})$	$Q_z(0.95|\mathbf{x})$
SCC	65.000	190.000	250.000	320.000	440.000
HerdSize	1.655	0.772	-0.582	-1.386	-5.577***
	(0.19)	(0.42)	(0.68)	(0.78)	(3.63)
HerdSizeSq	-0.213	-0.022	0.007	0.040	0.149***
	(0.71)	(0.76)	(0.80)	(0.57)	(5.17)
Security Guidelines	-1.956	-2.905	-3.187	-4.982	-55.422
	(0.24)	(0.52)	(1.57)	(0.86)	(0.96)
Mgmt Practices	7.179	0.006	-2.463	-4.350	-10.601***
	(0.73)	(0.00)	(1.52)	(1.20)	(5.21)
WesternState	-2.339	-36.013	-54.790***	-62.007***	-51.864*
	(0.07)	(0.68)	(8.70)	(19.008)	(1.87)
Traditional State	-4.909	-18.969**	-26.030***	-38.824***	-26.052***
	(0.11)	(2.38)	(4.64)	(3.00)	(9.727)
CowAge	4.400	2.895	5.829***	7.472	10.839*
	(0.22)	(0.54)	(4.66)	(0.86)	(1.65)
Organic	38.386	11.745	-24.946***	-41.432***	-86.639***
	(0.58)	(1.00)	(2.62)	(2.74)	(2.78)
HousingAge	-0.176	-0.308	-0.266	-0.620**	0.407
	(0.14)	(0.75)	(0.85)	(2.17)	(0.46)
SCCPremium	-11.224	-88.507***	-79.493***	-74.805***	-55.422
	(0.24)	(5.86)	(7.48)	(6.61)	(0.96)
VolPremium	21.783	-8.298	-22.085***	-30.522*	-63.702***
	(0.98)	(0.80)	(3.54)	(1.85)	(7.45)
TestPenalty	-34.646	-3.797**	-9.169	-14.654***	-6.102***
	(0.87)	(2.42)	(0.75)	(5.98)	(2.78)
PricePenalty	3.377	1.289	-0.157	-0.555	3.872
	(0.24)	(0.35)	(0.06)	(0.26)	(1.38)

***: Coefficient is significant at the 0.01 level. **: At the 0.05 level. *: At the 0.10 level.
Absolute values of z-scores in parentheses.
Marginal effects are calculated setting all continuous variables to their mean and all dummy variables to their mode, following Miranda (2008).

Table 4: Average Net Returns and the Share of Profitable Operations, by SCC Decile.

SCC Decile	All Dairy Operations		Dairy Operations with Greater than 500 Cows	
	Avg. Net Returns	*% of Profitable Operations*	*Avg. Net Returns*	*% of Profitable Operations*
1-10%	-$10.44	23.5 (153)[a]	-$0.49	56.5 (23)
11-20%	-$5.74	38.9 (157)	$1.93	71.8 (32)
21-30%	-$5.40	35.9 (131)	$0.71	68.9 (29)
31-40%	-$4.40	34.8 (164)	$1.33	75.0 (40)
41-50%	-$3.99	41.3 (109)	$2.74	71.8 (39)
51-60%	-$6.01	28.4 (201)	$1.01	65.7 (35)
61-70%	-$4.88	36.1 (83)	$2.77	78.9 (19)
71-80%	-$7.52	22.8 (202)	$0.79	53.5 (28)
81-90%	-$7.14	27.6 (130)	$1.70	75.0 (16)
91-100%	-$10.72	18.4 (223)	$1.61	65.2 (23)
Total	-$6.96	29.4 (1,553)	$1.43	68.3 (284)

a: Number of dairies is included in parentheses. The numbers are not equal across deciles due to the count nature of the data, which leads to several operations having identical SCC levels.

