Tracing the evolution of the aggregate U.S. milk supply elasticity using a herd dynamics model

Marin Bozic, Christopher A. Kanter, Brian W. Gould

Abstract:

The U.S. dairy sector is characterized by increasing volatility of milk prices, and consolidation in production as evidenced by declining number of dairy farms with an increasingly larger share of milk supplied from a small number of very large farms. Using aggregate national data, we build a mixed-frequency herd dynamics econometric model of the U.S. milk supply that updates and substantially amends the model first proposed by Chavas and Klemme. We implement a dynamic residual-based bootstrap technique that can be used in testing for changes in nonmarginal simulated long-run supply responsiveness, and trace the evolution of long-run milk supply elasticity from 1975 through 2010. Several papers in the past have suggested that long-run supply elasticity increases with dairy farm size, which implies that increased importance of large farms would increase aggregate long-run supply responsiveness. Contrary to this conclusion, we find a declining trend in long-run supply elasticity from 1975 through 2005. Persistence of such a decline would be a major cause for worry, as ever larger price swings would be needed to equilibrate the market in face of demand shocks. However, we find that milk supply is becoming more responsive since 2005 both to milk and feed price changes. Increasing responsiveness to feed prices further justifies focusing the next generation of the dairy policy instruments on managing dairy profit margins rather than just revenue streams.

JEL classification: Q11

Keywords: Milk supply; Dairy herd dynamics

1. Introduction

The U.S. dairy industry has experienced increased price volatility both at the farm level and for manufactured products over the last 20 years. Examining the ratio of the difference of the highest to the lowest monthly all-milk price observed over a particular time period, divided by an average price evaluated over the same period, we find that volatility has increased from 16.5% in 1980–1985, 32.5% observed over 1990–1995 to 67.3% in the 2005–2010 period. This increase in price volatility has occurred simultaneously with significant structural change in U.S. dairy farms, as evidenced by the declining number of farms and increasing share of milk supplied by few large farms. In 1980 the U.S. dairy herd was composed of 10.76 million cows with average annual yield of 11,981 pounds per cow. By 2010, the dairy herd had decreased by 15.5% to 9.1 million head with an annual per cow milk production of 21,148 pounds, a 77.8% yield increase, resulting in total U.S. milk production being 50.2% greater than in 1980. Although the total size of the U.S. dairy herd has declined, between 1980 and 2010 the average herd size increased from 32 to 146 head per farm. Furthermore, since 1993 the contribution to the total U.S. milk production from farms with less than 100 cows decreased from 45% to 15%. In contrast, in 2010, the largest 1.2% of U.S. dairy farms accounted for 32.5% of total U.S. milk production.1

Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

*Corresponding author: Tel.: (612) 624-4647; Fax: (612) 625-2729. E-mail address: mbozic@umn.edu (M. Bozic)

1 More detailed description of the U.S. dairy industry and recent dairy policy can be found in Blayney (2002) and Blayney et al. (2006).
In a market characterized by both inelastic demand and supply, large price swings are necessary for equilibrium to re-emerge in face of any shock, and volatility should not come as a surprise. The interesting question to pose is whether the significant ongoing consolidation in milk production can be expected to bring about higher supply responsiveness, thus changing the nature of the adjustment process. In a regional model of the U.S. milk supply Weersink and Tauer (1990) find that supply responsiveness is the highest in the Pacific region, which is characterized by having a larger-than-average farm size. Ade- laja (1991) used panel data from a sample of northeastern dairy farms and found that, in the short run, supply elasticities decrease with farm size, but in the long run, large farms are shown to be most price responsive. Similarly, Tauer (1998) finds that short-run elasticities are almost identical across New York dairy farms grouped by size, but larger farms appear to have higher long-run elasticity of supply.

These results would imply that increased importance of large farms should correspond to an increase in long-run supply responsiveness. In this article we update and amend the model first developed by Chavas and Klemme (1986) to examine how the long-run U.S. milk supply elasticity has evolved over the last three decades. Given the highly nonlinear nature of their model, and calculation method whereby long-run elasticities are obtained through a simulation, Chavas and Klemme (1986) only presented point estimates for supply elasticities. For this analysis we develop a bootstrapping technique to construct confidence intervals around estimated supply elasticities. We also use these confidence intervals to determine whether there has indeed been any change in the magnitude of price responsiveness.

2. Description of an econometric model of U.S. milk supply

In addition to articles noted earlier, additional research focused on examining U.S. dairy sector supply response can be found in LaFrance and de Gorter (1985), Thraen and Hammond (1987), Chavas et al. (1990), Chavas and Krauss (1990), Yavuz et al. (1996), USDA (2007), and FAPRI (2011). These analyses are limited in that they are either dated or they do not fully account for dairy herd dynamics. Given the earlier noted structural change and technological change of the U.S. dairy industry observed over the last two decades it is important to be as up-to-date as possible and an explicit account of herd dynamics is the appropriate modeling approach if one wishes to relate time horizon and supply responsiveness.

To provide a representation of the supply structure of the U.S. dairy industry, we adopt an econometric model similar to that used for policy analysis by USDA’s Agricultural Marketing Service (USDA, 2007). Under their modeling framework, total U.S. milk production in year t (MILKt) is the product of the number of milk cows in the U.S. dairy herd (COWt) and average yield per cow (YLDt). We introduce a mixed-frequency model of the milk supply by modeling herd dynamics using annual frequency, and modeling yield using quarterly data so as to account for the seasonality that has historically been observed in milk yield. Annual milk production is represented as

\[ MILK_t = COW_t \times \sum_{i=0}^{3} YLD_{t-i}, \]  

where \( t \) is the fourth quarter of year \( t \).

Our specification for dairy herd dynamics follows closely the model by Chavas and Klemme (1986) where producer culling/replacement decisions and the characteristics of dairy cow biology are explicitly accounted for. The understanding of biological and economic decisions governing the dairy herd dynamics can best be utilized by separately examining herd size and yield determinants via the use of two separate models.

The herd size specification used here is based on the 14-month dairy cow reproductive cycle assuming a nine-month pregnancy and five months between freshening (giving birth to a calf) and the next pregnancy. Cows produce milk from the initial birth until approximately two months prior to next birth, at which time they are removed from the milking herd to rest before the next delivery. A newborn calf takes approximately nine months to reach the weight of 500 pounds, the threshold used by USDA for classification as a replacement heifer. Heifers are first impregnated at approximately 15 months of age and give birth when approximately two years old. For our current model, a replacement heifer is a female calf at least one year of age at the beginning of the year and expected to enter the herd before the end of the year. Upon first calving, a replacement heifer is then considered to be a dairy cow and part of the dairy herd.

