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Is the Dairy Relief Program Really Working? Evaluating Maine's Tier Payment Program Using a Simulation Approach

Xuan Chen [1], Dylan Bouchard [2,*] and Gary Anderson [3]

[1] Department of Environmental Health, Emory University, Atlanta, GA 30322, USA; xuan.chen@emory.edu
[2] Department of Economics, North Carolina State University, Raleigh, NC 27607, USA
[3] Cooperative Extension, University of Maine, Orono, ME 04469, USA; garya@maine.edu
* Correspondence: dbboucha@ncsu.edu; Tel.: +1-207-695-7013

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Abstract: This study addresses a common empirical problem where researchers are only able to obtain financial records for farmers, which limits the potential for analyzing exit decisions. In particular, dairy cost-of-production studies (e.g., Farm Credit East and Cornell) often grant researchers access to online record systems, which contain only farm cost and revenue data. We develop and apply a simulation approach to coping with such data to analyze exit decisions. We model exit decisions as a function of profitability and seasonality. We find that the tier program reduces the number of farms that exit and allows farms to remain in business longer. Dairy farms are an important source of livelihood in rural Maine communities. With price floors in place, dairy farms are less affected by price volatility, and rural communities have improved financial sustainability.

Keywords: dairy; Maine; exit decision

1. Introduction

The rapid decline in the number of U.S. dairy farms over the past few decades has made dairy farm exit decisions an important topic for research. The structural change taking place is apparent: average farm size is growing, while the number of farms is declining [1]. From 2001–2009, the number of dairy operations declined 33%, despite a 15% increase in total milk production [2]. Further, the number of farms with more than 500 cows increased by approximately 20% in this period [2]. As a result, the share of milk produced by farms with more than 500 cows increased by 21%, while share of milk produced by farms with fewer than 500 cows fell by approximately 20% [2].

The trend of increasing farm size and decreasing number of farms has been consistent in the New England states (New England includes Maine, New Hampshire, Massachusetts, Connecticut, Vermont and Rhode Island), as well. Sobson [3] found that from 1993–2003, the average number of cows rose from 122–212, an increase of nearly 74%. Additionally, farms became more productive over this period. Pounds of milk sold per cow increased from 18,254–21,261, and milk sold per worker increased from 653,683–901,480 (Sobson, 2004). Further, average herd size for this sample has grown steadily from 288 in 2003 to 368 in 2012, an average of 2.8% per year or 28% overall [4]. In particular, the number of conventional dairy farms in Maine has fallen by nearly 100 farms from 2004–2014 (Maine Milk Commission, personal communications).

While profitability and price uncertainty are certainly important, studies in the literature have identified a variety of other factors that are relevant to farm-level exit decisions. Bragg and Dalton [5] conducted an analysis of a two-year panel of Maine dairy farms suggesting that older age, higher off-farm income, lower returns on variable costs and greater diversification all influence the probability a farmer will shut down. In addition, the authors suggested that federal and state programs would be effective in keeping dairy farmers in business. Similarly, Dong et al. [6] explored non-price determinants of exit and expansion decisions among U.S. dairy farms. They found that unpaid non-operator labor signals the presence of a successor, and greater long-term debt is indicative of commitment to future operation. Further, efficient farms tend to be larger and are more likely to remain operating than exit.

Foltz [7] considered the decisions to exit among Connecticut dairy farms with an emphasis on the Northeast Dairy Compact (NEDC). They found that higher cow productivity, local unemployment rate and population density all lessen the probability of dairy farm exits and that the NEDC maintained an extra 4% of Connecticut dairy farms in business. Tauer [8] employed a Dixit entry/exit model to investigate the price ranges expected to incentivize exit or entry into the dairy industry and found the per cwt (cwt is an abbreviation for hundredweight, which is 100 pounds or 45.36 km. Although cwt is not an SI unit of measurement, it is very common in U.S. agriculture.) entry and exit prices to be $17.52 and $10.84, respectively for a 500-cow farm. A 50-cow farm, however, was found to have respective entry and exit prices of $23.71 and $13.48 per cwt. Stokes [9] used Markov chain analysis to consider the determinants of dairy farm exit and expansion and found that higher milk prices lower the probability of exit, while higher milk price volatility, higher land values and presence of the dairy termination program all increase the probability of exit.

An approximate measure of dairy farm profitability is the milk-feed price ratio (MF), which employs the ratio of the all-milk price in dollars per cwt to a typical dairy feed cost index made up of alfalfa hay, soybeans and corn priced at 100 pounds of feed. Figure 1 displays the monthly average MF over this eleven-year period. The monthly average MF fluctuated from 2004–2014, reaching a high of $3.67 in 2004 and a low of $1.33 in 2012. As can be seen in the figure, dairy farm profitability was very volatile over this eleven-year period. Price stabilization programs in the form of subsidies are often employed to help dairy farms survive volatile market conditions. It should be noted that price seasonality plays a large role in inducing the volatility of dairy farm profitability.

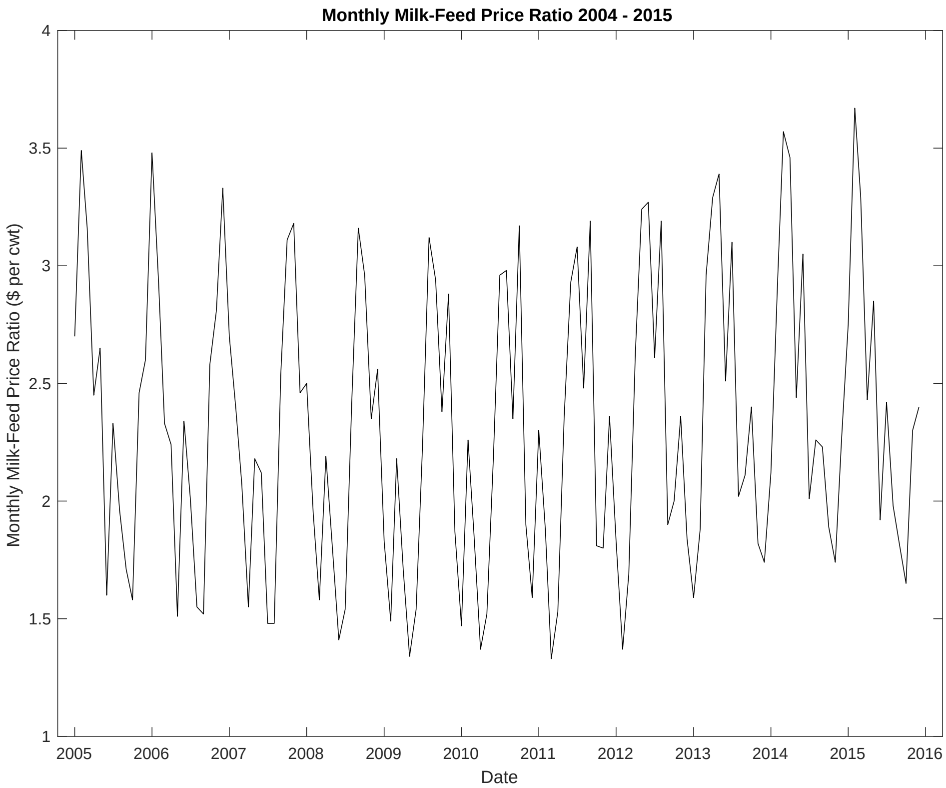

Figure 1. Monthly milk-Feed price ratio from 2004–2015. cwt, hundredweight.

