PRECISION DAIRY HERD MANAGEMENT, A QUANTILE APPROACH

Sub theme: Knowledge and Information

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Abstract:

Dairy producers have a variety of Precision Dairy technologies available to them, which creates the need for evaluation of new information streams generated by these technologies. At this point, a number of dairies are just collecting information, but may not have the technical skills or understanding to evaluate the data, let alone implement changes to their decision-making process. This issue has created the demand for research that integrates new decision criteria into daily herd management. Academics need experience with these new data sets and potential methodologies to contribute to producer-targeted recommendations. This case study serves as investigative research intended to gain familiarity with the complexities and availability of these types of data sets. This initial work has provided results that show significant relationships between newly available variables and milk production. While evidence suggests that increased efficiency is made possible by these precision technologies, the research addressing the significant hurdles to adoption is still in its infancy. This quantile regression analyzes a herd over one year to estimate a production function that uses cow-level input factors such as resting bouts, steps taken, eating time and body weight. Results demonstrate the ability of these technologies to create value to herd management strategies.

Keywords: *Precision Dairy (PD), Dairy, Quantile Regression*

Introduction

The motivation for this study is provided by the need for methods to examine data derived from Precision Dairy Technologies (PD). These technology sets include but are certainly not limited to, instruments and monitors that measure animal production, nutrition, health, fertility and environmental indicators (Borchers and Bewley, 2017a.) The quantity of new information is motivating innovation in herd management techniques on dairy farms that adopt these technologies. Furthermore, this work can provide additional insights on dairy management practices that could impact farm profitability.

While the PD offerings could generate variables that offer new decision-making criteria, the value of this new information is limited to the value added by their new analyses. Because these types of studies are also relatively new to dairy scientists and economists, there is a limited set of producer recommendations for the utilization of these data streams. The Coldstream Dairy Research Farm at the University of Kentucky employs and tests a diverse set of PD technologies. We are uniquely positioned to develop methods for how to integrate the data generated by these technologies into current herd management strategies (Coldstream, 2017).

One hurdle to the adoption of these technologies is the lack of understanding for how to utilize the alerts and data streams generates by the PD. “Recent estimates from researchers at the University of Kentucky indicate that producers disregard nearly 65% of health alerts generated by technologies (Borchers and Bewley, 2017b).” Technology that does not become a factor of production must contribute information that drives improved technical efficiency of the dairy farm. Otherwise, a producer would not adopt.

Dairy producers are encouraged to perform an investment analysis before adopting these technologies. Dolecheck and Bewley (2013) outline pre-investment considerations that need to be made before investing in any technology. Dolecheck and Bewley (2014) developed a decision aid to help producers determine if investing in heat detection technologies would add value to the farm. This routine analysis has caused debate among agricultural economists because many of these technologies can add value in both direct and indirect methods. For example, there are opportunities for labor savings (Bewley, 2013; Edwards et al., 2015; Shortall et al., 2016), improving the quality of life (Bongiovanni and Lowenberg-Deboer, 2004), and improving profitability (Bewley, 2010). However, as recently as 2013, Rutten et al. evaluated 126 studies that suggest there is no evidence that the information produced from PD technologies is being integrated with other farm or nonfarm data or being used in the decision-making process. Integration and analysis of the data collected are required for the decision making process. However, this portion of the process can be one of the most challenging for producers, which can limit the adoption of PD technologies (Borcher, 2015 and Russel and Bewley, 2013).

Some research leading to the motivation for this study includes the concept of applying a mean-variance approach to investment analyses of a portfolio of these technologies (Richard and Mark, 2016). Potentially one technology on its own does not maximize profit, but a combination of them might. This proposed approach requires the need to weigh the expected returns by the technology characteristics such as the value of information they provide. To start developing that metric, researchers need a better understanding of how the PT data informs the production function.

The focus of this study is to advance the statistical methods for analyzing individual cow parameters over time, but the challenges to the on-farm utilization of this PD data needs to be integrated into future research. Because the demand for this work ultimately lies in the value of the decision-making capability of these technologies, the key result of this research is an insight into new analytical herd management strategies.

Utilizing the PD technology information we can estimate the impact of these variables on a daily basis and potentially improve the decision-makers ability to identify potential changes that could be made within the herd. The objective of this research is to utilize PD derived variables such that more of the factors of milk production are identified at a more detailed level. While quantile regression has a long history in the applied economic literature, it has not been used for herd management criteria in this way.

