Spatiotemporal Analysis of Dairy Farm Productivity, Size, and Entry-Exit in the US

Heesun Jang
Dept. of Ag & Applied Economics
University of Wisconsin-Madison
hjang28@wisc.edu

Xiaodong Du
Dept. of Ag & Applied Economics
University of Wisconsin-Madison
xdu23@wisc.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

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Abstract: The US dairy industry has experienced significant structural changes in the last few decades. Dairy production has been consolidated into fewer but larger farms, and shifting toward Western and Southern states from traditional dairy regions including the Lake States and Corn Belt. The changes also involved significant entry and exit of small- and medium-sized farms. The paper attempts to characterize patterns of dynamic evolution of productivity, size, and entry-exit of dairy farms over time and across major production regions in the US. The analysis sheds light on the contribution of farm and regional characteristics on farm-level productivity changes. Regional differences in climate and economic interconnection between farm productivity and entry-exit are also examined with a focus on the distinction among dairy farm sizes.

Keywords: Control function, exit probability, heat stress index, production region.

1. Introduction

As with other livestock industries, the US dairy production has experienced significant structural changes for the last few decades. The structural changes have been reflected in increasing farm sizes and production variation across geographical regions. Dairy production has been consolidated into fewer but larger farms, and shifting toward Western and Southern States from traditional dairy regions including the Lake States and Corn Belt. Massive production growth in both traditional dairy states such as Texas and California, the latter of which surpassed Wisconsin to become the largest dairy producing state, and emerging western dairy states including Idaho, New Mexico, and Washington, are primarily responsible for the westward shift in recent years (Gould 2010). On one hand, in traditional dairy producing states, small and family-oriented farms dominate. On the other hand, farms take advantage of the economies of scale induced by technological improvement and grow large and industrialized in nontraditional dairy regions in recent years. For example, in 2007 the average herd size in Wisconsin was about 88 cows; typical dairy farms in California and Idaho have on average 824 and 633 cows, respectively (Gould 2010). While the number of dairy farms fell substantially and increasing share of milk is produced in large farms, the evolution of dairy industry involved significant entry and exit of small- and medium-sized farms over time (MacDonald and McBride 2009).

Such changes, on one hand, are likely to generate significant cost advantages. On the other hand, the shift of production to larger dairy farms on more limited land increases potential risk that would affect the smaller owner-operator producers as well as the local communities, for example, consolidation of the industry into a small number of large farms and environmental risks primarily from excess nutrients in manure.

Large dairy farms more likely adopt technologies that generate efficiency gains allowing them to exploit scale economies while focusing on high-volume and homogeneous output. It provides a strategic cost advantage and a greater likelihood for them to stay in the industry when output prices are low. On the contrary, integrated small and medium farms with homegrown feeds and family labors are partly shielded from input price volatility. This enables them to survive over stressful economic conditions and compete with large farms that rely more on purchased feed and hired labor. Therefore, farm productivity, farm size, and entry-exit are intertwined, and the dynamics of which are further complicated by significant differences in regional economic and underlying conditions.

In the current paper, we attempts to characterize dynamic patterns in farm productivity, size, and entry-exit of dairy farms over time and across production regions in the US. The analysis also sheds light on the impact of regional differences on productivity changes and farm dynamics. The interconnection between farm productivity and entry-exit is also examined with a focus on the distinction among dairy farm sizes.

The control function framework, e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2006), takes care of input simultaneity and sample selection problems in production function estimation. Built on the method, we estimate the production function for dairy farms in individual regions and obtain farm-level productivity estimates. Accounting for sample selection is especially important as we observe a significant number of farms entering to or exiting from dairy production in recent structural changes. Estimates of farm productivity and exit probability are then used to quantify how productivity and exit are intertwined with farm and regional characteristics.

The results show that productivity of dairy farms varies significantly across size groups and regions. The Pacific and Lake States regions exhibit relatively higher productivity than others. Emerging dairy regions have higher productivity than traditional dairy regions, but are more likely to exit from dairy farming. As expected, dairy farms with larger herds are more productive with lower exit rate. The relation between farm productivity and farm size is bell shaped, i.e., productivity increases with herd size till a certain level and declines afterwards.

The remainder of paper is organized as follows. In the next section, we review the related literature. The empirical framework and estimation method are laid out in Section 3. In Section 4, we turn to data description and analysis. Section 5 provides the results and we conclude in Section 6.

2. Literature Review

The relation between farm productivity, farm size, and entry-exit of the dairy industry is a recurring issue in the literature. Kumbhakar, Ghosh and McGuckin (1991) extend the stochastic frontier approach to investigate efficiency and its determinants of the US dairy farms in 1985. The authors find that large farms are more technically efficient but with relatively lower return to scale than small- and medium-sized farms. In a Markov model, Zepeda (1995) analyzes how various factors, including prices, interest rates, debt, drought, and policy, affect dynamics and structure of dairy farms in Wisconsin over 1972-1992. The results indicate that an increase in the milk-feed price ratio, i.e., milk price goes up relatively faster than feed price, encourages new entry and expansion of small and medium farms, thus increases the number of large farms.

Regional pattern of dairy farm sizes is examined in Sumner and Wolf (2002) by linking to heterogeneity in vertical integration and diversification across regions. Vertical integration, which relates to farm-produced inputs such as feed, replacement livestock, and labor, has a significant and negative effect on farm size. It implies that farms with a small herd size tend to be associated with a high level of vertical integration. But dairy farms in western and southern states are much larger than those in traditional dairy states even after taking into account the effects of vertical integration.

Foltz (2004) used the panel data of Connecticut dairy farms in 1996-2001 to examine the driving forces of farm size changes and exits along with the impact of regional price policy. The policy supported price floor is found to keep dairy farms from exiting and to increase average farm size. Employing the cross sectional data collected through the 2000 Agricultural Resource

Management Survey (ARMS), Tauer and Mishra (2006) found diseconomies of size in dairy farming. Use of nutritionist and milking parlor tends to decrease production cost and to increase efficiency. Hours per day a milking facility is used are associated with decreased cost frontier but inefficiency. Using the same ARMS dataset, Mosheim and Lovell (2009) analyze scale economies of dairy farms of different sizes across regions after accounting for inefficiency factors in the cost function estimation. They confirm that larger dairy farms become more efficient, which is consistent with the fact that average size of dairy farms has been increasing over time.

Spatial structure and location of dairy operations are examined in Isik (2004) with a focus on the impact of environmental regulation. Dairy farms are found to move across county/state borders to locations with relatively less stringent environmental regulations. Region-specific climate conditions and other local factors also have considerable impact on dairy location and production. Mayen, Balagtas, and Alexander (2010) analyze the 2005 ARMS data to quantify the difference of productivity and technical efficiency between organic and conventional dairy farms in the US. After controlling self-selection into organic production using a matching approach, the authors find that the two dairy technologies are not homogeneous and organic dairy technology is about 13% less productive than conventional farming. However, there is little empirical evidence that the technical efficiencies are significantly different.

With Wisconsin dairy farms' financial and production information collected by the Agriculture Financial Advisor (AgFA) program in 2007, Cabrera, Solis, and del Corral (2010) quantify the effect of the Bovine Somatotropin (bST) practice on milk production. In addition, production in WI is found to exhibit constant returns to scale and to be positively related to farm intensification, family labor contribution, specific feeding system and milking frequency. Alvarex, del Corral, and Tauer (2012) suggest a latent class model to distinguish groups of dairy farms employing heterogeneous technologies based on the unobservable farm characteristics.

Applying the method on a set of New York dairy farms, the authors find that farms with parlor milking system are more efficient than stanchion milking farms, the former of which are typically larger in size. Farms located in the Northeast are the most productive as the region has a competitive advantage of feed access, although soil quality is poorer and the growing season is shorter.