Several studies have been conducted to assess the effects of subsidies on exit decisions in the agricultural sector. Chau and Gorter [10] compared the impact of loan deficiency payments (LDPs) and production flexibility contracts (PFC) on the decisions to exit among the U.S. wheat farmers. The authors considered the absence of LDPs and PFC. They found that the removal of either payment will lead to higher exit probability among low-profit farms, but will do little to change total industry output so long as the low-profit farms are relatively small. Happe et al. [11] used simulation modeling to assess exit decisions among farms in the Slovak Republic. They found that in the short run, phasing in of farm payments retained existing farms to continue operating and incentivized successors to enter the industry. In the long run, the heterogeneous farm structure became more homogenous. Trnkova and Vasilenko [12] quantified the effects of subsidies on livestock farms in the Czech Republic on production, costs and technical efficiency. They found that subsidies increased total production, led to wasted resources and impaired farm efficiency. Similarly, Bezlepkina et al. [13] assessed the effects of subsidies on Russian dairy farms. They suggested that subsidies had a distorting effect on the input to output ratio, while subsidies also reduced credit constraints faced by farmers.

Our research objectives in this paper are as follows. First, we propose a simulation method for analyzing exit decisions with purely financial data that, to the best of our knowledge, no studies exist in the literature have yet employed. Specifically, we addresses a common empirical problem where researchers are only able to obtain financial records for farmers, which limits the potential for analyzing exit decisions. In particular, dairy cost-of-production studies (e.g., Farm Credit East and Cornell) often grant researchers access to online record systems, which contain only farm cost and revenue data. We develop and apply an approach to coping with such a type of dataset to analyze exit decisions. Our dataset contains milk prices, farm expenditures and farm output for conventional Maine dairy farms, but no information of household characteristics, which are usually considered to be non-economic determinants of dairy farm exit decisions. To cope with such pure financial data, we model exit decisions as a function of profitability and seasonality. Second, we apply our simulation technique to analyze the effectiveness of the Maine Dairy Relief Program in preventing farm exits of Maine dairy farms. We conduct counterfactual experiments to estimate differences in farm exits, industry output and industry profits that would have resulted in the absence of the Maine Dairy Relief Program.

The state of Maine has a unique tier-pricing program (also called the Maine Dairy Relief Program) established in 2004. The dairy farms in the state are categorized into four tiers based on their annual production levels. Farms move through each of the four tiers as their total production increases. All farms begin the year in Tier 1 and move into Tier 2 after they produce 16,790 cwt. Likewise, farms move to Tier 3 after producing 49,079 cwt. Farms producing more than 76,800 cwt move into Tier 4. The tier a farm is classified into therefore represents the tier in which it ends the production year. The state government issues a unique kick-in milk price for each tier. When the Boston Blend milk price dips below one tier's kick-in price, the tier program issues payments to farmers of that tier. The cost-of-production study aims to provide a precise baseline estimate of the cost of production for each tier so that state legislators can better manage the tier-pricing program, as directed by An Act to Encourage the Future of Maine's Dairy Industry (Chapter 648 H.P. 1445-L.D. 1945), established by L.D.1758 and defined in Maine Revised Statutes, Title 7, §3153-b. Given the nature of volatile production costs in dairy farming, it is important to update the baseline cost estimates for each tier every three years. The historical tier definitions and target prices are displayed in Tables 1 and 2 (L.D. 1945; L.D. 852; L.D. 1758; L.D. 1905).

Table 1. Historical tier definitions.

Tier	2004–2006	2006–2010	2010–2016
1	0–1,678,999	0–2,135,599	0–1,679,099
2	1,679,000–2,604,999	2,135,600–4,907,999	1,679,100–4,907,999
3	2,605,000 and up	4,908,000 and up	4,908,000–7,680,399
4	N/A	N/A	7,680,400 and up

Table 2. Historical target prices for each tier.

Time Period	Tier 1	Tier 2	Tier 3	Tier 4
2004–2006	$16.18	$15.59	$13.12	N/A
2006–2010	$18.68	$16.23	$15.43	N/A
2010–2012	$20.70	$18.07	$17.29	$16.51
2012–Present	$21.00	$20.36	$18.01	$17.83

Dairy is not only one of the most important industries and tax revenue sources in the state of Maine, but also a contributor of many positive externalities to Mainers such as open space for adjacent residents, employment opportunities for rural communities and access for consumers to purchase locally-produced dairy products. Given the shrinking number of Maine dairy farms, it is getting more and more important to carefully evaluate the impact of subsidies received under the Maine Dairy Relief Program. With volatile milk prices and rising production costs, farm families are losing their livelihood as small dairy farms shut down. In particular, we aim to investigate whether the policy goals of this program have been achieved. In this study, we apply our simulation framework to test the hypotheses that the Maine Dairy Relief Program reduces farm exits, postpones farm exits and has greater impacts on smaller farms.

The layout of this paper is as follows. Section 2 describes the data we employed to apply our simulation approach and further addresses our empirical problem. Section 3 formalizes our simulation methods and describes each step of the program in detail. Section 4 discusses our findings on the impacts of the Maine Dairy Relief Program and discusses cross-validation techniques. Lastly, Section 5 highlights some concluding remarks and policy suggestions from this study.

2. Data

We conduct simulations to assess the impact of the Maine Dairy Relief Program on exit decisions of conventional Maine dairy farms. The first dataset used is a set of four cross-sections of conventional Maine dairy farms including 72 farms from 2001, 60 farms from 2004, 36 farms from 2010 and 36 farms from 2013 (The farms included in each panel are different, with a few exceptions of farms showing up in multiple years. The sampled farms in the cost-of-production studies are carefully selected to be representative of the distribution of farm size and geography of the Maine dairy farm population. Sampling methods are consistent across years, and average cost estimates from the studies have been accepted by the state legislature. For reference, see [14] or [15].). These data contain each farm's annual output and expenses for the respective production years, from which we can calculate per unit costs, and come from the University of Maine dairy cost-of-production studies that are conducted every three years (see, for example, [14] or [15].). The second dataset contains annual output for all conventional dairy farms in Maine from 2004–2014 and total monthly output for the state during that period. The third dataset is made up of the historical tier prices and state premiums received by dairy farms in Maine since the program began in 2004. It is worth noting that our dataset is in contrast to that used by Bragg and Dalton [5] since our dataset contains only production and financial data, while their dataset includes non-financial farm-level variables, as well.