Methods

The Coldstream Dairy Research Farm at the University of Kentucky is a testing and proving ground for many technologies that are currently available to producers in the United States. All data is daily recordings from the PD technologies on cows on this farm. Data for this study is a combination of two datasets collected at the dairy (Tsai, 2017; Wadsworth et al., 2016). The data starts in June of 2014 and extends through July 2015, for an approximately one hundred cow rolling herd size. Specifically, these variables were selected because of data availability, and they can be considered key drivers in the production of milk.

Quantile regression offers some advantage with large data sets such as these. Because this method uses the median as a measure of center, as opposed to the mean as in OLS, the parameters can be estimated within subcategories of the data. This method is documented to be a tool for analyzing large, intense frequency data sets. It is chosen for its flexibility to isolate the effects of the factors of milk production by lactation characteristics.

This data set is considered to be unbalanced panel data, because cows leave and enter the milking herd, which is considered to provide the counterfactual of each other. A quantile regression technique was applied to the PD data, where the functional form was:

$$\text{Daily Milk Yield} = \beta_0 + \beta_1 \text{ Days in Milk} + \beta_2 \text{ Body Weight} + \beta_3 \text{ SCC} + \beta_4 \text{ Eating Time} \\ + \beta_5 \text{ Steps} + \beta_6 \text{ Resting Bouts} + \beta_7 \text{ THI}$$

where each of the variables follow the definition and units described in Table 1.

Table 1: Data Description

Variable	Definition	Units
Daily Milk Yield	Milk production	Lbs/Day
Days in Milk	Days since last calving	Days
Somatic Cell Count	Milk Quality / Health Indicator	Cells/mL
Body Weight	Body Mass, measured by walking across scale	Lbs
Steps taken	Activity Measure / Health Indicator	Steps/Day
Resting Bouts	Activity Measure / Health Indicator	Stand Up and Sit Down Cycles
Eating Time	Time spent at the Feed bunk eating	Minutes / Day
Temperature Humidity Index	Potential Heat Stress Indicator	Index

This analysis separates the herd into three quantiles: the 25th, 50th, and 75th percentiles. The 25th quantile represents the lowest performing cows in the herd while the 75the quantile represents the highest performing cows in the herd. “Performance levels” are based on the dependent variable, daily milk yield. This assignment of quantiles is used as starting point for this analysis. Future work could include justifying a more particular quantile selection method. The data was then separated first by lactation number, then by lactation stage. This sorting technique isolates the effects of the factors of production by performance level (quantile) and lactation characteristics.

Results

The results are reported in Table 2, which provide the parameter estimate and standard errors of each coefficient. The magnitude and coefficient signs were expected to change across the stage of lactation and also between quantiles. This would reinforce the conventional concept that input factors have differing impacts on milk production depending on the performance level of the individual cow or it's stage of lactation.

Comparing across the quantiles, we find that DIM is tightly clustered with the expected signs. THI is another variable of interest that has significance across the quantiles. However, it has the largest impact on the 25^{th} quantile because it is significant for all three DIM levels. When looking at this variable, you should consider the timeframe of the data from June 2014- July 2015. Kentucky is typically known for hot and humid summers, but in 2014 we had a cooler than average summer and a warmer than normal winter. Eating bouts were only found to be a significantly positive variable for the cows over 120 DIM. The one exception to this is for the top performing cows, where eating bouts had a significant impact on cows from 60-120 DIM.

Comparing within quartiles, we find that body weight has a significantly positive impact on the average cow, especially note the magnitude change between the 60-120 and the past 120 day group of cows. For the high preforming cow, a manager should find ways to minimize the steps taken if they are over 120 DIM. Also, they need to search for methods to get them to the feed bunk more often if they are over 120 DIM to keep their milk yields up.