Climate change impact on dairy productivity is considered in Key and Sneeringer (2014). Based on the 2005 and 2010 ARMS data, the authors assert that technical efficiency of dairy farms decline with heat stress. An increase in heat stress index of 1000 degree hours is expected to decrease milk production by about 0.38%. Simulating with climate-change induced heat stress, the authors find that milk production may be lowered by 0.60% to 1.35% with the largest loss occurring in the southern states.

3. Empirical Framework of Farm Productivity

In this section, we describe the empirical framework to obtain consistent estimates of the production function of milk, which are needed for the estimation of unobservable farm-level productivity. To produce Q units of milk, the farmer combines five inputs: labor (L), materials and energy (M), capital (K), feed (F), and cows (C). Labor includes full- and part-time hourly paid workers. Materials and energy correspond to inputs that are renewed on a regular basis, for example, fuels and electricity. Capital refers to machinery and equipment. Feed includes total amount of purchased feed, and cows are heads of dairy cows in active milk production. Total amount of milk produced also depends on the farm-specific productivity, denoted by ω, which is known to the farmers but unobserved by us. Denoting measurement error and idiosyncratic production shocks by u, we represent the production process as:

$$Q = f\left(L, M, K, F, C, \omega \mid b\right). \tag{1}$$

Where $b=\{b_l,b_m,b_k,b_f,b_c\}$ is a vector of parameters characterizing the milk production technology. Here we restrict our attention to Cobb-Douglas production function with a scalar Hicks-neutral productivity parameter across farms.

Following the literature, e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2006), we have the production function for farm i and period t specified as:

$$Q_{it}=L_{it}^{b_l}M_{it}^{b_m}K_{it}^{b_k}F_{it}^{b_f}C_{it}^{b_c}\exp\left(\omega_{it}+u_{it}\right). \tag{2}$$

Eqn. (2) enables us to apply the control function approach to obtain consistent estimates of the technology parameters in b. The log version of eqn. (2) is then given by

$$q_{it}=b_l l_{it}+b_m m_{it}+b_k k_{it}+b_f f_{it}+b_c c_{it}+\omega_{it}+u_{it}. \tag{3}$$

To obtain consistent estimates of the production function parameters, we need to control for unobserved productivity shocks, ω_{it}, which are potentially correlated with input demand. This is so-called input simultaneity problem. We deal with this problem by using the material demand (m_{it}) as a proxy for productivity. Let Z denote a vector of exogenous variables that potentially affect optimal inputs and capture the heterogeneity across farms. The optimal amount of materials is assumed to be determined by

$$m_{it}=m_t\left(c_{it},k_{it},\omega_{it},Z_{it}\right). \tag{4}$$

Assuming inversibility of the material input in eqn. (4), i.e., the monotonicity of material input in productivity holds, or $\partial m_{it}/\partial\omega_{it}>0$, we use the inverted eqn. (4), $\omega_{it}\equiv m_t^{-1}=\omega_t\left(m_{it},c_{it},k_{it},Z_{it}\right)$, to proxy for productivity in the estimation of the production function in (3).

Following the insight of Olley and Pakes (1996), we define an indicator function to control for the sample selection problem,

$$X_{it}=\begin{cases}1 & if\ \omega_{it}\geq\underline{\omega}_{it}\left(m_{it},c_{it},k_{it},Z_{it}\right),\\ 0 & otherwise.\end{cases} \tag{5}$$

where X_{it} is equal to zero if firm i exits between periods t and $t+1$, and equal one otherwise. We assume that the firm survives if the current period productivity, ω_{it}, is above the threshold level of $\underline{\omega}_{it}$.

The estimation procedure of the production function in (3) consists of three steps.

Step 1: Define $\phi_t\left(m_{it},c_{it},k_{it},Z_{it}\right)\equiv b_m m_{it}+b_k k_{it}+b_c c_{it}+\omega_t\left(m_{it},c_{it},k_{it},Z_{it}\right)$ and estimate eqn. (6).

$$\begin{aligned} q_{it} &= b_l l_{it}+b_m m_{it}+b_k k_{it}+b_f f_{it}+b_c c_{it}+\omega_{it}+u_{it} \\ &= b_l l_{it}+b_m m_{it}+b_k k_{it}+b_f f_{it}+b_c c_{it}+\omega_t\left(m_{it},c_{it},k_{it},Z_{it}\right)+u_{it} \\ &= b_l l_{it}+b_f f_{it}+\phi_t\left(m_{it},c_{it},k_{it},Z_{it}\right)+u_{it}. \end{aligned} \tag{6}$$

Note that in eqn. (6) all the terms related to inputs of m_{it}, c_{it}, k_{it} are combined into the flexible function of ϕ_t. The first stage provides us the estimates of the variable input parameters, b_l and b_f, as well as the estimated ϕ_t.

Step 2: Estimate the survival probability defined in eqn. (5) as follows:

$$\begin{aligned} \Pr\left(X_{it}=1\,|\,\underline{\omega}_{it}\left(m_{it},c_{it},k_{it},Z_{it}\right)\right) &= \Pr\left(\omega_{it}\geq\underline{\omega}_{it}\left(m_{it},c_{it},k_{it},Z_{it}\right)\,|\,\underline{\omega}_{it}\left(m_{it},c_{it},k_{it},Z_{it}\right)\right) \\ &= \psi\left(m_{it},c_{it},k_{it},Z_{it}\right) \\ &\equiv P_{it}. \end{aligned} \tag{7}$$

Eqn. (7) is approximated by a third-order polynomial series of $\left(m_{it},c_{it},k_{it}\right)$ and the interaction terms with the exogenous factors in Z_{it}.

Step 3: Estimate all other coefficients using the law of motion of productivity, which is assumed to be a first-order Markov process,

$$\begin{aligned} \omega_{it} &= E\left[\omega_{it}\,|\,\omega_{it-1},X_{it}=1\right]+\xi_{it} \\ &= g_t\left(\omega_{it-1},P_{it}\right)+\xi_{it}. \end{aligned} \tag{8}$$

where productivity is determined by one-period lagged productivity and survival probability quantified in Step 2. Standard Generalized Method of Moments (GMM) is applied on the moment conditions described in eqn. (9) to obtain the parameter estimates of b_m, b_c, and b_k.

Standard errors are obtained using the bootstrapping method.

$$(9) \qquad E\begin{pmatrix} & m_{it-1} \\ \xi_{it}(b) & k_{it} \\ & c_{it} \end{pmatrix} = 0 .$$

There has been more recent discussion on identifying all variable input coefficients in b in one step. In a latter section of empirical analysis, we verify the robustness of parameter estimates by considering the modifications suggested by Ackerberg, Caves and Frazer (2006). The authors highlight a potential problem of parameter identification Step 1 above. It can be shown that if a variable input is also a deterministic function of unobserved productivity and state variables, the estimated coefficient on the input is nonparametrically unidentifiable. Ackerberg, Caves and Frazer (2006) solve the issue by not identifying any parameters in the first step. Instead coefficients of all variable inputs are identified together with other parameters by forming a moment on the productivity shock. Collecting all inputs in $\phi_t(\cdot)$ in Step 1, we have:

$$(10) \qquad q_{it} = \phi_t\left(l_{it}, f_{it}, m_{it}, c_{it}, k_{it}, Z_{it}\right) + u_{it} .$$

Following Step 1, we obtain the estimates of expected output ϕ_t . Moment conditions in eqn. (9) are combined with those in eqn. (11) to identify all coefficients in the final step.

$$(11) \qquad E\begin{pmatrix} \xi_{it}(b) & \begin{matrix} l_{it-1} \\ f_{it-1} \end{matrix} \end{pmatrix} = 0 .$$

As discussed in Ackerberg, Caves and Frazer (2006), in some situations it would be more reasonable to assume that demand for labor at period t is chosen beforehand as it may involve firing, hiring, or training costs. In these cases, we can alternatively use the moment conditions in eqn. (12), which may generate more efficient estimates than using eqn. (11) where current labor demand is directly linked to current output.