While the maximum biological dairy cow age exceeds 20 years, intensive milking and frequent calving make cows susceptible to various diseases. Although such health problems are generally treatable, they tend to make the economic life of a cow much shorter than the maximum physical age, especially given reduced milk yields observed during later lactation cycles. When culled from the herd, a dairy cow is typically sold for slaughter. The age at which a cow is removed from the herd depends on a number of factors including expected future milk yield, current and expected prices (i.e., milk, feed, and slaughter price), higher yield potential of cow replacements, and current/expected replacement heifer costs. The U.S. dairy herd can be described not only by its size but also with respect to the cow age distribution within the herd. Both these characteristics are determined primarily by the timing of culling and subsequent cow replacement.

For the present study we assume that heifers enter the herd when they are two years old, and the maximum productive lifetime of a dairy cow is nine years. The term we use to refer to the nine age-related cohorts is productive age class. For each productive age class we create the variable CLASS that takes a value from one to nine. For example, for dairy cows between two and three years old, \( CLASS = 1 \), those between three and four years of age, \( CLASS = 2 \).
Table 1
Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Description</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>COW and HEIFER equations (annual data)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COW</td>
<td>1,000 head</td>
<td>Annual average number of dairy cows on dairy farms</td>
<td>3,150.98</td>
<td>167.54</td>
<td>2,914.13</td>
<td>3,577.50</td>
</tr>
<tr>
<td>HEF</td>
<td>1,000 head</td>
<td>Replacement heifers, 75% of published cattle inventory data for January 1 “500+ lbs heifers”</td>
<td>9,956.03</td>
<td>796.46</td>
<td>8,987.50</td>
<td>11,219.60</td>
</tr>
<tr>
<td>r</td>
<td>%</td>
<td>Operating loan real interest rate, Federal Reserve Bank of Chicago AgLetter, Seventh District Credit Conditions (Annual CPI, 1982–1984 = 100)</td>
<td>5.87</td>
<td>2.59</td>
<td>–0.23</td>
<td>10.43</td>
</tr>
<tr>
<td>FP</td>
<td>$2010/cwt</td>
<td>Real feed cost, 16% protein dairy ration (annual CPI 1982–1984 = 100)</td>
<td>8.69</td>
<td>3.17</td>
<td>5.12</td>
<td>17.31</td>
</tr>
<tr>
<td>SP</td>
<td>$2010/cwt</td>
<td>Omaha/Sioux Falls slaughter cow boning/utility price</td>
<td>74.33</td>
<td>26.02</td>
<td>42.16</td>
<td>156.50</td>
</tr>
<tr>
<td>Dum84</td>
<td>0/1</td>
<td>Dummy variable for Milk Diversion Program, active in 1984–1985</td>
<td>0.06</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dum86</td>
<td>0/1</td>
<td>Dummy variable for Whole-Herd Buy-Out Program, active in 1986–1987</td>
<td>0.06</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dum2000</td>
<td>0/1</td>
<td>Dummy variable for Federal Milk Marketing Order reform, active in 2000+</td>
<td>0.31</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>YIELD equation (quarterly data)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>YLD</td>
<td>lbs/quarter</td>
<td>Yield per cow</td>
<td>3,901.29</td>
<td>804.81</td>
<td>2,469.00</td>
<td>5,461.00</td>
</tr>
<tr>
<td>FP</td>
<td>$2010/cwt</td>
<td>Real feed cost, 16% protein dairy ration (Quarterly CPI 1982–1984 = 100)</td>
<td>8.70</td>
<td>3.26</td>
<td>4.77</td>
<td>18.55</td>
</tr>
<tr>
<td>DumQ2</td>
<td>0/1</td>
<td>Dummy variable indicating second quarter (April–June)</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DumQ3</td>
<td>0/1</td>
<td>Dummy variable indicating third quarter (July–September)</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DumQ4</td>
<td>0/1</td>
<td>Dummy variable indicating fourth quarter (October–December)</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DumQ5</td>
<td>0/1</td>
<td>Dummy variable for years after 1985, active in 1986–2010</td>
<td>0.69</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The parameters associated with the econometric model components outlined later are estimated for the period 1975–2010. Given the use of lagged explanatory variables in the herd size equation, data from 1966 to 2010 are used in estimation. Table 1 provides definitions and descriptive statistics for the variables used in the stochastic equations.

2.1. Modeling the COW equation

We assume that a dairy farm operator makes replacement and culling decisions at the end of each year. All cows that are in the ninth productive age class are removed from the herd and a decision is made as to how many cows within each of the remaining eight productive age classes will be kept in the herd for another year. The manager also adds to the dairy herd replacement heifers that have successfully calved. We represent the outcome of the above culling decisions by survival rates, \( S_{t,i} \), defined as the probability that a cow in the \( i \)th productive age class in year \( t \) will be selected to stay in the herd through the forthcoming year. Using the logistic functional form, we specify the survival rate as

\[
S_{t,i} = \frac{1}{1 + e^{Z_{t,i} \beta}}, \tag{2}
\]

Where \( Z_{t,i} \) is the vector of explanatory variables that capture economic conditions and government policies impacting selection decisions, and \( \beta \) is a vector of coefficients to be estimated. \( S_{t,9} \) is assumed zero, i.e., all cows that have completed nine years in the dairy herd are assumed to be culled.

Herd structure is incorporated into \( Z_{t,i} \) by two variables. First, as noted earlier, inclusion of the productive age class variables (\( \text{CLASS} \)) allows survival rates to differ across the nine productive age classes. Second, we include lagged values of the ratio of replacement heifers to dairy cows. A higher replacement ratio implies that more heifers are ready to enter the herd. Consequently, more of the older, less productive cows can be removed from the herd without reducing herd size. We hypothesize that the impacts of higher replacement ratios will differ across productive age classes. As such, we interact the \( \text{CLASS} = i - j \) and the associated replacement ratio, \( \frac{HEF_{t,i-j}}{COW_{t,i-j}} \). The impact of the economic environment on herd size is accounted for via the inclusion of four variables in \( Z_{t,i} \): the U.S. average All-Milk price\(^2\) (\( MP_t \)), feed price (\( FP_t \)), slaughter cow price (\( SP_t \)),

\(^2\) We account for the Milk Income Loss Contract (MILC) program by calculating the average payment per hundredweight and add this value to the U.S. All-Milk price.
and real interest rates ($r_i$). Detailed definitions and descriptive statistics of used variables can be found in Table 1.

Changes in the economic environment will influence each productive age class differently. When production is more profitable, the herd manager might decide to replace more of the older, less productive cows. Alternatively, when prices make for less lucrative production, it may not be profitable to invest in more productive, but expensive, replacement heifers, and that might be reflected in higher retention rates of older cows. To capture the differentiated price change impacts upon each productive age class, we use price–class interaction variables (e.g., $MP_{i-j} \times CLASS$) in the herd size Eq. (5). In contrast to Chavas and Klemme (1986) who use milk to feed and slaughter to feed price ratios as principal economic variables we allow the data to determine the relative milk-feed and slaughter-feed price impacts by including separate milk and feed price variables.