The farm-level cost and output data were collected through two distinct methods. Specifically, data for the 2001 and 2004 production years were collected through a mail survey, while data for the

2010 and 2013 production years were collected through an on-site interview approach. The Maine Milk Commission recorded the annual output (cwt) data of all conventional Maine dairy farms from 2004–2014. By definition, the production year begins in June and ends in May. Most notable, however, is the dramatic reduction in the number of conventional dairy farms in Maine. Over this eleven-year period, the number of conventional dairy farms in Maine decreased by 98 (Note that this is not the same as number of exits over this period (as in Table 3). After accounting for new entry over the observed period, this number is reflecting net exit.). Also notice that the Herfindahl–Hirschman index (HHI), which measures market power in an industry, has increased from 126.05 in 2004 to 224.06 in 2014, indicating an increase in firm concentration in the Maine dairy industry at the farm level. Since cost data of organic dairy farms are not available, our datasets only consist of conventional dairy farms. The output data for all conventional dairy farms did not include data on number of cows. That said, when a dairy farm exits the industry, most of the farm's cows typically get sold to another in-state dairy farm.

We also considered the proportion of farm exits by tier for the 484 farms for which we observe production in the sample period. Farms that exit and re-enter are included in the calculation as farms that exit. A farm's tier classification is defined by its largest tier achieved in the observed sample period (this means a farm that moves up in tier size is not counted as an exit). Table 3 displays the proportion of farms that exit at least once in each tier from 2001–2015. As can be seen, 84% of farms who exit at least once in this time period were Tier 1 farms. We observed that 64%, 37% and 30% of tier 1, Tier 2 and Tier 3 farms eventually exit, respectively. None of the Tier 4 farms in our dataset exit the industry in this time period. Of all farm-months in which a farm either stays or exits, exits represented less than 1% of these observations.

Table 3. Farm exits within each tier from 2004–2015.

	Tier 1	Tier 2	Tier 3	Tier 4
Farms that Exit	221	30	12	0
Total Farms in Tier	344	82	40	18
Proportion of Farms that Exit	64%	37%	30%	0%
Tier's Proportion of Total Exits	84%	11%	5%	0%

The tier definitions established by the Maine legislature have changed three times since the tier program began in 2004. Table 1 displays the historical tier definitions measured in pounds (rather than in cwt). Note the program began with three tiers of production size, but increased the number of tiers to four beginning in 2010. Likewise, the minimum prices for each tier have adapted to reflect increasing costs of production. The nominal target prices for each tier are displayed in Table 2.

Our dataset also contained Boston Blend and target tier prices by month from 2004–2015. The Boston Blend price varies considerably throughout time (see Figure 2). Notice that between January 2006 and September 2007, milk prices increased approximately $10 per cwt (nearly a 100% increase in the Boston Blend price). These prices tend to be very cyclical in nature, and this price volatility is a major factor in exit decisions of dairy farms. Figure 2 displays nominal target tier prices plotted against Boston Blend price to illustrate the revenue benefits of the Maine Dairy Relief Program to each tier.

As previously stated, our dataset lacks information of household characteristics of dairy farm exits such as farmer age and generational planning. Though our predictions might not be as accurate as with such information, we propose an alternative simulation method designed to cope with this empirical problem, given such that information is usually difficult to track and sometimes kept confidential.

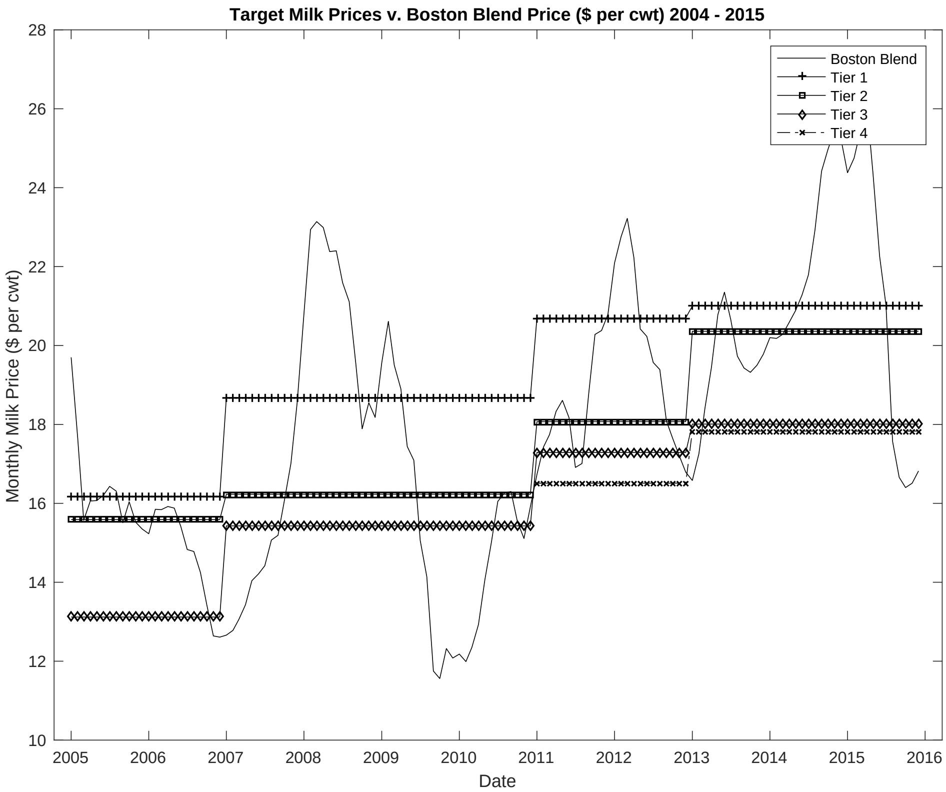

Figure 2. Monthly Boston Blend and target tier prices per cwt from 2004–2015.