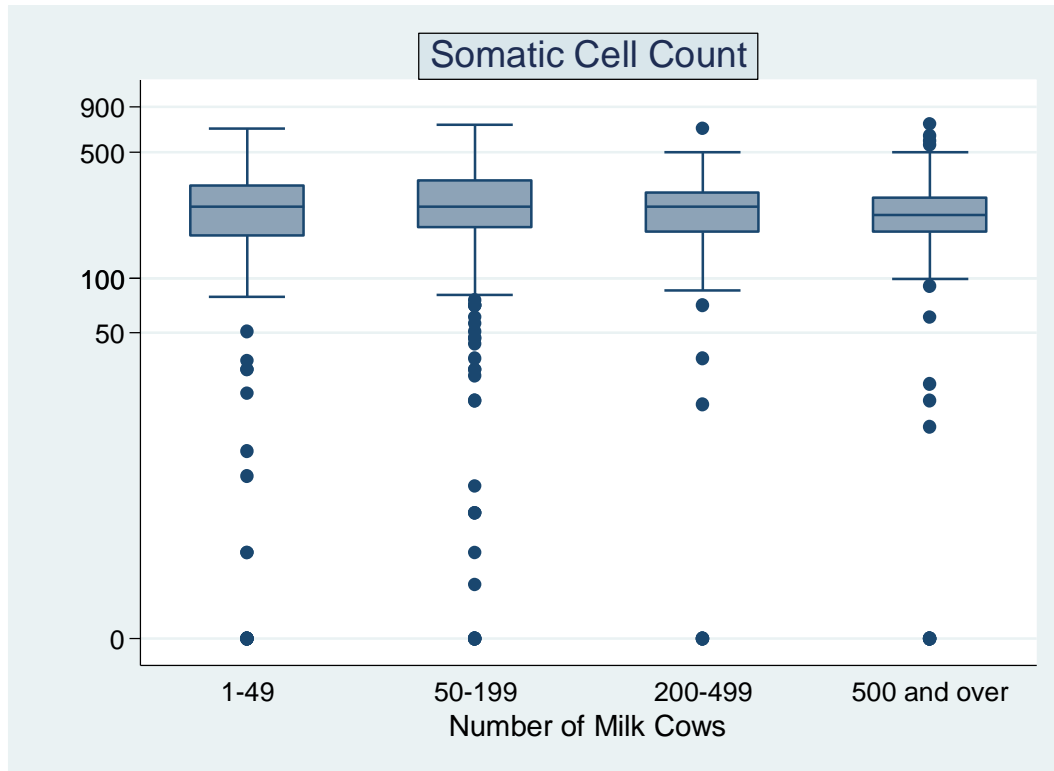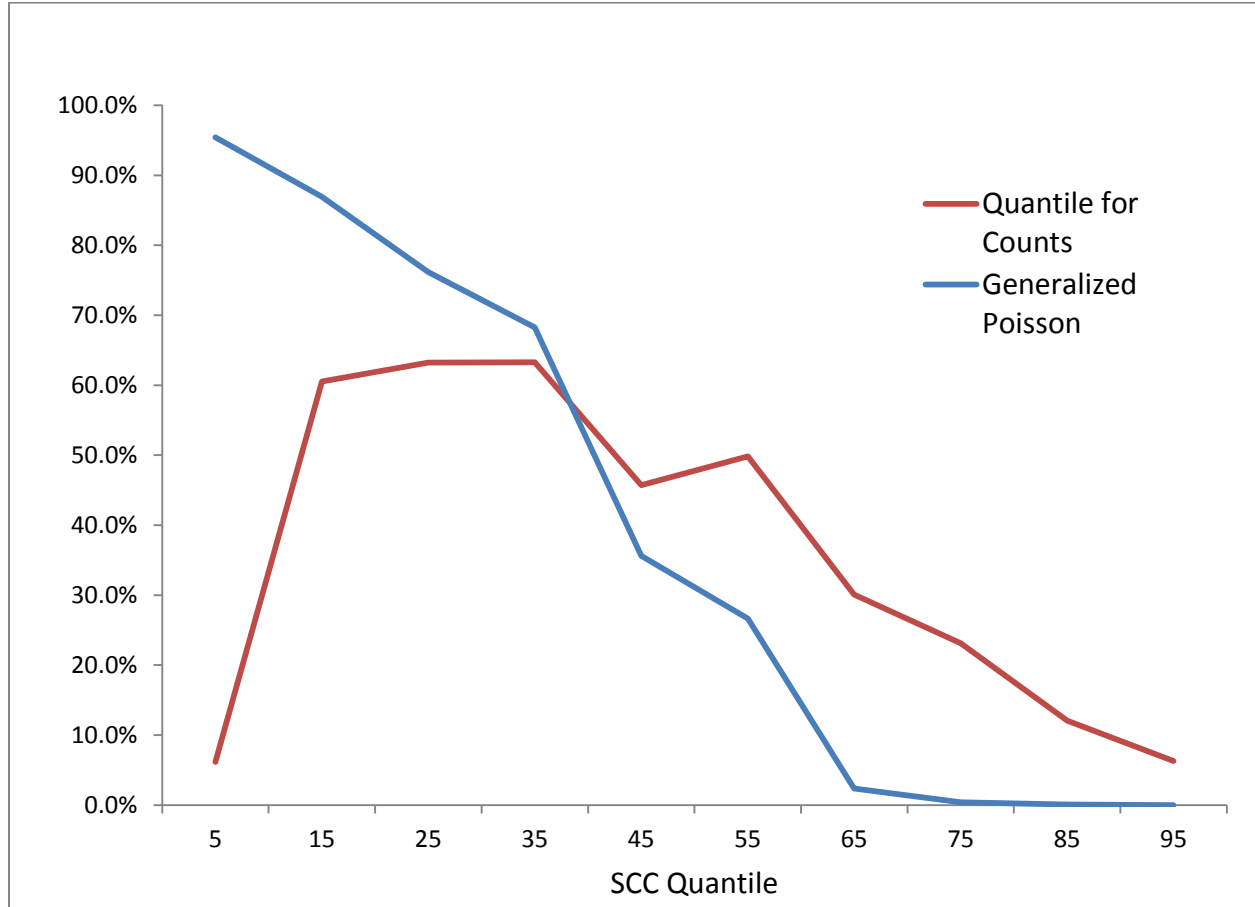**Figure 1: Box Plot of Somatic Cell Count by Dairy Herd Size.**