Given the above-mentioned specification for the survival rate $S_{t,i}$, the number of cows in the $i$th productive age class is determined by the product of the number of replacement heifers $i$ years ago and their retention rate, $R_{t,i}$, defined as the product of survival rates in the past $i$ selection decisions:

$$R_{t,i} = \prod_{j=1}^{i} S_{t-j,i-j},$$

where $j$ indexes previous years. As an example, to calculate the retention rate for cows entering the third age class in 1990 we have: $R_{1990,3} = S_{1987,0} \times S_{1988,1} \times S_{1989,2}$.

Total herd size ($COW_t$) can be represented as the sum of the number of cows in each of the nine productive age classes, $COW_{t,i}$. We specify a stochastic herd size equation that accounts for the relationship between the number of heifers in previous years and current dairy herd size and structure:

$$COW_t = \sum_{i=1}^{9} COW_{t,i} + \varepsilon_t = \left( \sum_{i=1}^{9} HEF_{t-i} \times R_{t,i} \right) + \varepsilon_t,$$

where $HEF_{t-i}$ are the number of heifers $i$ years prior to year $t$ and $\varepsilon_t$ is a stochastic error term. We can substitute the age-specific retention rate definitions from (3) into (4):

$$COW_t = \left( \sum_{i=1}^{9} HEF_{t-i} \prod_{j=1}^{i} \left( 1 + e^{-W_{j,i-1}} \right) \right) + \varepsilon_t,$$

Thus, given (5) we can predict not only the number of cows in the dairy herd but the distribution of cows across productive age classes. The $CLASS$ variable is related to summation index $i$ and multiplication index $j$ via the identity $CLASS = i - j$.

The complement to the survival rate is the age-specific culling rate $k_{t,i}$ defined as the proportion of the $i$th productive age class removed from the herd at the end of $t$.

$$k_{t,i} = 1 - S_{t,i}.$$ (6)

2.2. Modeling the HEF equation

Replacement decisions describe the selection of female calves to become replacement heifers. Underpinning the replacement decision is a representation of the probability $\Gamma_t$ of a cow being selected for reproduction, becoming pregnant, successfully calving, and the calf surviving until one year of age.

$$\Gamma_t = \frac{1}{1 + e^{W_{t,i} \gamma}},$$

where $W_t$ represents a vector of exogenous variables hypothesized to impact the calving/survival probability and $\gamma$ are parameters to be estimated.

The number of replacement heifers able to be impregnated in period $t$ can be represented as

$$HEF_t = 0.5 \left\{ (COW_{t-2} + HEF_{t-2}) \times \frac{1}{1 + e^{W_{t,i} \gamma}} \right\} + \zeta_t,$$ (8)

where $\zeta_t$ is a stochastic error term. The value 0.5 represents the fact that half of newborn calves are assumed to be male animals and cannot be used as a cow replacement. The male-to-female calve ratio can be altered with the use of sexed semen, but that technology was not widely used prior to 2008 (Overton, 2007; de Vries and Nebel, 2009). In the above-mentioned we depart from Chavas and Klemme (1986) and adopt the specification of Schmitz (1997) where we model the pool of fertile animals that can produce offspring to include not just dairy cows in period $t-2$, but also replacement heifers at that time. Thus we include $HEF_{t-2}$ in (8).

The level of technology is accounted for in (8) by a simple trend variable, and economic variables and government policy hypothesized to impact $\Gamma_t$ are the same as in (5). To understand how prices influence replacement heifer numbers, recall that it takes one year for a female calf to grow into a replacement heifer ready to freshen and that a cow is pregnant for nine months before giving birth to a replacement heifer calf. The relevant pool of dairy animals that could give birth to calves that will have grown to replacement heifers by period $t$ consists of cows and replacement heifers in period $t-2$. The number of replacement heifers available today is first determined by how many of these cows and replacement heifers were chosen to be impregnated in period $t-2$ and how many animals were culled.
Culling decisions are influenced by prices observed in period \( t - 3 \). A second factor impacting the number of replacement heifers available today is the share of female calves that are selected to be grown into replacement heifers. To capture the effect the economic environment has on this decision we include prices in period \( t - 1 \).

2.3. Modeling the YLD equation

In contrast to the COW and HEF specifications, the yield equation is modeled using quarterly data due to seasonality in milk yields and to better account for short-term impacts of changes in milk and feed prices, as well as to avoid potential endogeneity issues by using lagged prices rather than current period prices. In forecasting annual milk production, annual yield is then found as a simple sum of quarterly yields. We assume that potential yield grows linearly in time, adjusting for seasonality. We define potential yield in quarter \( t \) as

\[
YLD^P_t = \beta_0 + \beta_1 \bar{T} + \beta_2 \text{Dum} Q_2 + \beta_3 \text{Dum} Q_3 + \beta_4 \text{Dum} Q_4 + \beta_5 (\text{Dum} Q_2 \times \bar{T}) + \beta_6 (\text{Dum} Q_3 \times \bar{T}) + \beta_7 (\text{Dum} Q_4 \times \bar{T}) + \beta_8 \text{Dum} 85 + \beta_9 (\text{Dum} 85 \times \bar{T}),
\]

(9)

where \( \bar{T} = t - 1974 : Q4 \). We allow changes in seasonality with time, as regional shifts in milk production from the Midwest to more western states and improvements in herd management that have occurred over the study period may have dampened the significance of the “spring flush,” i.e. increased yield in spring due to improved weather and feed conditions, as well as potentially higher drop in yield during summer months due to increased heat problems. Finally, to account for the beneficial impact of government policies in the 1980s on yield, we allow for a continuity-preserving change in slope in 1985.

Potential yield can be thought of as long-run average trend yield whose dynamics are governed solely by technological and genetic improvements. Changes in yield from one quarter to the next are assumed to arise from economic shocks and random weather conditions, as well as reversion to potential yield. We allow the speed of correction back to trend yield to vary depending on the economic environment. Our stochastic yield equation can be represented via the following:

\[
\Delta YLD_t = (\alpha_1 + \alpha_2 \text{MP}_{t-1})(YLD_{t-1} - YLD^P_t) + \beta_1 \Delta MP_{t-1} + \beta_2 \Delta FP_{t-1} + \nu_t,
\]

(10)

where \( \text{MP}_{t-1} \) is the average milk price over previous four quarters, \( \Delta MP_{t-1} = MP_{t-1} - MP_{t-2} \) is the change in the milk price, \( \Delta FP_{t-1} = FP_{t-1} - FP_{t-2} \) is the change in feed prices from the previous quarter, \( \nu_t \) is a stochastic error term, and \( YLD^P_t \) is defined by (9). Therefore, in (10), prices play a dual role. Average milk price over the previous four quarters is used to model the speed of adjustment to potential yield, and changes in the previous quarter milk and feed prices have a direct short-term impact on yield.