$$(12) \qquad E\begin{pmatrix} \xi_{it}(b) & \begin{matrix} l_{it} \\ f_{it-1} \end{matrix} \end{pmatrix} = 0 .$$

4. Data

In the current study, we put together farm-level data from USDA Census of Agriculture over 1987-2007. The census is conducted every five year. So the panel data we use consists of observations in the years of 1987, 1992, 1997, 2002, and 2007. A numeric farm-level identifier is used to link farms longitudinally for panel data construction. Any farm producing and selling $1,000 or more of agricultural products during the census year should be included in the census. The census is a comprehensive survey of existing farms as all farms who received a census report form are mandated to participate in the census by law, even if they did not operate in the census year. In our study, for the production function estimation, we focus only on the dairy farms that generate above 80% revenue from dairy products. As production function estimation requires detailed input information, it restricts our samples to the farms that report detailed input expenditure data or fill in the long form of the census report.[1]

All input expenditures are deflated using appropriate price indices, most of which are taken from USDA Agricultural Prices at state or regional level. In each census year and for selected dairy farms, we observe (i) revenues from crops and livestock as well as dairy products, (ii) market value of all machinery and equipment, and (iii) total expenditures on feed, livestock expenses, contract labor, hired labor, utilities, fuel, and number of dairy cows. To obtain a measure of farm-level output, we deflate dairy revenue by state-level annual average milk price, which is obtained from the USDA Agricultural Prices Summary. To compute real labor input, we deflate expenditures on hired and contract labor by region-specific hourly wage rates available from the Farm Labor Survey maintained by the National Agricultural Statistics Service (NASS) of USDA. Feed is measured by the sum of expenditures on purchased feed and livestock

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[1] For the descriptive analysis of exits and estimation of exit probability, we utilize the whole dairy farm sample, which is defined as farms producing positive amount of dairy products (not necessarily generating 80% revenue), as no information on input expenditures is needed.

expenses. The corresponding quantity measure is computed by deflating feed expenditure with 16% protein dairy feed prices at regional level in the USDA Agricultural Prices Summary. Livestock expenses are deflated by state level milk cow prices sold for dairy herd replacement.

We combine farm expenditures on fuel and electricity to measure material input. Fuel and electricity expenditures are deflated by regional diesel and electricity prices, respectively. Similarly, market values of farm machinery and equipment are deflated by state-specific price index for farm machinery and equipment from USDA productivity accounts. The reported input expenditures are for the whole farm production. We separate the input expenditure for milk production by multiplying the corresponding total input expenditure with the share of dairy revenue. We assume that a farm's input costs are shared proportionally among final products.[2]

Following the definition of production region definition of USDA (Blayney 2002), we aggregate 48 continental US states into the 10 regions shown in Figure 1. Table 1 presents descriptive statistics of constructed variables for average farm in each region. The average farm size, measured in both milk production and herd size, is biggest in the Pacific region followed by Mountain, which contain emerging dairy states such as California, Idaho, and New Mexico. Average farm in the two regions produces about six times more milk that that in traditional dairy regions such as Lake States, Corn Belt, and Northeast, with an average herd size over five times greater than the traditional regions.

Southern Plains includes Texas, one of top dairy producing states. Average milk production is more than doubled what produced in an average farm in the regions of Lake States, Corn Belt, and Northeast. Many small farms are located in the traditional dairy states, including Wisconsin, Minnesota, Michigan, Iowa, Ohio, New York, and Pennsylvania, with an average herd size of 150, even smaller than the national average. Average farm size in Corn Belt is slightly lower

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[2] In the study of tobacco industry, Kirwan, Uchida,and White (2012) also employ the farm-level panel data of Census of Agriculture. They obtain the output measure by deflating total revenue from all farm products by the composite price index of agricultural output. Doing so imposes the assumption that all farm products share the same production technology.

than that in Lake States and Northeast. The other regions, including Delta States, Appalachian, and Southeast, are not considered to be significant dairy producing regions.

Table 2 presents descriptive statistics of national average of dairy farms over time. It is clear that national average output and herd size increase significantly over 1987-2002. Average milk production has more than tripled in 2002 compared with that in 1987. But both output and herd size declined in 2007 to the level of 1997. Over the sample period, output per cow increased from 136 in 1987 to 196 in 2002, and then slightly decreased to 183 in 2007.

Table 3 shows national average farm characteristics grouped by entry, exit, and survival. A farm is defined as an new entry in period t if the farm didn’t show up in the sample of dairy farms in period $t-1$, but appears in the sample of period t. Similarly, if a farm produces a positive amount of dairy products in period t but not in $t+1$, the farm is defined as exit in period t. A farm is considered as survival in t if the farm is included in the sample in both periods t and $t+1$. Descriptive statistics in Table 3 indicate that average output and herd size of new entrants are greater than exiting and survival farms. Both exiting and survival farms produce approximately same level of outputs with similar herd sizes on average, but exiting farms have relatively lower level of capital than the survivals.

Table 4 shows entry-exit trends in each production region over the sample period of 1987-2007. Rate of entry was greater than that of exit in all regions until 1997. The trend was reversed in 1997 and more farms exited rather than entered over 1997-2007 in all regions, suggesting that the number of dairy farms has been declining over the last decade. The trend of exit is the highest in Southern Plains, followed by Delta States and Southeast regions. Lake States had the most significant entry until 1997, while the entry was the least significant in the same region over 1997-2007. Net exit rate, the difference between exit and entry rates, is the largest in Lake States over 1997-2007. Among the important dairy regions, Southern Plains followed by Mountain and Pacific show significant entry over the period of 2002-2007.

5. Empirical Results

Farm Productivity

For comparison, Table 5 presents the OLS regression results of production function estimation with time and state fixed effects. If we assume that the productivity measure, ω_{it}, constant across farms and over time, the estimated constants in Table 5 represent the productivity estimates. The results show that the Pacific region has the highest productivity followed by Mountain and Southern Plains. Lake States is one of the least productive regions. Instead of constant return to scale (CRS), which is rejected by the OLS estimates, all regions exhibit increasing return to scale in dairy production.

Table 6 reports the estimation results of the control function framework described in eqns. (6)-(9). We call it LP estimation. As discussed above, OLS estimates are biased given that it doesn't account for the input simultaneity and sample selection problems in the production function estimation. If we expect input demand to be positively correlated with productivity but independent to exit, the OLS method is expected to generate positive biases in the estimated coefficients. If input demand is negatively correlated with exit but not with productivity, the OLS estimates should be negatively biased. If input demand is correlated with both exit and productivity, direction of the biases depends on relative magnitude of the correlations.

The coefficient estimates of capital and cows reported in Table 6 is different from those in Table 5. The coefficients on capital are generally lower and those for cows are higher in LP estimation. This implies that the correlation of capital with productivity is somewhat stronger than that between capital and exit. Similarly, the correlation of cow numbers with exit is stronger than that with productivity.

Tables 7 and 8 show ACF estimation results with l_{it} or l_{it-1} as the instrument, the procedure of which are described in eqns. (10)-(12). Compared with OLS and LP estimation, the estimates for cows are higher in nontraditional dairy regions such as Pacific and Mountain, but lower in traditional dairy regions like Lake States and Northeast. Estimated coefficients are in general more significant with l_{it} than l_{it-1} as instrument. We cannot reject the CRS hypothesis in Northern Plains, Delta States, and Appalachian, but important dairy regions still exhibit increasing return to scale.

We compute farm productivity ω_{it} using the coefficient estimates of the production function in Table 7 as below:

$$\omega_{it} = q_{it} - b_l l_{it} - b_m m_{it} - b_k k_{it} - b_f f_{it} - b_c c_{it} . \tag{13}$$

Figure 2 summarizes the results and presents the distribution of farm productivity in the Pacific and Lake States, the top two dairy producing regions. Farms in both regions show roughly the same level of productivity around the mean, but some dairy farms in Pacific show higher productivity while some in Lake States has lower productivity than others. Figure 3 plots the distribution of exit probability in the two regions indicating that dairy farms in Pacific have higher exit probability than those in Lake States.