	Table 2: Milk Production Function Coefficients					
	DIM < 60		60 < DIM < 120		DIM > 120	
	Parameter Estimate	Std. Error	Parameter Estimate	Std. Error	Parameter Estimate	Std. Error
	25th Quantile					
DIM	0.435**	0.066	-0.071	0.033	-0.136**	0.004
SCC	0.000**	0	0.000**	0	0.000	0
Body Weight	0.072**	0.007	0.033**	0.006	0.002	0.002
Steps Taken	0.003*	0.002	0.002*	0.001	0	0
Resting Bouts	0.011	0.007	0.01*	0.005	-0.016**	0.003
Eating Time	0.036	0.013	-0.001	0.009	0.02**	0.004
THI	-0.476**	0.109	0.265**	0.066	0.186**	0.056
Intercept	-45.393**	11.382	4.591	10.645	77.592**	5.765
	50th Quantile					
DIM	0.337**	0.057	-0.057	0.049	-0.159**	0.003
SCC	0.000**	0	0.000**	0	0.000*	0
Body Weight	0.061**	0.007	0.057**	0.006	0.007**	0.002
Steps Taken	0.002	0.001	0.003	0.002	0	0
Resting Bouts	0.011	0.007	0.006	0.006	-0.015**	0.002
Eating Time	0.009	0.009	0.015	0.015	0.005	0.002
THI	-0.248	0.188	0.007	0.071	0.157**	0.04
Intercept	-13.91	11.287	-8.762	9.943	93.408**	3.969
	75th Quantile					
DIM	0.359**	0.083	-0.121	0.029	-0.164**	0.005
SCC	0.000**	0	0.000**	0	0.000	0
Body Weight	0.044**	0.007	0.076**	0.004	0.009**	0.002
Steps Taken	0.003**	0.001	0.001	0.001	-0.001**	0
Resting Bouts	0.002	0.012	0.003	0.004	-0.012**	0.003
Eating Time	-0.01	0.01	0.044**	0.008	0.008*	0.003
THI	-0.107	0.163	0.088	0.091	0.268**	0.039
Intercept	18.521	13.978	-26.804**	6.92	95.335**	4.383
*Significant at the 5% level, **Significant at the 1% level						

Discussion

Analyzing these variables were found to make small but significant contributions to milk production. For example, body weight can inform herd management decisions because body weight's impact on milk production starts to model the feed efficiency of large frame cows as compared with smaller-framed cows. Body weight findings inform feeding group decision criteria. The difference in magnitude of body weight's effects on milk production between a cow's second and third stage of lactation was found to be 0.030 – 0.060 lbs/day. This small but significant difference between stages of lactation could indicate that later lactation animals should be fed a lower cost ration, which aligns with current producer recommendations. The value this analysis provides is a way to replace feeding group assignments that are typically based on producer observation, instinct, and milk record alone with assignments that are generated from PD technology. This would ensure that assignments are more precise and therefore more cost effective.

The value of this early work is not in the results alone, but the development of the methodology. This framework provides a starting point for adjustment to the model specification and separation of the panel data. After performing this statistical analysis, we now understand that the value of the new information is embedded in analyzing the relationships among coefficients across the stage of lactation or across performance-based quantiles. Refining the statistical inference of these relationships can innovate dairy herd management beyond its past potential.

Conclusions

While developing the techniques for formal analysis of this data is interesting for academics, communication with farm managers and industry professionals should continue to motivate the progression of this work. Another study worth investigating is the opportunity for benchmarking across farms. Farms with PD technology currently compare their data across their cows, but comparing across farms would provide more information as to what is considered "normal" or "productive" behavioral and physiological indicators. However, one caution with this is that each farm as its unique set of factors that have to be accounted for during the analysis.

While individual producers will make day-to-day decisions on their herd, if they pool their data with other farms of similar production practices, an average and top performing benchmark could be developed, as it has been for row crop farms (KFBM, 2015). One technique that may be worth exploring would be to establish a framework that compares this year's cow performance to last year, the year before, and so on. This horizontal analysis technique utilizing benchmarks across time within the same farm would control for characteristics unique to that farm's production practices, technology sets, and microclimate weather patterns. While there are opposing thoughts to the merit of benchmarking altogether, this concept is familiar to dairy producers and may provide a starting point for producers to get perspective on their precision data.

Further investigation using this quantile technique may involve separating the herd first by lactation stage and then lactation number. This re-ordering of procedures would provide a different understanding of the same herd and may reveal different relationships among the factors of milk production. Along the theme of data organization, another advancement of this work would be to include more quantiles or quantiles that are fit specifically to this herd. In this work, 25th, 50th, and 75th quantiles were designated as a starting point, but customizing this technique could lead to a better understanding of the nature of herd dynamics. A continuation of this project would be to include an economic variable into the analysis. The advancement of this work could evolve the future of precision dairy herd management as well as inform the need for continued dairy science research.

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