The simpler structure of the yield equation may make it appear that the effects of economic explanatory variables are straightforward to interpret. In fact, price impacts on yield are theoretically the most challenging to capture as there are possibly two opposing effects. One of the most important day-to-day decisions a dairy farm operator must make pertains to the feed ration. With high milk prices and/or low feed costs, the producer would like to increase the feed ration to capture the opportunity for additional income by increasing the yield from cows currently in the herd. Furthermore, these relative price changes impact the desired herd size of many producers. That is, dairy farm operators with relatively high milk prices would like to enlarge their herds and those farm operators who intended to exit the industry may decide to postpone retirement. If there is a scarcity of replacement heifers, with those that are available being relatively expensive, producers will tend to increase the retention rate of older cows, not just to increase their milk output, but also to increase the future pool of heifers. Retaining older cows increases the overall herd size. However the larger share of less productive animals in the herd will work to decrease yield, even while increasing milk production. While we expect the overall effect of increases in milk price or decreases in feed price to be positive, it is important to remember that, should the impact be small, it may be the net effect of two opposing strong influences.

Our approach resolves several problems with the yield equation in Chavas and Klemme (1986) and USDA (2007). In particular, in the USDA model, all shocks to yield are treated as permanent, while our model allows for gradual attenuation of shock effects as yield is modeled as a trend-stationary process. In addition, both Chavas and Klemme and USDA use contemporaneous prices as explanatory variables, likely to emphasize the fact that adjustments to yield can be done quickly. That may induce endogeneity problems, which we avoid by using quarterly data with lagged explanatory variables.

2.4. The role of policy in the model

The role of government policy in the model merits a separate discussion. The impact of policy on the equations in the preceding section is captured through the inclusion of a set of binary variables meant to represent the effect of specific government policies on the U.S. dairy industry. In the early 1980s there was a large surplus of milk production due to relatively high support prices introduced several years earlier. The first government program designed to restore market equilibrium was the Milk Diversion Program (MDP), in effect from January 1984 to March 1985. Under this program participating producers were eligible for payments of $10 per hundredweight on the difference between their “base period” sales and actual sales, provided their actual sales were between 5% and 30% below base (Boynton and Novakovic, 1984; Lee and Boisvert, 1985). The binary variable Dum84 is used to capture the effect of this program.
The MDP was complemented by the Dairy Herd Termination Program (DHTP) in effect from September 1986 to the end of 1987, and accounted for by variable \( \text{Dum}86 \). Under the DHTP participating farmers were paid to slaughter or export their entire dairy herds and not to resume production for at least five years.

Under our model structure we assume that all selection decisions are undertaken at the end of a calendar year. Thus herd size and structure at the beginning of the year are determined by past selection decisions. The MDP and DHTP policies were modeled as influencing selection decisions made at the end of 1984 for the MDP, and at the end of 1986 and 1987 for the DHTP (Table 1). As an example, in cow equation, \( \text{Dum}84 \) will take a value based on the following rule:

\[
\text{Dum}84 = \begin{cases} 
1 & \text{if } t - (i + 1 - j) = 1984 \\
0 & \text{otherwise} 
\end{cases}, \tag{11}
\]

where \( t \) is the year for which herd size and structure is predicted, and \( i \) and \( j \) are indexes of summation and multiplication in (5). For instance, to predict dairy herd size and structure in 1987 \( (t = 1987) \), we need to predict the number of cows that are entering the fifth productive age class in 1987 \( (i + 1 = 5) \). Those cows were in the second productive age class in 1984, the time the Milk Diversion Policy was active \( (j = 2) \), and therefore selection decision for those cows in 1984 were affected by the policy, i.e., \( t - (i + 1 - j) = 1984 \). Although this policy was in effect for just over one year, it directly impacted the herd size and structure for almost the entire next decade.

Rules for assigning values to these binary variables will be different in the heifer equation. The policies represented by the above-mentioned dummy variables could have affected the number of heifers in year \( t \) by changing the probability that a male calf \( (t - 1) \) will be grown into a replacement heifers and/or by impacting the number of cows and heifers \( (t - 2) \) selected to stay in the herd, thus changing the base of animals that are used to produce dairy calves later grown to replacement heifers. For example, the MDP in effect in 1984 influenced the number of heifers in 1985 through impact on calves, and the number of heifers in 1986 through the impact on cow culling rates in 1984. Therefore, the appropriate rule for assigning values to \( \text{Dum}84 \) in the heifer equation is

\[
\text{Dum}84_H = \begin{cases} 
1 & \text{if } t - 1 \text{ or } t - 2 = 1984 \\
0 & \text{otherwise} 
\end{cases}. \tag{12}
\]

Due to its design, the DHTP had a more complex impact on the data generating process for replacement heifers. To maintain simplicity, and since heifers are counted at the beginning of the year, we assume that the DHTP impacted the number of heifers measured at the beginning of 1987 and 1988:

\[
\text{Dum}86_H = \begin{cases} 
1 & \text{if } t - 1 = 1986 \text{ or } 1987 \\
0 & \text{otherwise} 
\end{cases}. \tag{13}
\]

2.5. The role of expectations in the production decision

In our model, cows are treated as capital goods, hence culling and replacement decisions are best analyzed if understood as investments in the dairy herd, and thus we also need to address the issue of expectations. Schmitz (1997) uses linear forecasts of next period prices as a way to model expectations. Implicit in his approach is the assumption that only expected next period prices matter for the decision-making process. If that was so, using last observed prices would be equivalent to assuming naïve adaptive expectations, i.e., implying that expected prices in the next year are the same as last observed. However, when a dairy producer makes a decision, he needs to take into account expected prices not just in the next period but also the entire term structure of prices over a cow’s potential remaining lifetime. We use lagged prices as an attempt to capture the complex impact of last observable price on culling and replacement decisions in a tractable manner.

In his analysis of U.S. poultry producers, Chavas (1999) finds that only a small minority of producers used rational expectations in making investment decisions, while the majority employed backward-looking expectations. It would not be surprising to find that in the dairy sector the share of producers who base their investment decisions on historical prices is even larger. The Dairy Industry Advisory Committee concludes that tax-treatment of dairy farm income induces farmers to invest a large share of profits in those years when profit margins are good (USDA, 2011). Such behavior is consistent with modeling last observed price as an important driver of herd investment decisions.

---

\( ^6 \) The dairy herd termination auctions organized under the CWT program from 2003 to 2010 had an objective of increasing the speed of herd contraction in periods when milk prices are below the level needed for profitable production. For more details concerning this program access the following URL: http://www.cwt.coop.
2.6. Interpretation of marginal effects

In cow and heifer Eqs. (5) and (8) the explanatory variables are used within a survival rate function, specified as being logistic. In heifer equation this represents the probability a female calf will be successfully delivered and selected to be grown into a replacement heifer, while in the dairy herd equation survival rate captures the probability that a dairy cow will be selected to remain in the dairy herd for one more year. With an exponential function in the denominator, this implies that the marginal effect of a change in an exogenous variable on survival probability will have the opposite sign as the estimated coefficient.