Following Olley and Pakes (1996), we measure industry productivity in period t, ω_t, as average farm-level productivity weighted by shares of industrial output, s_{it} for farm i. Let $\bar{s}_t$ and $\bar{\omega}_t$ be un-weighted average share of output and un-weighted average productivity, respectively. Define $\Delta s_{it} \equiv s_{it} - \bar{s}_t$ and $\Delta\omega_{it} \equiv \omega_{it} - \bar{\omega}_t$. The industry productivity can be decomposed into the average productivity ($\bar{\omega}_t$) and the sample covariance of productivity and output ($\sum_{i=1}^{I_t} \Delta s_{it} \Delta\omega_{it}$). Positive and larger covariance indicates that higher share of output is produced from more productive farms and it leads to higher industry productivity. The decomposition can be expressed as:

(14)[3]

$$\begin{aligned} \omega_t &= \sum_{i=1}^{I_t} s_{it}\omega_{it} \\ &= \sum_{i=1}^{I_t}\left(\bar{s}_t + \Delta s_{it}\right)\left(\bar{\omega}_t + \Delta\omega_{it}\right) \\ &= I_t\,\bar{s}_t\,\bar{\omega}_t + \sum_{i=1}^{I_t}\Delta s_{it}\Delta\omega_{it} \\ &= \bar{\omega}_t + \sum_{i=1}^{I_t}\Delta s_{it}\Delta\omega_{it} \end{aligned}$$

where I_t is the total number of dairy farms in period t. Table 9 reports the decomposition results. Averaged over all periods, Pacific and Lake States are those with the highest industry productivity, followed by Corn Belt, Northern Plains and Northeast. In general, all significant dairy producing regions have relatively higher productivity than others. All regions experienced positive productivity growth from 1987 to 2002, but decreased over the period 2002-2007. Positive and large covariance is observed in Lake States and Corn Belt consistently over the whole sample period.

Productivity, Farm Size, and Geography

One step further, based on the ACF estimates of productivity and exit probability in Table 7, we estimate the impact of farm and regional characteristics on farm productivity and exit. One of important regional heterogeneity lies in climate. It is well documented that heat stress of cows is a major source of production losses in dairy industry (Collier and Zimbelman 2007). To quantify the heat stress of dairy cows across regions, we construct the Temperature Humidity Index (THI). The THI measure has been widely used to explain the combined effects of temperature and humidity. It is expected that when the THI exceeds 72, cows begin experiencing heat stress; if higher than 78, milk production is seriously affected. Let T_{ct}^{db} denote a dew-point temperature (^{o}C) in county c at time t, and T_{ct}^{dp} a dry-bulb temperature (^{o}C) in county c at time t. The THI in county c at time t is constructed as follows:

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[3] Eqn. (16), Olley and Pakes (1996), p. 1290.

$$(15) \qquad THI_{ct} = T_{ct}^{db} + 0.36 T_{ct}^{dp} + 41.5 .$$

The temperature data are derived from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM). The PRISM provides estimates of precipitation and temperature at 4×4 kilometer grid cells for the entire US. The PRISM is considered as one of the most reliable climatic data source on a small scale.[4] We construct the THI index for individual counties in each time period by overlapping the US map on PRISM data and then taking the simple average across grid cells in each county. Figure 4 shows a map of average THI index over the sample period of 1987-2007. Regions such as Southern Plains, Delta States, and Southeast have average THI index in the range of 63 to 72, suggesting that these regions are not suitable for dairy production in terms of climate condition.

Denote D_r and D_{st} the regional and farm size dummies at time t, respectively. We use the following specification to quantify the climate impact on milk productivity,

$$(16) \quad \omega_{it} = \delta_0 + \delta_1 \omega_{it-1} + \delta_2 P_{it} + \delta_3 THI_{ct} + \sum_{r=1}^{R} \delta_4 THI_{ct} D_r + \sum_{s=1}^{S} \delta_5 S_{it-1} + \mathrm{B}_{it}^{'} \sigma + \gamma_r + \gamma_t + v_{it} .$$

We collect all other controls in the vector B_{it} with σ the corresponding coefficients. The control variables include farm operator's age, days of off-farm work, and operation's age that are available from the census. The interaction term between THI_{ct} and D_r captures changing effects of THI_{ct} across regions. Eqn. (16) also contains lagged productivity (ω_{it-1}) and probability of exit (P_{it}) as assumed in the law of motion of productivity in eqn. (8). The regression also includes dummies for farm size groups at time $t-1$, S_{it-1}, and region and time fixed effects. As indicated in Table 10, we define ten farm size groups based on the number of dairy cows.

Table 10 reports the estimation result. Farm productivity in the previous period is positively associated with current farm productivity, whereas probability of exit is negatively associated with current productivity. The THI index is positively associated with farm productivity in

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[4] See http://www.prism.oregonstate.edu for further details.

Pacific, Mountain, and Southern Plains, but negatively correlated with farm productivity in Appalachian and Southeast. The impact of the THI in other regions is insignificant. In addition farm productivity increases with farm size till the size group 6 with less than 1,500 cows, then decreases with larger farm sizes.

Farm Sizes, Productivity, and Exit.

To examine the impact of individual and regional characteristics on farm exit, we estimate the following regression, in which we switch the dependent variable to exit probability, P_{it} , and remove all lagged control variables.

$$(17) \quad P_{it} = \delta_0 + \delta_1 \omega_{it} + \delta_2 THI_{ct} + \sum_{r=1}^{R} \delta_3 \omega_{it} D_r + \sum_{r=1}^{R} \delta_4 THI_{ct} D_r + \sum_{s=1}^{S} \delta_5 S_{it} + \mathrm{B}_{it}^{'} \sigma + \gamma_r + \gamma_t + v_{it}$$

Table 11 reports the estimation result. We see that farm productivity is positively related to exit in emerging dairy regions including Pacific, Mountain, and Southern Plains, while higher farm productivity reduces exit probability in traditional dairy regions such as Lake States, Corn Belt, and Northeast. The THI is negatively associated with exit in Pacific and Northeast but the association is positive in Delta States, Appalachian, and Southeast. Probability of exit increases with farm size till size group 6 with less than 1,500 cows, then decreases for larger farms. Dairy farm operators with greater days of off-farm work are more likely to exit.

6. Conclusion

The current study attempts to provide explanation for the recent geographic shift and consolidation of the US dairy industry. We contribute to the literature by investigating the linkages between farm productivity, size, and entry-exit in major production regions across the US. For doing so, we construct the farm-level panel data over 1987-2007 from the USDA Census of Agriculture, which has been the only longitudinal data available for the US agriculture. The chosen sample periods cover significant structural changes in the US dairy industry.

The results show that top dairy producing regions, both traditional and emerging, have higher productivity than others. Specifically dairy farms in Pacific and Lake States regions have the highest productivity followed by those in Corn Belt, Northeast, and Mountain. Favorable climate conditions and accessibility of feed and labor (either purchased or home-provided), provide considerable comparative advantage of dairy production in the Pacific and Lake States regions, which is indicated by the factors' positive impact on farm productivity. While higher productivity leads to low probability of exit in traditional dairy regions, productivity is positively associated with exit probability in non-traditional dairy regions. Controlling other factors, productivity increases with farm size until the level of 1,500 cows in a farm and decreases for larger farms. Farm with more than 1,500 cows, however, is also associated with lower probability of exit.

The paper concludes with two caveats. First, our measures of production inputs are limited as we assume the proportionality of input expenditures where the expenditures are divided over all products by shares of revenue. Furthermore, homegrown feed and family labor are not reflected in the reported input expenditure and thus have not been accounted for in the production function estimation, which may be important for traditional dairy farms. Second, the applied empirical framework is essentially static. A potential extension would be to develop a dynamic model to examine the inter-temporal aspects of productivity growth. We see this paper as the first step towards investigating spatial and temporal changes of the US dairy industry.