3. Approach

Prior to conducting simulations, we estimated a preliminary cost function in order to generate stochastic profits in the later simulation steps. We use the panel data of Maine dairy cost-of-production studies to estimate per unit variable costs as a quadratic function of output with a time trend. These data come from the University of Maine dairy cost-of-production studies that are conducted every three years (see, for example, Kersbergen et al. (2010) or Chen et al. (2013)). Average variable cost (AVC) includes hired labor, feed, equipment and repairs, livestock, milk marketing, crops and real estate and unpaid labor valued at a CPI adjusted $10 per hour. AVC was estimated as a polynomial function of output including a time trend using ordinary least squares regression (After converting all costs to 2013 dollars, we estimate the AVC equation treating the data as a cross-section. The time trend is included to reflect dairy production costs rising over time (see Chen et al., 2013). As one anonymous referee pointed out, including annual dummies instead of a time trend would allow for influence from the 2009 financial crisis. However, annual dummies do not allow for future forecasts to be made in our model; hence, we chose to use a time trend instead.). While estimating this equation for each tier separately may reflect average costs more accurately, Tiers 3 and 4 have too few observations to estimate a regression (We thank an anonymous referee for pointing this out. While the estimation of AVC includes all tiers, the forecasted $A\hat{V}C$ in the simulation considers tiers separately. See Table 4 for estimates.).

$$AVC = \beta_0 + \beta_1 cwt + \beta_2 cwt^2 + \theta Trend + \epsilon \quad (1)$$

The panel data contain farm-level information from four years, and the CPI adjusted cost values are all in 2013 dollars. We expect per unit costs to fall at a decreasing rate as output increases.

In order to use these estimation results for simulations, it is necessary to test the error distribution for normality. The Shapiro–Wilk, Kolmogorov–Smirnov, Cramer–von Mises and Anderson–Darling tests were employed to test the two error distributions for normality. For both distributions, all four tests failed to reject the null hypothesis of normality distributed residuals at the 10% level.

The following five steps of the simulation program were iterated 1000 times:

1. Calculate stochastic profits based on error distribution from AVC regression.
2. Determine outlier fences based on stochastic profits and exit decisions.
3. Estimate the binary probit of exit decision for non-outliers.
4. Assign the exit probability for each observation based on probit estimates and the outlier rule.
5. Forecast exit decisions for each observation based on exit probabilities.

In Step 1, values are randomly drawn from the residual distribution of the AVC regression and added to deterministic AVC estimates to calculate stochastic AVC for all Maine dairy farms from 2004–2014. Variable profits are calculated using milk prices with price supports from the tier program.

Second, we calculated rule-of-thumb filters based on average stochastic variable profit per cwt in the previous six months as follows,

$$\pi_{i,t}^{(6)} = \frac{\sum_{s=t-6}^{t-1}(Price_{i,t} * cwt_{i,t} - AVC_{i,t} * cwt_{i,t})}{\sum_{s=t-6}^{t-1} cwt_{i,t}} \tag{2}$$

Then, we can categorize all the farm-month observations into two groups: either farmer i at time t stays in business such that $\boldsymbol{S} = \{\pi_{i,t}^{(6)} : cwt_{i,t} > 0\}$ or farmer i at time t quits such that $\boldsymbol{E} = \{\pi_{i,t}^{(6)} : cwt_{i,t-1} > 0, cwt_{i,t} = 0\}$. It is worth noting that a farm that switches from conventional to organic dairy production is counted as an exit (while a richer version of this model would distinguish between switching to organic and shutting down altogether, our dataset contains no information about organic farm characteristics). Next, we search for the criteria to distinguish farmers' choices between exit and stay. We choose the average variable profit as the indicator. If the average variable profit per cwt in the past six months is below a certain value, then the farm will exit. Otherwise, the farm remains in business. The exit and stay filters are the 95th and 5th percentiles of the sets $\boldsymbol{S}$ and $\boldsymbol{E}$, respectively. Equivalently, the stay filter, denoted $\pi^{(s)}$, corresponds to the $(0.95) * (|\boldsymbol{S}| + 1)$th order statistic of the set $\boldsymbol{S}$, and the exit filter, denoted $\pi^{(e)}$ corresponds to the $(0.05) * (|\boldsymbol{E}| + 1)$th order statistic of the set $\boldsymbol{E}$.

Third, we ran a binary probit with exit decision as the dependent variable on 22 observations not satisfying the rule-of-thumb filter. The maximum likelihood estimation of the probit model was originally proposed by Fisher [16]. Bragg and Dalton [5] used a binary choice model to consider exit decisions. They use both financial and non-financial explanatory variables to analyze exit decision. Due to our data constraints, exit decision is modeled as a function of seasonality, price and AVC lags in the previous six months (As one anonymous referee pointed out, other variables may also be relevant to exit decisions, such as age and education [5]. Due to limited data availability, our explanatory variables are constrained to financial data, and our approach is useful in similar scenarios where only limited financial information is available.).

$$Exit_{i,t} = f(Season_t, Price_{i,t-1}, ..., Price_{i,t-6}, AVC_{i,t-1}, ...AVC_{i,t-6}) + \epsilon_{i,t} \tag{3}$$

Fourth, we assigned the corresponding probit probability of exit for observations not satisfying the rule-of-thumb filters and assigned filtered out observations an exit probability calculated according to Bayes' rule. Probit probabilities were based on prices in the absence of price supports. Hence, probabilities used to forecast exit decisions correspond to:

$$P(Exit_{i,t} = 1) = \begin{cases} \Phi(X_{i,t}'\beta + \epsilon_{i,t}) & \text{if } \pi^{(e)} < \pi_{i,t} < \pi^{(s)} \\ P(Stay|\pi_{i,t}^{(6)} > \pi^{(s)}) & \text{if } \pi_{i,t} \leq \pi^{(s)} \\ P(Exit|\pi_{i,t}^{(6)} < \pi^{(e)}) & \text{if } \pi^{(s)} \geq \pi_{i,t}, \end{cases} \tag{4}$$

where:

$$P(Stay|\pi_{i,t}^{(6)} > \pi^{(s)}) = \frac{P(\pi_{i,t}^{(6)} > \pi^{(s)}|Stay) * P(Stay)}{P(\pi_{i,t}^{(6)} > \pi^{(s)})}, \tag{5}$$

and:

$$P(Exit|\pi_{i,t}^{(6)} < \pi^{(e)}) = \frac{P(\pi_{i,t}^{(6)} < \pi^{(e)}|Exit) * P(Exit)}{P(\pi_{i,t}^{(6)} < \pi^{(e)})}. \tag{6}$$

While the probit technique has been used by other authors to model exit decisions (see, for example, Bragg and Dalton [5]), the forecasted probability Equations (6)–(8) above were developed by the authors.