Given the above, we would expect the All-Milk milk price coefficient in cow and heifer equations shown in Table 2 to be negative as we anticipate the heifer and cow survival rates to be positively related to milk price. Other things equal, the higher the milk price, the greater the expected profitability associated with milk production and a reduced incentive for culling female calves or dairy cows. In the herd size equation, increases in the All-Milk price will stimulate higher substitution of more productive freshened heifers for old cows. Therefore, we expect the coefficient of the All-Milk price–age class interaction variable to be positive. Thus we expect higher culling rates of older cows (lower survival rates) as milk price increases. Conversely, our initial hypotheses are that higher feed and slaughter prices have a positive impact on heifer and milk cow cull rates and reduce the substitution of heifers for aging cows.

As reviewed earlier, the MDP and DHTP dairy policies had as their primary objective the reduction in the U.S. herd size. We expect a negative effect of these policies on both cow and heifer survival rates. This implies that we expect positive coefficients on the associated policy-related binary variables in the herd size Eq. (5). Even though it decreased the number of dairy cows, the MDP did not have a requirement that producers permanently leave the dairy industry. As such, we expect the producers to react by a short-term reduction in the milking herd while the policy is active, but at the same time increasing the number of female calves grown for replacement, in anticipation of a subsequent increase in the demand for heifers, after the policy terminates. We expect the sign of the estimated Dum84 coefficient to be negative in the heifer Eq. (8).

As stated before, our model is built on a foundation laid by Chavas and Klemme (1986). Our model departs from their framework in four principal areas. First, we use real prices rather than price ratios. Using price ratios amounts to treating the doubling of all prices as neutral inflation with no influence on production and investment decisions, a restriction we wish to avoid. Second, the heifer equation allows for a time trend in reproduction rates to allow for advances in breeding, heifer management, and a trend to higher replacement rates. In addition, the pool of animals that can breed new heifers is expanded to include lagged replacement heifers. We also allow for asymmetry of response in heifer supply to changes in prices. Third, we attempt to identify the impact of policy interventions through several dummy variables that capture the herd and yield effects of major federal policy changes. Finally, the yield equation is completely remodeled to eliminate endogeneity issues, and allow for speed of reversal to trend to vary with economic incentives.

Table 2


Table 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>HEF_t</td>
<td>1.24 Dum84 - 0.032 Dum2000 DumCLASS</td>
<td>(0.021)</td>
</tr>
<tr>
<td>COW_t</td>
<td>3.24 Dum84 - 0.032 Dum2000 DumCLASS</td>
<td>(0.021)</td>
</tr>
<tr>
<td>ΔYLD_t</td>
<td>-2.43 122.55 DumQ2 - 286.74 DumQ3 - 404.34 DumQ4</td>
<td>(0.984)</td>
</tr>
<tr>
<td>MILK_t</td>
<td>1.38 DumQ2 - 5.15 DumQ3 - 0.329 DumQ4</td>
<td>(0.984)</td>
</tr>
</tbody>
</table>

Note: Newey–West heteroskedasticity and autocorrelation robust standard errors are in parentheses. The variables are defined as follows:

- $T_t$—annual time trend (1975 = 1; 2 = 1976; etc.).
- $Q_t$—quarterly time trend (1 = 1975Q1, 2 = 1975Q2, etc.).
- $HEF_t$—replacement heifers, calculated as 75% of heifers over 500lbs. on dairy farms on 1 Jan. (1,000 head).
- $COW_t$—the annual average number of dairy cows on dairy farms (1,000 head).
- $YLD_t$—Yield per cow (lbs/quarter).
- $MILK_t$—Total annual U.S. Milk production.
- $r_t$—real interest rate for operating loans.
- $MP_t$—U.S. All-Milk price plus MILC payments ($/cwt).
- $FC_t$—the value of a 16% protein dairy ration (51% corn, 41% hay, 8% soybeans) ($/cwt).
- $SP_t$—Omaha/Sioux Falls cattle slaughter cow boning/utility price ($/cwt).
- $CLASS_i$—binary variable that is equal to zero only when $CLASS$ is equal to zero, and one otherwise.
- DumCLASS—binary variable identifying the Milk Diversion Program active in 1984.
- Dum2000—binary variable identifying Federal Milk Marketing Order reform (1 if $t \geq 2000$).
- DumQ2, DumQ3, DumQ4—binary variables for quarters.
3. Estimation of an empirical model of the U.S. milk supply

We estimate each of the stochastic equations separately using nonlinear least-squares methods via the Gauss–Newton (GN) algorithm. Given the degree of nonlinearity of (5) and (8) the sum of squared errors (SSE) functions are likely not globally convex over the parameter space implying the potential for numerous local SSE minima. To ensure that the algorithm converges to a global minimum, we first performed a “wide-range” search where we estimated (5) and (8) 2,000 times, with each estimation based on different randomly drawn vectors of starting values centered around zero. The best-fitting coefficient estimates were then used in a “narrow” search where models were estimated another 2,000 times, with randomly drawn vector of starting values centered around the best-fitting values from the “wide-range” search phase, and with spread equal to three standard deviations from the point estimation. The result presents the solution with the lowest SSE obtained from this two-step process.

3.1. Estimation of parameter standard errors

The use of small samples, such as the one used here, to estimate the parameters of a highly nonlinear model implies that the applicability of large sample theory may be inappropriate, and any estimate of coefficient asymptotic standard errors and results of tests for significance based on asymptotic normality must be interpreted cautiously. One clear indicator that large sample theory performs poorly for a particular model would be if bootstrap estimates of confidence coefficient intervals were much different than the same confidence intervals based on asymptotic theory.

To determine if our model exhibits such discrepancy, we use a dynamic residuals-based bootstrapping procedure to obtain alternative estimates of parameter confidence intervals.7 The bootstrapping procedure is used to dynamically simulate alternative samples assuming the estimated coefficients are the true unknown parameter values, and the model structure is the true data generating process. Alternative dependent variable vectors are generated by using random draws from the joint empirical distribution of estimation residuals. We use the percentile-t method to obtain bootstrap confidence intervals of parameter estimates and compare them with asymptotic confidence intervals based on the original parameter information matrix (Hansen, 2008). In our empirical application bootstrapped and Information Matrix based confidence intervals were found to be consistent.