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Table 1. Descriptive Statistics: Average and Standard Deviation (Standard errors are in the parentheses)

	Milk Production	Labor	Capital	Material	Feed	# Cows	# Obs.
All Regions	49,243 (119,659)	9,411 (24,324)	174,492 (581,215)	1,062 (2,675)	1,112 (3,187)	268 (603)	47,164
1. Pacific	166,183 (218,820)	25,460 (39,295)	137,713 (265,116)	2,490 (3,714)	4,382 (6,368)	840 (1,087)	4,343
2. Mountain	148,337 (260,497)	27,810 (50,571)	541,013 (1,160,325)	3,300 (7,315)	3,385 (6,462)	802 (1,334)	2,665
3. Northern Plains	36,896 (113,680)	6,320 (20,503)	71,080 (104,076)	1,000 (2,960)	774 (2,897)	213 (589)	1,829
4. Southern Plains	60,502 (118,755)	11,509 (29,623)	48,541 (78,336)	1,352 (3,108)	1,674 (3,390)	394 (705)	2,035
5. Lake States	28,157 (54,995)	5,453 (13,467)	69,204 (97,600)	713 (1,214)	437 (1,105)	147 (247)	13,898
6. Corn Belt	25,833 (84,240)	4,515 (15,718)	61,461 (145,042)	648 (2,063)	489 (2,096)	145 (368)	5,908
7. Delta States	20,662 (25,039)	4,655 (7,033)	107,004 (152,221)	673 (893)	575 (868)	152 (151)	809
8. Northeast	28,605 (49,211)	7,017 (15,872)	366,231 (996,534)	662 (1,051)	582 (1,127)	155 (227)	10,552
9. Appalachian	19,703 (24,329)	5,409 (8,061)	114,224 (159,999)	674 (921)	468 (731)	130 (138)	3,968
10. Southeast	64,094 (123,266)	19,436 (43,935)	200,406 (295,648)	1,704 (2,946)	1,837 (4,026)	413 (728)	1,157

Table 2. Descriptive Statistics Over the Sample Period, 1987-2007. (Standard errors are in the parentheses)

	1987	1992	1997	2002	2007
Output	20,804	31,386	42,317	67,345	44,011
	(36,589)	(60,287)	(82,547)	(135,825)	(122,608)
Labor	6,558	8,049	9,686	11,977	8,239
	(13,588)	(18,111)	(21,688)	(25,989)	(24,967)
Capital	65,201	90,899	133,606	204,755	182,592
	(355,740)	(210,071)	(538,891)	(625,455)	(605,012)
Material	431	616	849	1,402	999
	(645)	(1,003)	(1,633)	(2,716)	(2,985)
Feed	527	828	1,025	1,367	1,059
	(1460)	(1,971)	(2,564)	(3,331)	(3,398)
# Cows	152	203	280	343	240
	(228)	(336)	(509)	(659)	(625)
# Obs.	2,420	2,969	3,146	14,817	23,812

Table 3. Descriptive Statistics on Entry, Exit, and Survival.

	All	Entry	Exit	Survival
Output	49,243	57,107	47,484	47,624
	(119,659)	(145,184)	(96,912)	(115,871)
Labor	9,411	10,235	9,227	9,255
	(24,324)	(26,591)	(20,073)	(24,488)
Capital	174,492	147,038	152,531	186,727
	(581,215)	(408,033)	(499,764)	(634,447)
Material	1,062	1,164	1,025	1,046
	(2,675)	(3,106)	(1,910)	(2,671)
Feed	1,112	1,326	1,031	1,068
	(3,187)	(3,822)	(2,461)	(3,094)
# Cows	268	308	266	258
	(603)	(722)	(501)	(586)
# Obs.	47,164	10,512	7,904	31,215

Table 4. Descriptive Statistics on Entry and Exit by Production Regions.

	Entry				Exit			
	1987-1992	1992-1997	1997-2002	2002-2007	1987-1992	1992-1997	1997-2002	2002-2007
All Regions	29.8	30.5	29.8	30.4	20.0	24.9	46.6	47.2
1. Pacific	29.9	29.2	38.3	36.0	22.2	23.1	40.3	45.1
2. Mountain	25.7	27.4	38.5	48.5	16.9	22.4	41.5	50.6
3. Northern Plains	26.0	28.3	35.9	35.5	15.0	20.7	48.4	59.2
4. Southern Plains	32.1	30.8	49.4	59.7	25.8	33.2	50.8	65.7
5. Lake States	35.2	36.3	24.1	19.2	23.5	31.6	48.8	42.3
6. Corn Belt	24.5	24.7	33.4	34.0	13.8	16.5	42.2	48.8
7. Delta States	27.4	26.4	37.4	40.1	15.1	15.6	42.4	64.7
8. Northeast	26.9	27.7	25.9	27.8	19.5	23.5	46.0	43.9
9. Appalachian	31.2	30.5	36.2	45.1	23.1	24.0	45.9	56.6
10. Southeast	24.3	24.7	47.0	50.9	14.4	16.2	46.2	65.1

Table 5. OLS with Fixed Effects (Standard errors are in the parentheses)

	All Regions	1 Pacific	2 Mountain	3 Northern Plains	4 Southern Plains	5 Lake States	6 Corn Belt	7 Delta States	8 Northeast	9 Appalachian	10 Southeast
Labor	0.05^{c}	0.10^{c}	0.06^{c}	0.06^{c}	0.07^{c}	0.05^{c}	0.04^{c}	0.04^{c}	0.03^{c}	0.05^{c}	0.06^{c}
	(0.001)	(0.005)	(0.006)	(0.006)	(0.007)	(0.001)	(0.003)	(0.01)	(0.002)	(0.004)	(0.01)
Feed	0.10^{c}	0.07^{c}	0.10^{c}	0.09^{c}	0.09^{c}	0.10^{c}	0.09^{c}	0.11^{c}	0.12^{c}	0.10^{c}	0.04^{c}
	(0.001)	(0.005)	(0.006)	(0.008)	(0.008)	(0.002)	(0.004)	(0.01)	(0.003)	(0.006)	(0.009)
Capital	0.06^{c}	0.04^{c}	0.03^{c}	0.09^{c}	0.04^{c}	0.07^{c}	0.08^{c}	0.05^{c}	0.06^{c}	0.07^{c}	0.04^{c}
	(0.001)	(0.005)	(0.006)	(0.009)	(0.008)	(0.003)	(0.004)	(0.01)	(0.003)	(0.006)	(0.009)
Material	0.08^{c}	0.06^{c}	0.06^{c}	0.15^{c}	0.04^{c}	0.13^{c}	0.08^{c}	0.11^{c}	0.06^{c}	0.07^{c}	0.07^{c}
	(0.002)	(0.006)	(0.007)	(0.01)	(0.008)	(0.004)	(0.005)	(0.01)	(0.004)	(0.006)	(0.01)
# of Cows	0.74^{c}	0.74^{c}	0.75^{c}	0.62^{c}	0.76^{c}	0.75^{c}	0.75^{c}	0.71^{c}	0.78^{c}	0.72^{c}	0.80^{c}
	(0.002)	(0.008)	(0.01)	(0.01)	(0.01)	(0.005)	(0.007)	(0.02)	(0.006)	(0.01)	(0.01)
Constant	3.85^{c}	4.12^{c}	4.03^{c}	3.60^{c}	4.01^{c}	3.63^{c}	3.85^{c}	3.77^{c}	3.88^{c}	3.73^{c}	3.94^{c}
	(0.01)	(0.04)	(0.05)	(0.06)	(0.06)	(0.02)	(0.03)	(0.10)	(0.03)	(0.05)	(0.08)
CRTS	reject	reject	reject	reject	reject	reject	reject	reject	reject	reject	reject
Time Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
State Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
# Obs.	47,164	4,343	2,665	1,829	2,035	13,898	5,908	809	10,552	3,968	1,157

Note: The superscripts, a, b, and c, denote significance at 0.10, 0.05, and 0.01 levels, respectively.