Fifth, we forecasted exit decisions for each farm-month combination based on the assigned probabilities of exit. To determine the impacts of the Maine Dairy Relief program, the simulation average forecasted number of months produced is compared to the observed number of months produced with tier prices for each farm. Additionally, the average across simulations of probit coefficients and rule-of-thumb filters is compared to deterministic outcome. Lastly, the industry profits with and without price supports are compared.

$$Forecast_{i,t} = \begin{cases} 0 & \text{if } u_{i,t} > P(Exit_{i,t} = 1) \\ 1 & \text{if } u_{i,t} \leq P(Exit_{i,t} = 1) \end{cases} \tag{7}$$

where:

$$u_{i,t} \sim U(0,1). \tag{8}$$

Finally, to obtain robust results, we repeat the aforementioned five steps 1000 times to get the projections of profit, number of farms and industry output.

Table 4. Average variable cost (AVC) estimation results.

Variable	Estimate	S.E.	*p*-Value
Intercept	−818.387	127.8017	<0.0001
cwt	-5.6×10^{-5}	1.15×10^{-5}	<0.0001
cwt^2	1.18×10^{-10}	3.24×10^{-11}	0.0004
Trend	0.41924	0.06376	<0.0001

4. Results

We adopted a simulation approach to explore the sampling distribution of the parameters of interest. Namely, the outlier fences, probit output coefficients and forecasts were recorded and averaged across 1000 iterations. The results from the simulations were then compared to the observed values with price supports from Maine's Dairy Relief Program. In order to estimate the program's impact as a safety net for Maine dairy farms, we assumed a lack of price supports when forecasting exit decisions in the simulation. Specifically, we considered the differences in the number of farms producing, industry profit, industry output in each tier, as well as overall market concentration.

The estimation results for AVC are displayed in Table 4. A negative coefficient for output and positive coefficient for squared output were observed. These results were significant at the 1% level and consistent with the hypothesis that AVC fell at a diminishing rate with output. These results indicate that economies of scale existed in the Maine dairy industry, which could be explained by volume discounts received on large purchases from larger farms.

Further, our per-unit cost estimates suggest that AVC was minimized at approximately 237,288 cwt per year, and the time trend values indicate that real AVC increased approximately \$0.42 per year. In 2010, for instance, our estimation indicated a short-run shut-down price of \$17.64. It should be noted that this AVC curve is an average across farms that does not reflect idiosyncrasies that may result from other factors (e.g., management experience) (Especially with smaller farms, many farms will have AVC higher than the market price. This demonstrates the need for the Maine Dairy Relief Program to keep farms from shutting down.). In addition, the time trend term was rather a linear approximation of increased costs of producing milk as a function of time. While tiers representing smaller farms are guaranteed higher prices by price floors implemented in the tier program, larger-farm tiers tended to have lower costs per cwt, as demonstrated by the per-unit cost regressions.

The average stay and exit outlier fences across 1000 iterations were 4.41 and −4.07, respectively (see Table 5). Observations categorized as non-outliers according to these outlier fences were used to estimate a binary probit in each iteration. Since a decrease in profitability should increase the probability of exit, we expected the price coefficients to be negative and the variable cost coefficients to be positive. Table 6 displays the average probit parameter estimates from the simulations (The lack of statistical significance for many of the coefficient estimates was likely due to having a small sample size. Additionally, for both price and AVC, lags were highly collinear with previous lags. Consequently, inflated standard errors could also contribute to the lag of significance for many of the AVC and price lags. Further, farmers were likely to have a decision lag, which may also explain why only the three (six) month lag for price (AVC) was significant. The focus of this study, however, was not on analyzing exit determinants, as we were unable to obtain data on many key exit determinants. While this is a limitation of this study, our focus was to propose and apply a method for analyzing exit decisions with limited data. We are thankful for one anonymous referee for pointing this out.). The seasonality dummies were all associated with negative coefficients, indicating that the base season, summer, has the highest probability of exit. The AVC coefficients in the simulation setting were all positive except for the first lag, as was hypothesized. Four of the six coefficients of lagged prices were correctly hypothesized as negative. Consistent with the findings of Stokes [9] and Bragg and Dalton [5], we found that higher farm profitability decreased the probability of exit.

Table 5. Outlier fences

	Stay Filter $\pi^{(S)}$	Exit Filter $\pi^{(E)}$
Simulation Average	4.41	−4.07

Table 6. Probit coefficient estimates.

Variable	Estimate	Std. Error
Intercept	−4.103 ***	0.348
Fall	−0.512 ***	0.069
Winter	−0.487 ***	0.066
Spring	−0.557 ***	0.067
Price Lag 1 Month	−0.009	0.028
Price Lag 2 Month	−0.036	0.044
Price Lag 3 Month	0.127 ***	0.051
Price Lag 4 Month	−0.035	0.052
Price Lag 5 Month	0.063	0.051
Price Lag 6 Month	−0.043	0.033
AVC Lag 1 Month	−0.002	0.005
AVC Lag 2 Month	0.0005	0.005
AVC Lag 3 Month	0.004	0.005
AVC Lag 4 Month	0.005	0.005
AVC Lag 5 Month	0.007	0.005
AVC Lag 6 Month	0.010 **	0.005

*, **, *** denote 10%, 5% and 1% statistical significance, respectively.

The final part of the simulation was to forecast a decision to remain in business or exit for all farm-months in which we observed production. The probability of exiting for a given farm-month was assigned a value based on whether or not the observation satisfied the outlier filter in that particular iteration. If the value of variable profit per cwt in the previous six months satisfied the outlier filter, then an exit probability was calculated according to Bayes' rule in Equations (7) and (8). If the farm-month was filtered out, the associated probit probability was assigned.

To forecast these exit decisions, the probability of exiting in each farm-month was compared to a draw from a uniform distribution of about (0,1). If the draw from the uniform distribution was less than the probability of exit, then the farm was forecasted to exit. Otherwise, the farm was forecasted to remain in business. Once a farm was forecasted to exit, forecasts were not generated for subsequent months unless re-entry was observed for the farm. This framework allowed for an intuitive comparison of the number of months produced between the observed reality and the forecasted outcome in the absence of price supports.

The tier program affected industry profits in two ways. First, without price supports, farms exited sooner and more often, meaning fewer months of production. Second, the tier program increased producer milk prices. To assess the impact of the tier program on industry profitability, we considered differences between observed profits with price supports and forecasted profits without price supports from the simulations. In particular, we plotted industry profit per cwt and average industry profit per farm with and without price supports (see Figures 3 and 4, respectively). Average profit per cwt and profit per farm for Tiers 1–3 were very similar with and without price supports. While lower prices reduced the profits of individual farms, lower profit farms exited sooner, offsetting the lower prices. For Tier 4 farms, exit decisions by lower-profit Tier 4 farms actually led to net increases in estimated average profit per farm and profit per cwt without price supports.