4. Overview of estimation results

Results obtained from grid searches indicated nonconvexity of the SSE function in herd size (5) and heifer (8) equations, but also give us confidence that in each nonlinear regression the global minimum is indeed found. For example, in the estimation of the herd size equation, under the “wide-range” search phase (i.e., step 1), 371 out of 2,000 rounds converged. Since our parameters appear in an exponential term, it is reasonable to assume that for values far away from the minimum, the SSE function will not behave properly. In the “narrow-range” search phase (i.e., step 2) all 2,000 rounds converged and 83 unique minima were found. Second ranked minima in the “narrow-range” search had SSE 39.8% higher than the result identified as the global minimum. In contrast, for the heifer equation only one unique minimum was found in the “narrow range” search. For both equations and in both search phases, most of the rounds that converged did so to the solution that was ultimately ranked as the best.

The estimated coefficients for the three stochastic equations are presented in Table 2. Ljung–Box tests results indicate the presence of residual autocorrelations in all three equations (Greene, 2008, p. 729). Therefore we calculate asymptotic standard errors via the Newey–West heteroskedasticity and autocorrelation robust covariance matrix (Greene, 2008, p. 643). These standard errors are shown in parentheses in Table 2. Estimating the above three equations by nonlinear least squares, we obtain a high degree of in-sample prediction accuracy; with a maximum absolute prediction error of 0.5% for the cow equation, 1.2% for the heifer equation, and 0.7% in the yield equation. In Fig. 1 we provide a representation of the actual, static prediction and dynamic simulations of the number of heifers and size of the U.S. dairy herd. By static prediction we refer to an in-sample, one step ahead forecast. In contrast, dynamically simulated predictions are obtained by using past predicted cow and heifer values in forecasting. In addition we provide a bootstrapped 95% confidence interval for dynamically simulated values.

In the heifer equation, all estimated coefficients were found to be statistical significant at the 95% confidence level except for $SP_{t-1}$, $FP_{t-1}$, $MP_{t-3}$, and $DUM2000$. All statistically significant coefficients in the heifer equation were found to have the expected sign, except for the first lag of the interest rate $r_{t-1}$. We find evidence of asymmetry in effect of milk prices on the number of replacement heifers. A decline in milk prices has a stronger effect on heifer numbers. This makes sense, at least in the short run, as it is easier to shrink than to expand a dairy herd. In the yield equation, we find evidence of shifts in seasonal yield patterns, consistent with migration of dairy production to Western states. In the herd size equation, we find all key variables significant at 99% confidence level except for real interest rates, $DUM2000$, CLASS, cow slaughter price, and class–slaughter interaction variable.

We fail to find evidence that feed prices influence yield. This result may be driven by the fact that high and volatile feed prices

---

7 A detailed description of this procedure can be found in Bozic and Gould (2009). The GAUSS software system was is used in estimation. Due to the computationally intensive estimation, bootstrap and simulation, time needed for calculations is 24 hours on a standard dual-core PC notebook.
have been a major drive of profit margins only in the last several years, while our model is estimated over the past 35 years. We find weak evidence that higher milk prices increase the speed of adjustment to potential (trend) yield.

In Table 3 we show estimates of the 2010 distribution of the U.S. dairy herd across cow age, the associated class-specific cull rates, and predicted marginal impact of price changes on culling rates of each cow productive age class. For example, the culling rate for cows in the first productive age class, which corresponds to cows between two and three years of age, is 18.4%. This implies that of the cows that survived the first year in the herd, 18.4% will be culled in 2010. Increase in milk price by 10% over average real All-Milk price for 2010 ($18.29/cwt) would decrease the culling rate by 1.8% to 16.6%.
5. Evaluation of long-run price effects on the U.S. milk supply

To evaluate the long-run (10-year) impacts of price changes on the U.S. dairy herd we address the following question: If real prices remain constant over the next 10 years, what will be the impact on U.S. milk production? To address this question, we evaluate 10-year production profiles under the following three price scenarios (2010 $):


(ii) Scenario 2: Prices remain at 2007 levels. It should be noted that 2007 was a relatively good year for the dairy industry with the average All-Milk price being $19.87. The average Corn grain price was $3.52/bu, hay was $135.60/ton, and average Soybean price was $8.04/bu.

(iii) Scenario 3: To investigate the long-run impact of extremely high feed costs, under this scenario we assume that real corn and soybeans prices over the next 10 years are constant at the high levels observed during June 2011, but the milk price is lower: Corn $7.00/bu, Soybeans $14.50, Hay $116.00, All-milk: $19.00/cwt.

For all scenarios, annual per cow milk production improvements are assumed to be governed by the same trend in potential yield. Figure 2 is used to portray milk production under the above three scenarios over the 2011–2020 period. In addition we have plotted the bootstrapped confidence interval for Scenario 1.

It is not surprising that the milk price environment represented by Scenario 2 generates a large increase in milk production relative to the Scenario 1 base case. Scenario 2 production is above the upper 95% Scenario 1 production confidence interval starting in 2013. Similarly, the high feed cost scenario, Scenario 3, generates significantly lower milk production levels starting with production in 2012. In 2012, milk production under Scenario 3 is 2.5% less than the milk production under Scenario 1. This relative decline increases to 18.8% by 2018.

Long-run adjustment dynamics can be best understood by analysis of long-run elasticities of the number of replacement heifers, herd size, and milk production to changes in milk, feed, and slaughter prices. Our long-run elasticities measure the impact of a one-time permanent 10% increase of a particular price in the base period on forecasted number of heifers, U.S. herd size, and total U.S. milk production $J$ years ahead, as compared to the base scenario where prices over the forecasting period are assumed to be equal to prices in base year. In Table 4 we provide point estimates of the milk and feed price elasticities along with the limits that define the 2.5 (Low) and 97.5 (High) percentiles of the empirical distribution of bootstrapped long-run elasticities averaged over the 1978–1982 and 2006–2010 periods. Regardless of the starting year, the elasticities increase with the length of forecasting period given that it takes time for herd size to fully adjust to changes in economic environment.

To investigate the issue of long-run supply responsiveness, in Fig. 3 we plot the 10-year milk supply elasticities with respect to milk and feed prices, calculated for each year in the sample. When we compare the elasticities across different starting periods we find that All-Milk price responsiveness of the milk supply exhibits downward trend from the beginning of our estimation period in 1975 through 2005. We found this result surprising, as one might reasonably expect the opposite. With better genetics, improved heifer management, and larger farms we expected to find evidence that the industry would likely adjust to favorable price changes more quickly than compared to 20 years ago when the percentage of milk originating from small- to medium-sized operations was much greater than today. As indicated in the Introduction, that would be consistent with results from Weersink and Tauer (1990), Adelaja (1991), and Tauer (1998).