Table 6. LP Estimates (Standard errors are in the parentheses).

	All Regions	1 Pacific	2 Mountain	3 Northern Plains	4 Southern Plains	5 Lake States	6 Corn Belt	7 Delta States	8 Northeast	9 Appalachian	10 Southeast
Labor	0.04^c (0.001)	0.10^c (0.01)	0.06^c (0.007)	0.06^c (0.007)	0.06^c (0.009)	0.04^c (0.002)	0.03^c (0.003)	0.04^c (0.01)	0.02^c (0.003)	0.06^c (0.005)	0.06^c (0.01)
Feed	0.10^c (0.003)	0.06^c (0.008)	0.10^c (0.009)	0.08^c (0.01)	0.09^c (0.01)	0.10^c (0.004)	0.07^c (0.005)	0.10^c (0.02)	0.11^c (0.007)	0.10^c (0.009)	0.05^c (0.01)
Capital	0.03^c (0.003)	0.02^c (0.01)	0.01 (0.01)	0.03^b (0.01)	0.04^b (0.01)	0.02^c (0.005)	0.05^c (0.005)	0.05^a (0.03)	0.01^c (0.004)	0.05^c (0.01)	0.03^b (0.01)
Material	0.07^c (0.01)	0.09^c (0.03)	0.13^c (0.04)	0.17 (0.11)	0.05 (0.04)	0.05^b (0.02)	-0.03 (0.03)	0.01 (0.01)	0.11^c (0.03)	0.06^a (0.03)	0.02 (0.04)
# of Cows	0.80^c (0.01)	0.78^c (0.02)	0.75^c (0.02)	0.66^c (0.11)	0.81^c (0.02)	0.83^c (0.02)	0.88^c (0.03)	0.84^c (0.08)	0.78^c (0.03)	0.75^c (0.04)	0.86^c (0.04)
CRTS	reject	reject	reject	not reject(1)	reject	reject	reject	reject	reject	reject	reject
# Obs.	47,164	4,343	2,665	1,829	2,035	13,898	5,908	809	10,552	3,968	1,157

(1) Fail to reject the null hypothesis at 5% significance level.

Note: The superscripts, a, b, and c, denote significance at 0.10, 0.05, and 0.01 levels, respectively.

Table 7. ACF Estimates with l_t as Instrument (Standard errors are in the parentheses).

	All Regions	1 Pacific	2 Mountain	3 Northern Plains	4 Southern Plains	5 Lake States	6 Corn Belt	7 Delta States	8 Northeast	9 Appalachian	10 Southeast
Labor	0.05^c	0.03	0.06^b	0.02	0.09^b	0.04^c	0.06^c	0.12	0.05^c	0.04^c	0.05^a
	(0.005)	(0.02)	(0.02)	(0.04)	(0.03)	(0.007)	(0.01)	(0.18)	(0.01)	(0.01)	(0.03)
Feed	0.07^c	0.12^c	0.04	0.14^a	0.06	0.14^c	0.009	0.004	0.12^c	0.04	0.04
	(0.01)	(0.03)	(0.03)	(0.08)	(0.08)	(0.02)	(0.03)	(0.30)	(0.03)	(0.03)	(0.09)
Capital	0.03^c	0.03^c	0.02^b	0.03	0.03	0.02^c	0.05^c	0.05	0.01^c	0.05^c	0.04^b
	(0.002)	(0.009)	(0.01)	(0.02)	(0.02)	(0.007)	(0.008)	(0.05)	(0.005)	(0.01)	(0.01)
Material	0.07^c	0.08^b	0.09^b	0.22	0.03	0.05^a	0.02	-0.08	0.11^c	0.06	0.02
	(0.01)	(0.03)	(0.03)	(0.16)	(0.06)	(0.02)	(0.04)	(0.28)	(0.02)	(0.05)	(0.06)
# Cows	0.81^c	0.78^c	0.83^c	0.59^c	0.82^c	0.79^c	0.89^c	0.95^b	0.75^c	0.83^c	0.89^c
	(0.02)	(0.04)	(0.06)	(0.12)	(0.08)	(0.02)	(0.05)	(0.37)	(0.04)	(0.06)	(0.09)
CRTS	reject	reject	reject	not reject(1)	reject	reject	reject	not reject(1)	reject	not reject(1)	reject
# Obs.	47,164	4,343	2,665	1,829	2,035	13,898	5,908	809	10,552	3,968	1,157

(1) Fail to reject the null hypothesis at 5% significance level.

Note: The superscripts, a, b, and c, denote significance at 0.10, 0.05, and 0.01 levels, respectively.

Table 8. ACF estimates with l_{t-1} as instrument (Standard errors are in the parentheses).

	All Regions	1 Pacific	2 Mountain	3 Northern Plains	4 Southern Plains	5 Lake States	6 Corn Belt	7 Delta States	8 Northeast	9 Appalachian	10 Southeast
Labor	0.06^{c}	0.02	0.02	-0.006	0.13^{b}	0.06^{c}	0.04^{c}	0.18^{b}	0.06^{c}	0.05^{b}	-0.08
	(0.009)	(0.02)	(0.04)	(0.05)	(0.06)	(0.01)	(0.01)	(0.09)	(0.01)	(0.02)	(0.07)
Feed	0.07^{c}	0.14^{c}	0.06	0.15^{b}	0.05	0.13^{c}	0.01	-0.03	0.12^{c}	0.03	0.09
	(0.01)	(0.03)	(0.05)	(0.07)	(0.09)	(0.02)	(0.03)	(0.34)	(0.03)	(0.03)	(0.07)
Capital	0.03^{c}	0.02^{b}	0.03^{a}	0.03	0.02	0.02^{c}	0.05^{c}	0.05	0.01^{b}	0.05^{c}	0.06^{b}
	(0.003)	(0.01)	(0.01)	(0.02)	(0.02)	(0.006)	(0.009)	(0.04)	(0.005)	(0.01)	(0.02)
Material	0.07^{c}	0.10^{c}	0.11^{b}	0.25^{a}	0.03	0.04^{a}	0.04	-0.14	0.10^{c}	0.06	0.08
	(0.01)	(0.03)	(0.04)	(0.14)	(0.06)	(0.02)	(0.04)	(0.13)	(0.03)	(0.03)	(0.05)
# of Cows	0.81^{c}	0.75^{c}	0.83^{c}	0.59^{c}	0.80^{c}	0.78^{c}	0.89^{c}	0.99^{b}	0.75^{c}	0.83^{c}	0.93^{c}
	(0.02)	(0.05)	(0.07)	(0.13)	(0.12)	(0.03)	(0.04)	(0.48)	(0.05)	(0.06)	(0.10)
CRTS	reject	reject	reject	not reject(1)	reject	reject	reject	not reject(1)	reject	not reject(1)	reject
# Obs.	47,164	4,343	2,665	1,829	2,035	13,898	5,908	809	10,552	3,968	1,157

(1) Fail to reject the null hypothesis at 5% significance level.

Note: The superscripts, a, b, and c, denote significance at 0.10, 0.05, and 0.01 levels, respectively.

Table 9. Decomposition of Industry Productivity.