Figure 2: The Percentage of Correct SCC Predictions, by Quantile, for Count Regression and the Generalized Poisson.

Appendix A: Details on the Formulation of *SecurityGuidelines* and *ManagePractices*

In the ARMS survey, farm managers were asked to answer "yes" or "no" to a series of questions pertaining to the security guidelines and management practices in place. The applicable guidelines and practices are detailed in table A.1. For the purpose of this study, each operation is given scores based on both categories, called *SecurityGuidelines* and *ManagementPractices*, respectively. The score in each case is calculated as the total number of yes responses with categories.

Table A.1: Biosecurity Guidelines and Management Practices Depicted in ARMS.

Biosecurity Guidelines		
Name	**Description**	**Percentage of farms**
Guideline1	Farm had guidelines for allowing visitors in animal areas	19.40
Guideline2	Farm determined the geographical source of incoming cattle	17.73
Guideline3	Farm trained employees on the introduction and spread of disease	11.63
Guideline4	Farm had guidelines regarding foreign travel by employees	8.24
Management Practices		
Name	**Description**	**Percentage of farms**
ArtifSemination	Farm used artificial insemination for genetic selection	5.58
Embryo	Farm used embryo transplants for genetic selection	10.26
ControlBreed	Farm controlled the breeding/calving season	10.62
VetService	Farm used regular scheduled veterinary services	13.17
Nutritionist	Farm used a nutritionist to design mixes or purchase feed	11.09
FeedDelivery	Farm used a computerized delivery system	12.81
ProdRecords	Farm kept individual cow production records	11.33
OnFarmComputer	Farm used an on-farm computer to manage dairy records	11.45
Internet	Farm accessed the internet for dairy information	7.30
ForwardPurchase	Farm used forward purchasing to lock in input prices	2.85
PriceDiscounts	Farm negotiated price discounts with suppliers for inputs	0.95

Source: Authors calculations based on 2005 ARMS.

Appendix B: Details on the Formulation of *TestPenalty* and *PricePenalty*

In the 2005 ARMS Survey, farm managers were asked a series of questions pertaining to the requirements and interests of their milk buyers. One question in particular asked about the testing requirements posed by buyers and the consequences faced for not meeting these requirements. There are eight testing requirements listed in the question. They are as follows.

Does the buyer of your milk or your milk cooperative require:

a. Testing for extra water?
b. Testing for antibiotic residue?
c. Testing for pesticides or other residue?
d. Testing for PI (Pasteurization Incubation)?
e. Testing for SPC (Standard Plate Count)?
f. Your cows to pass a test for tuberculosis?
g. Your cows or milk to be tested for other pathogens (such as Salmonella, Campylobacter, Cryptosporidium, Listeria, E. coli.)?
h. You to follow a Hazard Analysis and Critical Control Point (HACCP) program or the Performance-Based Dairy Farm Inspection System?

For each requirement, the farm manager's answer has three components. The first is to mark yes or no. The next two components are only relevant if the answer to the first part is yes. They are: Are you receiving a premium for meeting this requirement? and: What is the consequences of not meeting the requirement? Farm managers are provided with a code to answer the consequences portion of the question, with the following choices:

1. Issued only a warning.
2. Buyer/cooperative sends out a representative.
3. Required to attend training course.
4. Buyer/cooperative reduces price/fee paid.
5. Buyer/cooperative would not purchase milk.
6. Buyer/cooperative cancels or does not renew contract.
7. Milk tested more frequently.
8. No consequence.
9. Other consequence.

TestPenalty is calculated as the number of tests required of the farm manager for which the consequence of failure is additional testing, or option 7. *PricePenalty* is the number of tests for which the consequence is a reduction in the price paid, or option 4. Given that there are eight potential requirements, the indexes range from 0 to 8.

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