Given the size of the confidence intervals around those point estimates, we need a formal test to conclude if the decline in estimated price responsiveness is statistically significant. We simulate the distribution of differences of average 10-year
Table 4
Short and intermediate run elasticities of U.S. dairy supply to milk and feed price changes

<table>
<thead>
<tr>
<th>Years since price change ($j$)</th>
<th>1978–1982</th>
<th>2006–2010</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Elasticity of</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$HEF_t$ w.r.t. $MP_{t-j}$</td>
<td>0.078</td>
<td>−0.104</td>
</tr>
<tr>
<td></td>
<td>0.041</td>
<td>−0.011</td>
</tr>
<tr>
<td>$COW_t$ w.r.t. $MP_{t-j}$</td>
<td>0.055</td>
<td>−0.005</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elasticity of</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$HEF_t$ w.r.t. $FP_{t-j}$</td>
<td>−0.006</td>
<td>−0.069</td>
</tr>
<tr>
<td></td>
<td>0.039</td>
<td>0.019</td>
</tr>
<tr>
<td>$COW_t$ w.r.t. $FP_{t-j}$</td>
<td>−0.034</td>
<td>−0.050</td>
</tr>
<tr>
<td></td>
<td>−0.031</td>
<td>−0.049</td>
</tr>
</tbody>
</table>
Note: All three scenarios take a set of feed and milk prices and keep them constant at a given level for 2011–2020 period. Scenario 1 is consistent with average 2012 futures prices observed in late June 2011. (Corn: $6.50/bu, Soybeans: $14.00/bu, All-Milk: $19.00/cwt, and Hay: $116/ton). Scenario 2 takes average 2007 prices (Corn $3.52/bu, Soybeans: $8.04/bu, All-Milk: $19.87, and Hay: $135.60/ton). Scenario 3 examines the impact of extreme feed prices, as we have briefly seen in futures markets in June 2011, but with lower milk prices (Corn $7.00/bu, Soybeans $14.50, Hay $116.00, All-Milk: $17.00/cwt).

Fig. 2. Impact of alternative price scenarios on future U.S. milk production.

elasticities in the period 2001–2005 versus 1978–1982. If the null hypothesis of no change is correct, than the distribution of differences should be centered on zero. We reject the null hypothesis if the number of simulations in which average 10-year elasticities in the period 2001–2005 are less price-responsive than in 1978–1982 account for less than 5% of the total number of bootstrap simulations. Results of these tests are presented in Table 5. Results confirm the decline in the supply elasticities with respect to milk prices through 2005, however comparing the same benchmark period with 2006–2010 we no longer find a decrease in supply responsiveness.

To explore the potential causes for the decrease in the All-Milk price elasticities through 2005, we exploit the fact that while we only observe annual inventory data for cows, the structure of our model allows us to predict the herd structure by age at any year in the sample. In Fig. 4 we plot the distribution of herd by cow age and retention rates for each age class for two time periods, 1978–1982 and 2005–2010. The implication from this figure is that while cow retention rates for cows age three to five (first three lactations) have changed little over these two time periods older cows are substantially less likely to be kept in herd. For dairy operations, the major adjustment to changes in the economic environment is accomplished via herd culling and replacement activities. When dairy farm operators experience positive changes in the economic environment and they desire to expand their herd, they can (i) keep current milking cows longer in the herd while maintaining previous number of replacement heifers entering the herd or (ii) increase the share of female calves that are grown into replacement heifers and ultimately added to the herd. It is important to note that the younger the herd, the higher is the replacement ratio needed to keep the herd size unchanged.

The downward trend in long-run price responsiveness may be the result of increases in involuntary cull rates that makes it harder for dairy farm operators to increase the retention rate of cows in the process of adjustment to favorable changes in economic environment. Hadley et al. (2006) report that in herds participating in Dairy Herd Improvement program (DHI), health culls, i.e., culls induced by health problems of a cow, constitute 79.5% of all culls. If the share of health culls in all culls has increased over time that would imply that culls are starting to be less of an economic decision, and are increasingly a consequence of biological constraints.

However, a more convincing explanation could be that long-run price responsiveness simply varies along the supply curve. Small increases in milk prices may not bring about substantial additional investments if the returns are meager to start with. However, if returns are originally already sufficient to cover opportunity costs of money, permanent increases in the milk price that allow for extra returns may bring about substantial new investments to the dairy sector. Increases in responsiveness in recent years might be due to very lucrative milk production over 2007–2008. However, the long-run elasticity remained higher in 2009, a year that will be remembered as a period when the dairy sector experienced a particularly difficult economic environment. This may reflect a number of important influences in recent years. For example, De Vries and Nebel (2009) assert that a technology that will have a significant impact on dairy
supply is the increased adoption of sexed semen in replacement to heifer breeding as it would increase the pool of available replacement heifers. The increase in estimated supply elasticities in the second half of the 2000s could reflect that. Alternatively, it could be the case that herd adjustment programs operated by CWT induce faster adjustment of the herd size to economic conditions. Although we could not establish the link directly in our model, Brown (2011) suggests that the CWT herd retirement program had a substantial net impact on U.S. dairy herd size.

The consolidation in milk production could be another reason behind the decrease of supply responsiveness. Lower total number of dairy farmers may imply a smaller ability to adjust to milk oversupply by the exit of less efficient or retiring farmers. In addition, large farms, if operated at their maximum efficiency may have little scope to increase herd size in the face of high milk prices, without changing the barn capacity. Furthermore, due to high fixed costs, they may have less incentive to reduce their herd size when profit margins are low.

It is interesting to examine if supply elasticity with respect to feed prices exhibit similar trends. From Fig. 3, there is no clear trend in long-run supply responsiveness to feed prices. These elasticities were much smaller than the milk price elasticities until very recently. Dramatic increases in feed prices in the last several years have altered this pattern, and using formal tests we find that milk supply responsiveness to feed prices has been significantly higher in the period 2006–2010 than in the period 1978–1982 (Table 5).

6. Conclusions

Several papers in the past have suggested that long-run supply responsiveness increases with dairy farm size. We seek to trace the evolution of long-run milk supply elasticity over the last three decades, a period characterized by both increasing price volatility and dairy farm size. Only a model that explicitly accounts for herd dynamics has a chance of successfully
relating time horizon to supply responsiveness. For that reason we adopt the modeling framework from Chavas and Klemme (1986) whereby milk production is conceptualized as a product of dairy herd size and yield per cow, stochastic elements that are modeled separately.

We contribute to the literature by introducing a mixed-frequency approach that allows us to model yield using quarterly data, while dairy herds and replacement heifer pools are modeled using annual frequency. That allows us to model the yield as a trend-stationary process with the economic environment inducing both short-term shocks and impacting the speed of reversion to trend yields. While yield is the channel through which short-term adjustments to milk prices can be made, dairy herd size responsiveness governs the medium- and long-run supply. In addition, we design and implement a dynamic residual-based bootstrap technique that can be used to calculate confidence intervals for nonmarginal simulated long-run supply responsiveness and tests for changes in those elasticities through time.

We obtain strong in-sample predictive power and very high significance of key economic and herd structure variables. In years for which our estimation period overlaps with those used in previous research, our results on 10-year price elasticities are more conservative than those in Chavas and Klemme (1986), but are comparable to results reported by Chavas and Krauss (1990).