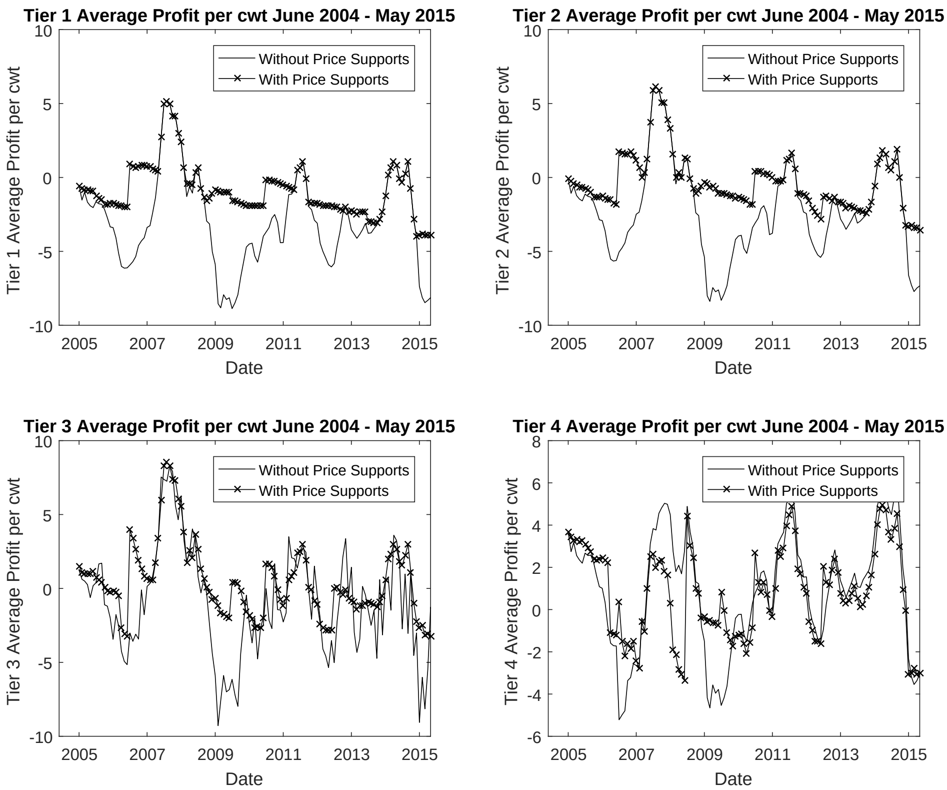

Figure 3. Industry profit per cwt by month with and without price supports.

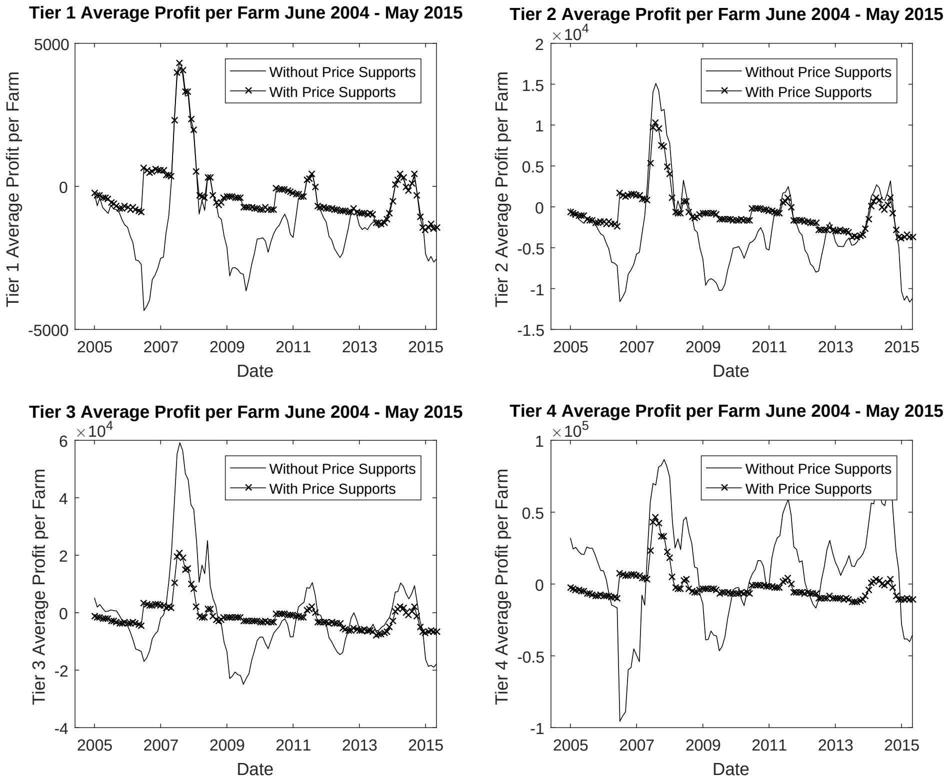

Figure 4. Industry profit per Farm by month with and without price supports.

Fewer farms and industry production led to greater market concentration. Hence, we considered the effects of price supports on annual industry HHI. With price supports, industry HHI rose from approximately 126.23–224.06 over the 11-year period observed (see Figure 5). Without price supports, our estimates indicated that HHI would have risen as high as 647.82 by the end of the period in 2015, an approximate difference of 423.76 (189%). Thus, our simulations suggest that the effects of price supports in preventing farm exits consequently led to increased market competition. This finding suggests that small dairy survival was considerably impacted by price supports. In general, deviations from the efficient cost frontier were more dangerous for small farms, since per-unit costs tended to be higher. It should be noted there likely would have been fewer entrants into the industry, particularly Tier 1 entrants, in the absence of price supports.

Tables 7 and 8 compare the remaining number of farms (since we treat new entrants as fixed (non-stochastic), comparing the remaining number of farms with and without price supports is a comparison of net exit) and industry output in the final observed month of May 2015 with and without price supports. The simulation results indicate the tier program has had a substantial impact on reducing farm exits within each tier. Our results indicate that each tier was heavily impacted by the price supports. Specifically, the proportional decreases in each tier ranged from 64% in Tier 1 to 75% in Tier 2. Moreover, the estimated change in total number of industry farms was from 232 farms to 77 farms, an approximate decrease of 67%. These findings are in contrast with the findings of Foltz (2004), who found the NEDC only kept an additional 4% of farms in business. The proportional changes in industry output for each tier were very similar. Overall industry output was forecasted to drop by approximately 70% in the absence of price supports. As can be seen in Figures 6 and 7, the estimated gaps in industry output and number of farms, respectively, incurred from removing price supports were steadily increasing throughout the 11-year period. With less milk being produced in Maine, fewer employees would be demanded by dairy farms in the state, resulting in additional income losses beyond those of the dairy farmers themselves. Thus, to fully assess the benefits of the

Maine Dairy program, one must acknowledge the industry spillover effects beyond just changes in dairy farm profits.