	All Regions	1 Pacific	2 Mountain	3 Northern Plains	4 Southern Plains	5 Lake States	6 Corn Belt	7 Delta States	8 Northeast	9 Appalachian	10 Southeast
1987											
Industry (ω_t)	4.07	4.20	3.98	4.04	3.88	4.20	4.09	3.71	4.06	3.88	3.84
Average ($\overline{\omega}_t$)	4.03	4.20	3.99	4.04	3.89	4.18	4.06	3.71	4.06	3.85	3.87
Covariance ($\sum_{i=1}^{I_t} \Delta s_{it} \Delta \omega_{it}$)	0.03	-0.002	-0.009	0.0003	-0.005	0.02	0.03	-0.0007	-0.004	0.03	-0.02
1992											
Industry	4.15	4.21	4.09	4.15	3.95	4.25	4.20	3.78	4.14	4.02	3.86
Average	4.11	4.23	4.10	4.16	3.96	4.23	4.17	3.74	4.14	3.98	3.88
Covariance	0.03	-0.02	-0.009	-0.01	-0.005	0.02	0.02	0.04	-0.008	0.03	-0.02
1997											
Industry	4.11	4.22	4.05	4.23	3.93	4.22	4.14	3.79	4.10	3.99	3.97
Average	4.09	4.24	4.09	4.19	3.94	4.20	4.11	3.77	4.11	3.97	3.99
Covariance	0.02	-0.01	-0.03	0.04	-0.004	0.02	0.03	0.01	-0.008	0.02	-0.01
2002											
Industry	4.33	4.43	4.27	4.30	4.17	4.39	4.38	4.14	4.31	4.18	4.16
Average	4.32	4.45	4.30	4.26	4.17	4.37	4.35	4.14	4.31	4.16	4.20
Covariance	0.006	-0.02	-0.03	0.04	0.005	0.01	0.03	-0.003	-0.002	0.01	-0.03
2007											
Industry	4.23	4.25	4.14	4.17	4.04	4.32	4.29	3.92	4.23	4.09	3.98
Average	4.25	4.28	4.22	4.16	4.07	4.31	4.26	3.91	4.24	4.07	4.06
Covariance	-0.01	-0.03	-0.07	0.008	-0.02	0.01	0.03	0.008	-0.01	0.01	-0.08
Industry Productivity (Averaged Over All Periods)	4.17	4.26	4.10	4.17	3.99	4.27	4.22	3.86	4.16	4.03	3.96

Table 10. Determinants of farm-level productivity (Standard errors are in the parentheses)

Lagged Farm Productivity	0.32^c (0.009)	*Size Group Dummies*	
Probability of Exit	-0.02^b (0.01)	51 ≤ cows ≤ 100	0.006^a (0.003)
THI Index	0.001^c (0.0004)	101 ≤ cows ≤ 200	0.014^c (0.003)
THI and Region Interaction			
THI × Mountain	-0.002^c (0.0008)	201 ≤ cows ≤ 400	0.016^c (0.003)
THI × Northern Plains	-0.001 (0.001)	401 ≤ cows ≤ 800	0.016^c (0.004)
THI × Southern Plains	-0.007^c (0.002)	801 ≤ cows ≤ 1500	0.0002 (0.004)
THI × Lake States	-0.001 (0.001)	1501 ≤ cows ≤ 2500	-0.016^c (0.005)
THI × Corn Belt	-0.001 (0.001)	2501 ≤ cows ≤ 3500	-0.012 (0.008)
THI × Delta States	0.002 (0.002)	3501 ≤ cows ≤ 5000	-0.02^b (0.010)
THI × Northeast	-0.0001 (0.0007)	5001 ≤ cows	-0.036^b (0.014)
THI × Appalachian	-0.003^c (0.001)	Operator’s age	0.0002 (0.0005)
THI × Southeast	-0.008^c (0.001)	Operator’s age squared	-0.0000002 (0.0000004)
		Days of off-farm work	-0.0006 (0.0006)
		Operation’s age	-0.00005 (0.0001)
		Constant	2.74^c (0.20)
Time Fixed Effect: yes			
Region Fixed Effect: yes			

Note: a, b and c denote significance at 0.10, 0.05, and 0.01 levels, respectively.

Table 11. Determinants of Farm Exits (Standard errors are in the parentheses).

Farm-productivity	0.12^{c} (0.007)	*Size Group Dummies*	
Farm Productivity and Region Interaction			
Productivity × Mountain	-0.06^{c} (0.01)	$51 \leq \text{cows} \leq 100$	0.011^{c} (0.0009)
Productivity × Northern Plains	-0.17^{c} (0.01)	$101 \leq \text{cows} \leq 200$	0.016^{c} (0.0009)
Productivity × Southern Plains	0.06^{c} (0.01)	$201 \leq \text{cows} \leq 400$	0.015^{c} (0.001)
Productivity × Lake States	-0.20^{c} (0.009)	$401 \leq \text{cows} \leq 800$	0.012^{c} (0.001)
Productivity × Corn Belt	-0.19^{c} (0.009)	$801 \leq \text{cows} \leq 1500$	0.006^{c} (0.001)
Productivity × Delta States	0.11^{c} (0.01)	$1501 \leq \text{cows} \leq 2500$	0.002 (0.002)
Productivity × Northeast	-0.23^{c} (0.01)	$2501 \leq \text{cows} \leq 3500$	-0.003 (0.004)
Productivity × Appalachian	-0.007 (0.01)	$3501 \leq \text{cows} \leq 5000$	-0.013^{b} (0.005)
Productivity × Southeast	0.29^{c} (0.01)	$5001 \leq \text{cows}$	-0.05^{c} (0.006)
THI	-0.001^{c} (0.0002)	Operator's age	-0.0004^{b} (0.0001)
THI and Region Interaction		Operator's age squared	0.0000004^{c} (0.0000001)
THI × Mountain	0.001*** (0.0003)	Days of off-farm work	0.0004^{a} (0.0002)
THI × Northern Plains	-0.0007 (0.0005)	Operation's age	-0.00002 (0.00003)
THI × Southern Plains	0.001^{b} (0.0007)	Constant	0.09 (0.07)
THI × Lake States	0.001^{b} (0.0004)		
THI × Corn Belt	0.0005 (0.0004)		
THI × Delta States	0.005^{c} (0.0009)		
THI × Northeast	0.0008^{c} (0.0003)		
THI × Appalachian	0.005^{c} (0.0006)		
THI × Southeast	0.005^{c} (0.0006)		
Time Fixed Effect: yes		Region Fixed Effect: yes	

Source: USDA-ERS. 2002. “The Changing Landscape of US Milk Production”.

Figure 1. Farm Production Regions.