In response to calls for changes in U.S. dairy policy, it is crucial to provide policy makers with a comprehensive framework that can be used to forecast both short-term and long-run impacts of changes in dairy policy. Several conclusions emerge from our study. First, given the large difference between short- and long-run responses of production to price changes, policy makers should consider more than short-run responses to future policy changes. What may in the short run seem like a minor impact that does not disturb market equilibrium can indeed lead to large production surpluses after more time has passed and dairy herd size has had adequate time to adjust to the new policy environment. As the experience from late 1970s and early 1980s has hopefully taught us, unintended medium-run consequences may dwarf the impact of well-intended policy measures that seem to work in the short run.

Second, despite dramatic yield improving technological change, improved genetics, and the increasing importance of large farms, all of which we would expect to increase milk production, we find that short-run responses dominate in both the short- and long-run. Therefore, policy makers should be aware of the medium-run consequences of policy changes, as medium-run consequences can be significant and may dwarf the impact of well-intended policy measures that seem to work in the short run.
supply price responsiveness, we find a declining trend in long-
run supply responsiveness from 1975 through 2005. If such a
decline were to persist or continue that would be a major cause for
worry, as ever larger price swings would be needed to quickly
equilibrates the market in face of demand shocks. However, we
find that milk supply is getting more responsive in recent sev-
eral years both to milk and feed prices. These issues are best
further explored by models that utilize farm-level data that can
allow for heterogeneous farm responses to price swings. In ad-
dition, increasing responsiveness to feed prices further justifies
focusing the next generation of the dairy policy instruments on
managing dairy profit margins rather than just revenue streams.

Acknowledgments

We have benefited from helpful discussions with Jean-Paul
Chavas, Ed Jesse, and participants at the Department of Agri-
cultural and Applied Economics, University of Wisconsin-
Madison Applied Economics Workshops and the Institute of
Economics — Zagreb seminars. We thank an anonymous referee
for many detailed constructive comments. The usual disclaimer
applies.

References

Adelaja, A., 1991. Price changes, supply elasticities, industry organization, and
dairy output distribution. Am. J. Agric. Econ. 73, 89–102.
Bailey, K., Ishler, V., 2007. Tracking milk prices and feed costs. Department of
Agricultural Economics and Rural Sociology, Penn. State University.
[http://future.aae.wisc.edu/publications/TrackMilkPrice.pdf, August.]
No. 978, ERS, USDA, Washington, DC.
Blayney, D., Gehlhar, M., Bolling, C.H., Jones, K., Langely, S., Normille,
Report, No. 28, ERS, USDA, Washington DC.
rules and procedures governing the operation of the milk diversion program
(MDP). Staff Paper 84-1, Dept. of Agric. Econ., Cornell University.
Bozic, M., Gould, B. W. 2009. The dynamics of the U.S. milk supply: Impli-
cations for changes in U.S. dairy policy. AAE Staff Paper 540, Dept. Agric.
Appl. Econ., University of Wisconsin-Madison.
Brown, S. (2011). The Economic Effects of the CWT program. Available at:
http://www.cwt.coop/sites/default/files/pdf/Economic-Effects-of-CWT-
Chavas, J-P., 1999. On the economic rationality of market participants: The
case of expectations in the U.S. pork market. J. Agric. Res. Econ. 24(1),
19–37.
Chavas, J.-P., Klemme, R., 1986. Aggregate milk supply response and invest-
in the U.S. Lake states. J. Agric. Econ. 41, 75–84.
Chavas, J.-P., Kraus, A.F., Jesse, E., 1990. A regional analysis of milk supply
response in the United States. N. Cent. J. Agric. Econ. 12, 149–164.
dairy model. Available at: http://www.fapri.iastate.edu/models/dairy.aspx,
Hansen, B., 2008. Econometrics, Unpublished manuscript. Available at:
http://www.ssc.wisc.edu/bhansen/econometrics/, accessed September 10
2009.
LaFrance, J. T., de Gorter, H., 1985. Regulation in a dynamic market: The
United States dairy industry. Am. J. Agric. Econ. 67, 821–832.
Am. J. Agric. Econ. 79, 532–542.
Paper, Charles H. Dyson School of Applied Economics and Management,
Cornell University.
econometric model documentation for model calibrated to USDA
agricultural baseline projection to 2016. Available at: http://www.ams.
usda.gov/AMSV1.0/getfile?DocName=STELPRDC5056334, accessed
June 27 2011.
USDA, 2011. Recommendations for public policy to improve dairy farm prof-

Table 5
Tests for changes in long-run price responsiveness

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>HEIFER</td>
<td>54</td>
<td>1,793</td>
</tr>
<tr>
<td>(0.014)*</td>
<td>(0.448)</td>
<td></td>
</tr>
<tr>
<td>COW</td>
<td>145</td>
<td>3,676</td>
</tr>
<tr>
<td>(0.036)*</td>
<td>(0.081)</td>
<td></td>
</tr>
<tr>
<td>YLD</td>
<td>1,096</td>
<td>903</td>
</tr>
<tr>
<td>(0.274)</td>
<td>(0.226)</td>
<td></td>
</tr>
<tr>
<td>PROD</td>
<td>140</td>
<td>3,676</td>
</tr>
<tr>
<td>(0.035)*</td>
<td>(0.081)</td>
<td></td>
</tr>
<tr>
<td>HEIFER</td>
<td>207</td>
<td>3,942</td>
</tr>
<tr>
<td>(0.052)</td>
<td>(0.014)*</td>
<td></td>
</tr>
<tr>
<td>COW</td>
<td>921</td>
<td>3,999</td>
</tr>
<tr>
<td>(0.230)</td>
<td>(0.000)*</td>
<td></td>
</tr>
<tr>
<td>YLD</td>
<td>989</td>
<td>895</td>
</tr>
<tr>
<td>(0.247)</td>
<td>(0.224)</td>
<td></td>
</tr>
<tr>
<td>PROD</td>
<td>906</td>
<td>3,999</td>
</tr>
<tr>
<td>(0.227)</td>
<td>(0.000)*</td>
<td></td>
</tr>
</tbody>
</table>

Note: Tests were performed using simulated long-run forecasts of the series
tested; 3,999 simulation rounds were used. Reported figures indicate the num-
ber of rounds in which the average long-run elasticity in the later period was
higher (in absolute value) than the long-run elasticity in the earlier period,
denoted \( N_{21} > N_{12} \). Reported \( p \)-values in the brackets are calculated simply as
\( \min(N_{21}, N_{12})/3999 \). Intuitively, very small \( p \)-values relate to
events highly unlikely under the null hypothesis of no change in supply respon-
siveness. For example, comparing the supply responsiveness to change in milk prices, we
find that in only 145 out of 3,999, or 3.6% of rounds was the milk production
10-year elasticity with respect to milk price higher in the period 2001–2005