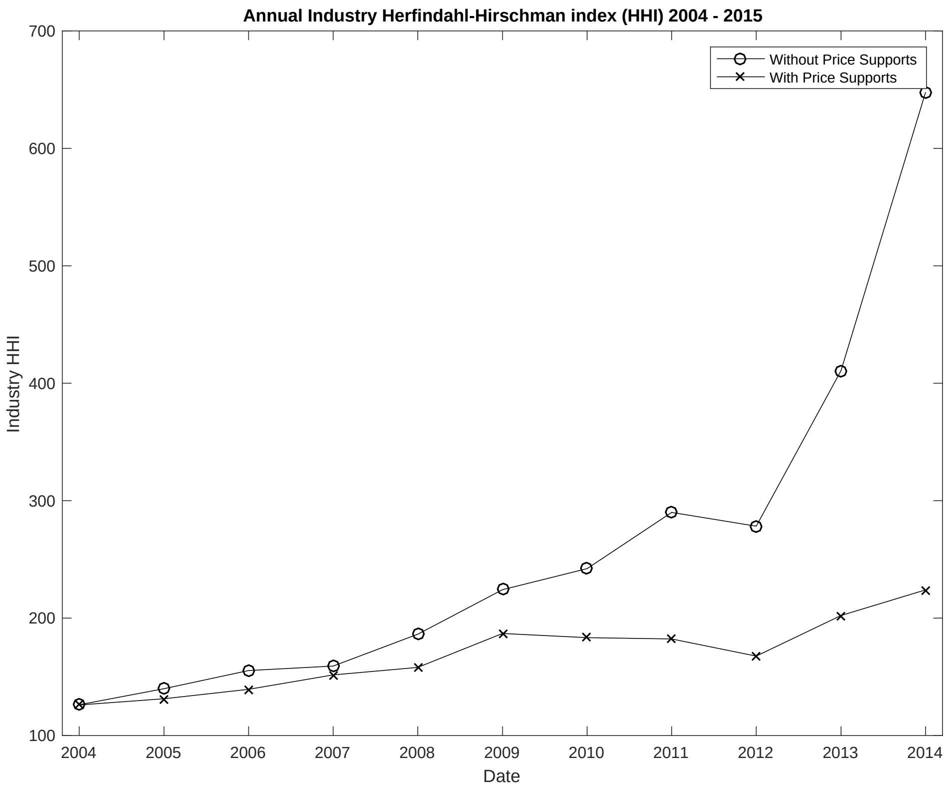

Figure 5. Industry HHI with and without price supports from 2004–2015.

Table 7. Total number of farms remaining in May 2015 with and without price supports.

	With Price Supports	Without Price Supports	Difference
Tier 1	133	49	84 (63%)
Tier 2	52	13	39 (75%)
Tier 3	29	9	20 (69%)
Tier 4	18	6	12 (67%)
Overall	232	77	155 (67%)

Table 8. Total industry output (cwt) in May 2015 with and without price supports.

	With Price Supports	Without Price Supports	Difference
Tier 1	52,213	16,948	35,265 (68%)
Tier 2	82,997	21,695	61,302 (74%)
Tier 3	96,768	28,843	67,924 (70%)
Tier 4	244,871	77,879	166,990 (68%)
Overall	476,849	145,367	331,482 (70%)

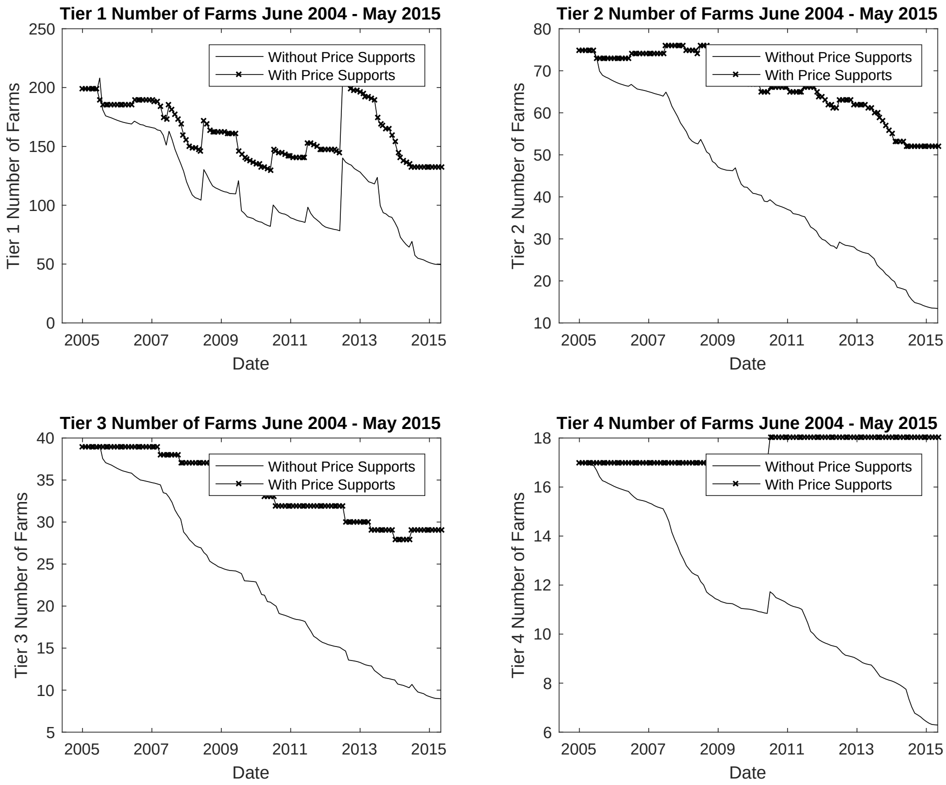

Figure 6. Number of farms by month with and without price supports.