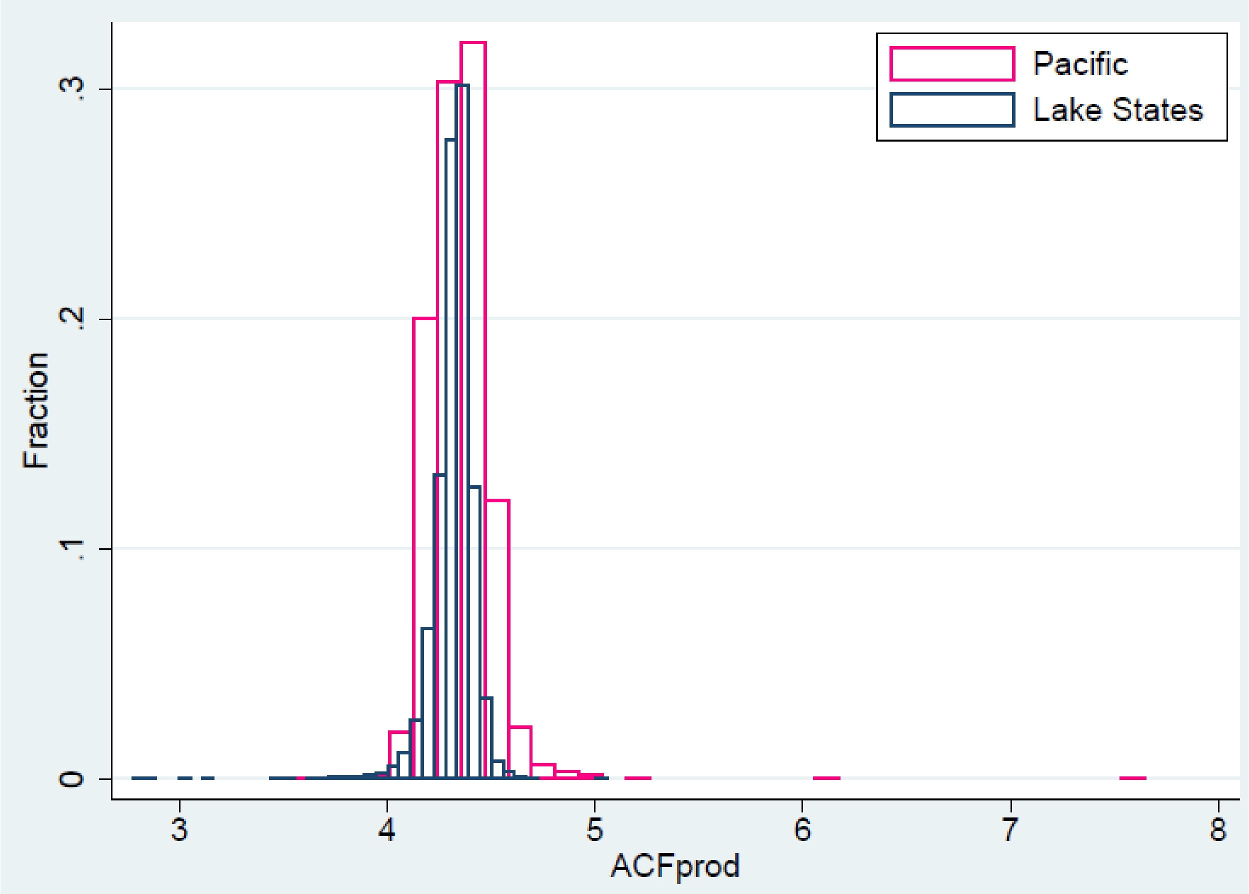

Figure 2. Distribution of Farm Productivity in the Pacific and Lake States Regions.

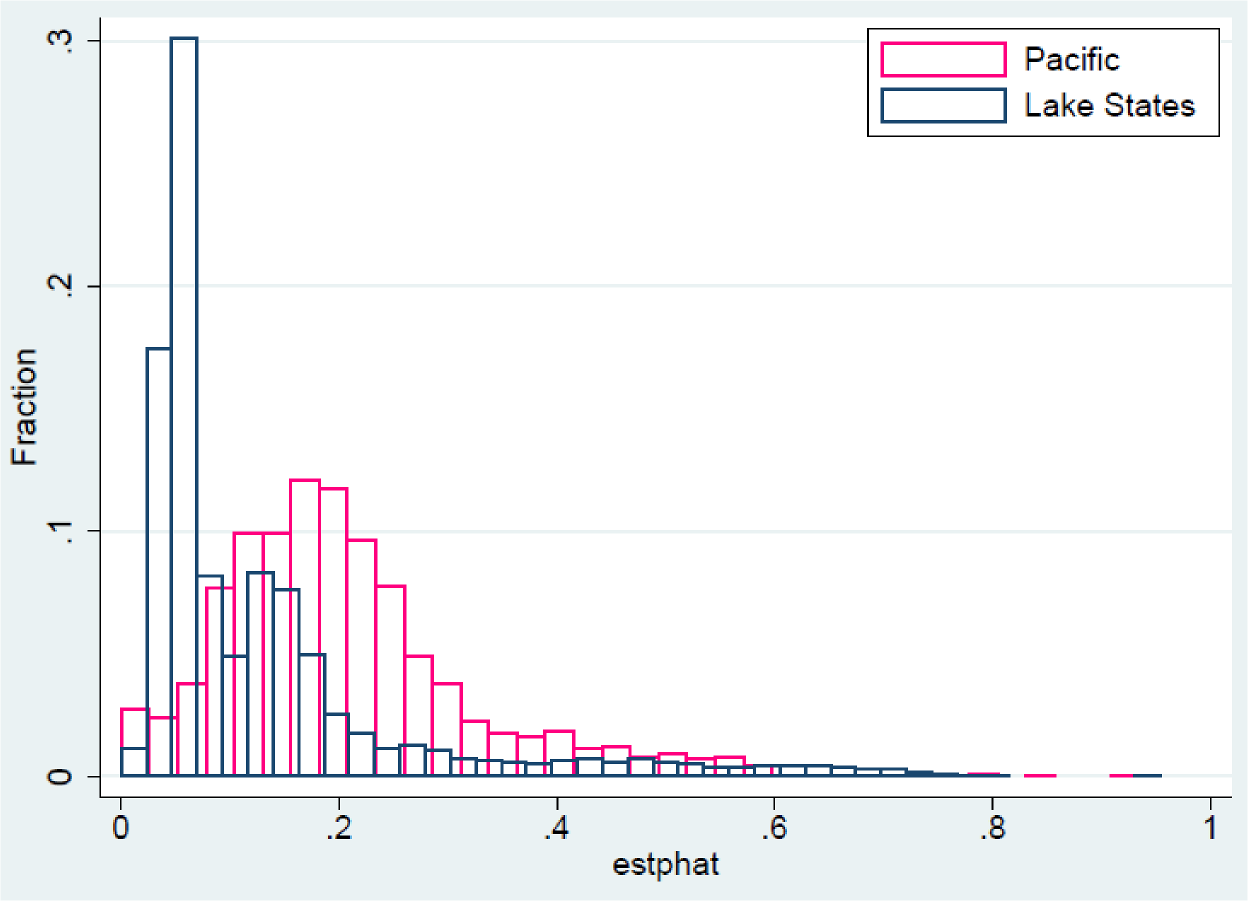

Figure 3. Distribution of Exit Probability.

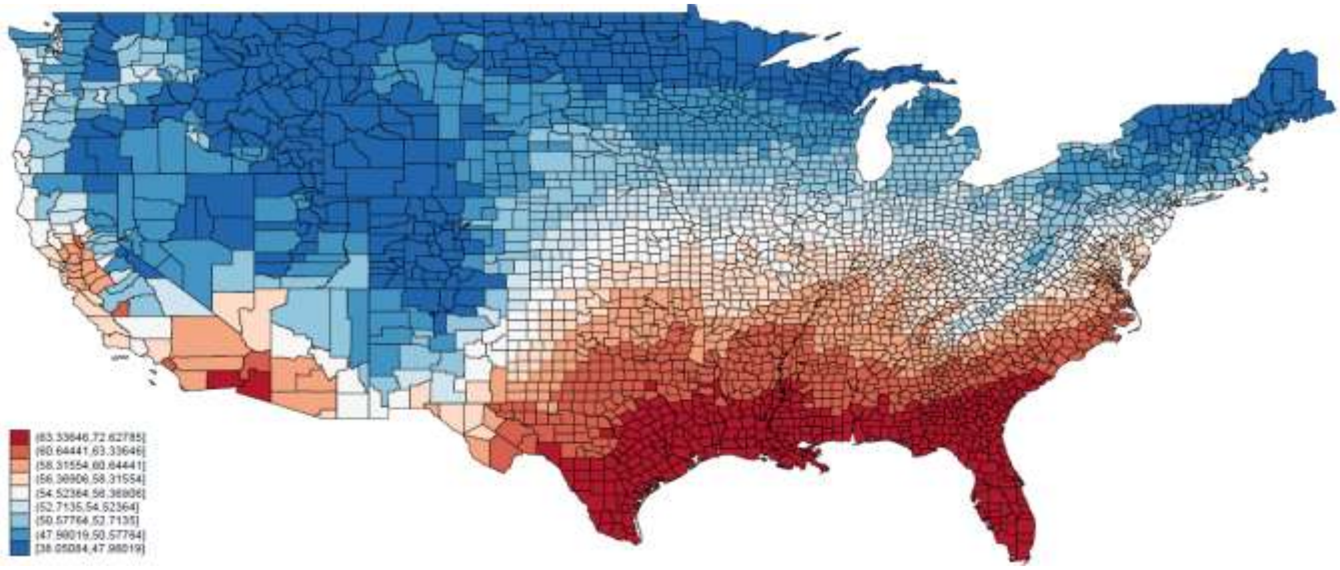

Figure 4. Average County THI, 1987-2007.