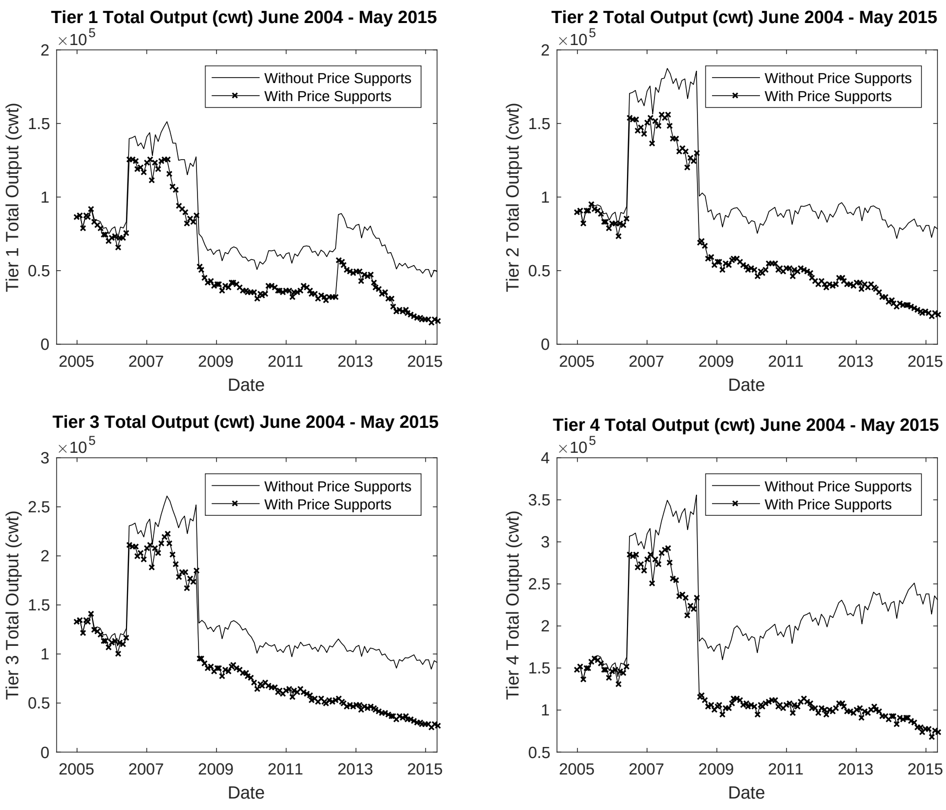

Figure 7. Industry production (cwt) by month with and without price supports.

To assess the predictive validity of our modeling approach, we employed cross-validation techniques to measure the model's forecast accuracy. The technique selects a subset of data to be used as training data to fit the model, while the remaining observations are used to test the forecast accuracy. We use observations from 2004–2012 as training data and observations from 2013 and 2014 to measure prediction error by comparing the forecasted values with price supports to corresponding observed values. The process was repeated 100 times, and the average accuracy rate calculated across iterations of the program was found to be 95.7%, suggesting the model had relatively high predictive validity. Farms producing in the last two years of the dataset were observed to produce 19 of 24 months on average, while the forecast average was 15 of 24 months on average, indicating the model may have been slightly biased toward forecasting an exit earlier than observed.

5. Conclusions and Discussions

This study develops a novel approach of simulation modeling that deals with the empirical problem of an incomplete dataset to model farm exit decisions. Specifically, the developed approach copes with a lack of data on non-economic determinants of the exit decision by modeling the exit decision as a function of seasonality and profitability. Further, we applied this model to assess the effectiveness of price supports under the Maine Dairy Relief Program. Though our predictions would have been more accurate with complete data on non-economic exit determinants, our cross-validation techniques indicate that our model has high predictive accuracy.

Using a sample of 204 conventional Maine dairy farms, average variable cost was estimated as a quadratic function of output with a time trend. Using the saved residuals, stochastic variable costs were estimated each for 484 Maine dairy farms from 2004–2015. A binary probit was conducted on a subset of observations not satisfying the outlier filters in order to calculate exit probabilities. For outliers, the probability of exit was calculated according to Bayes' rule in Equations (7) and (8). Non-outliers were assigned an exit probability calculated from the probit coefficient estimates. Exit decision forecasts were based on these exit probabilities in each iteration of the simulation program.

We compared the forecasted number of farms that exit without price supports to the observed number of farms that exit with price supports for each tier. As expected, our results indicate that the program has had a substantial impact on preventing farm exits. While Tier 1 saw the greatest revenue benefits, Tiers 2, 3 and 4 received substantial benefits, as well. The finding that smaller farms receive more benefit from these price supports is intuitive for two reasons. First, smaller farms tend to have higher costs, given the presence of economies of scale in the Maine dairy industry. Second, tiers categorized by small farms are designated higher target prices than tiers with large farms, meaning the subsidies to farms in smaller tiers occur more frequently in larger payments per cwt. Overall, our results indicate that there would have been approximately 67% fewer farms and 70% less milk produced in the Maine dairy industry by the end of the observed period in May 2015. Additionally, our simulations indicate that market concentration would increase substantially (approximately 189%) in the absence of price supports. Thus, we conclude that by preventing dairy farm exits, the Maine Dairy Relief Program leads to increased market competition.

It is important to consider the policy implications of the study's conclusions. The Maine Dairy Relief Program was designed to increase industry sustainability and to help prevent dairy farm exits. From 2003–2015, tier payments have amounted to over $66 million with over sevenbillion pounds of milk produced by participating farms. Critics of the program argue the amount of tax-payer dollars allocated to the program is too large. One must weigh the economic benefits of the program against the opportunity cost of taxpayer dollars spent to assess the policy properly. Dairy farm exits in the absence of price supports would have numerous spillover effects, most notably the loss of on-farm jobs. The loss of incomes for both farm workers and farm owners would lead to lower levels of expenditure among these agents. Our results suggest that the program is working to prevent farm exits as intended, but complete cost-benefit analysis requires measuring the job losses due to farm exits, which is beyond the scope of this study and so is left as an extension for future research. Another extension to this research would be to model the decision to switch from conventional to organic dairy farming, though we were unable to model this decision, as we had no data on organic farm production costs.

Dairy farms play an important role in rural Maine communities. As volatile prices and rising production costs have led many small farms to shut down, many families have lost their source of income. As the Maine dairy relief program has given dairy farms a more stable source of income, the financial sustainability of the industry has improved. Small farms are those most affected by price volatility due to economies of scale. Of course, the same is true for other states, as well. As the trend of smaller farms shutting down has become more prevalent, rural communities across the U.S. have been affected by milk price volatility. Thus, similar price stabilization programs are likely to contribute positively to financial sustainability in rural communities in other states, as well.

In short, our findings indicate that the Maine Dairy Relief Program has a considerable impact on Maine dairy farms. Milk price variability is a serious concern that drives producer exit decisions. That said, the Maine dairy relief program creates effective price floors that increase the profitability of Maine dairy farms, stabilize profits and reduce producer uncertainty. We find that the tier program substantially contributes to the financial sustainability of the Maine dairy industry by reducing the number of farms that exit, keeping farms in business longer and increasing farm profits. Had the tier-pricing program not been adopted in 2004, there would likely be far fewer dairy farms operating in Maine today.

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