# Technology Adoption Decisions in Dairy Production and the Role of Herd Expansion

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Technology adoption in dairy production allows for higher milk yield and lower per-unit costs. The importance of herd expansion and other factors to adoption was examined using a multinomial logit model and data from the USDA's 1993 Farm Costs and Returns Survey. Predicted probabilities of adoption were used to simulate the effect of herd expansion on milk production. Results identified age, size, and specialization in dairy production as important in increasing the likelihood of adopting a capital-intense technology. Education and size of operation positively impacted the decision to adopt a management-intense technology. Age, education, credit reserves, size, and increased usage of hired labor positively influenced the decision to adopt a combined capital- and management-intense technology.

A generally held view among economists (Cochrane 1965, 1979; Musser and White; Weersink and Tauer) that technological change is a major determinant of structural change is perhaps most relevant to farms that specialize in dairy production. The expense of advanced "labor-saving" technologies which could be afforded by larger operations has also worked in restraining "open" entry into dairy farming (Perez). A result of this, along with the fact that technological change limited to milk production has also influenced specialization in dairy farming, is that the structure of U.S. milk production has become characterized by fewer but larger farms, a notion affirmed by a recently released study by the Economic Research Service (Manchester and Blayney).

Many studies have identified the importance of risk perferences and information to technology adoption (Just and Zilberman; Feder and Slade; Kinnucan et al.). Higher tolerance towards risk-taking because of greater wealth and a more diversified portfolio, and greater endowment of human capital by operators of large firms provide an explanation to why larger farms tend to have additional incentives or natural propensities for technological adoption. Studies by Huffman (1977) and by Lin find that higher levels of farm operator education are likely to induce adoption of new technology. The finding that education may facilitate the diffusion of new technology has long been attributed to the fact that it enhances one's ability to receive, interpret, and understand new information (Nelson and Phelps; Welch).

Because of the attending structural implications to technological adoption, and in order to identify factors that contribute to the adoption decision, the objective of this paper is to present the development of a model of the decision to adopt from among a set of alternative technologies that are available to dairy operators. The model emphasizes the role of farm expansion on the probability of adopting from among several mutually exclusive technologies.

Testing the hypothesis that farm size influences technological adoption is accomplished by specifying and estimating a multinomial logit (MNL) that encompasses selected technological choices available to the dairy farm operator and a set of explanatory variables, including size of the operation. The model, which is similar to one used by Zepeda (1990b), allows for the direct estimation of the effect of farm size and other relevant factors on the operator's choice between two specific technologies—a capital-intensive and a management-intensive technology.[1] The analysis presented in this paper extends Zepeda's work in two areas. First, the data is based on a multi-state sample of dairy farms from the Farm Costs and Returns Survey (FCRS), it is not only for California as in Zepeda. Second, estimated coefficients from the MNL model are used to simulate the effect of farm

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expansion on total milk production. The simulation results provide useful information to policymakers on the extent of supply response and potential dairy surpluses as farms attempt to remain competitive by adopting new technologies and by increasing the scale of their operation.

The next section provides a delineation of the theoretical framework used in analyzing technology adoption. This is followed by a section that describes the data and model specification. Empirical results are provided in section four. Simulation of the impact of herd expansion on total milk production and conclusions and implications constitute the contents of the last two sections.

## Theoretical Framework

In the context of the general economic framework for analyzing technology adoption originally specified by McFadden (1981) and implemented in the literature (Zepeda 1990a, 1990b; Misra, Carley, and Fletcher), consider a sample of N dairy farm operators, each choosing from among a set of $M$ discrete technologies. As Huffman (1985) notes, farmers are expected to choose or adopt the technology that gives the largest expected discounted net return, or utility. Accordingly, let the following describe the expected utility ($U$) of the $j$th technology for the $i$th farmer:

$$(1)\quad U_{ij} \geq \max(U_{ik} \mid k = 1,2,\ldots,M;\ k \neq j) = Z_i'\beta_j + \varepsilon_{ij},\ i = (1,2,\ldots,N),$$

where $Z_i$ is a (1 × q) vector of the $i$th operator's personal, farm, and enterprise attributes affecting his or her decision to choose technology $j$; $\beta_j$ is a vector of parameters associated with $Z_i$; and $\varepsilon_{ij}$ is a stochastic component of the $i$th farmer's objective function given the $j$th technology.[2] Since only the outcome of the farmer's choice is observed—not $U_{ij}$—the modeling of the farmer's decision to choose from a set of $M$ discrete technologies requires creation of the following variable:

$$(2)\quad I_{ij} = \begin{cases} 1 \text{ if } U_{ij} \geq U_{ik}; & k = 1,2,\ldots,M,\quad k \neq j, \\ 0 \text{ otherwise} \end{cases}$$

where $I_{ij} = 1$ if the $i$th farmer chooses the $j$th technology, and $I_{ij} = 0$ otherwise. The probability of the $i$th farmer selecting the $j$th technology is:

$$(3)\quad \begin{aligned} P_{ij} &= \text{Prob}(I_{ij} = 1) \\ &= \text{Prob}(U_{ij} \geq U_{ik}) \\ &= \text{Prob}(\varepsilon_{ik} - \varepsilon_{ij} \leq Z_i'\beta_j - Z_i'\beta_k) \\ &= \text{Prob}(\xi_i \leq Z_i'\beta_j - Z_i'\beta_k, \quad k = 1,2,\ldots,M, \\ &\quad k \neq j). \end{aligned}$$

Under the assumption that $\varepsilon_{ik}$ and $\varepsilon_{ij}$ are independently and identically distributed with Weibull density functions, and that their difference $\xi_i$ has a logistic distribution, McFadden (1974) has shown that the conditional probability for choice $j$ is:

$$(4)\quad P_{ij} = \text{Prob}(I_{ij} = 1) = \frac{\exp(Z_i'\beta_j)}{\sum_{k=1}^{M} \exp(Z_i'\beta_k)}; \quad j = (1,2,\ldots,M),$$

which, alternatively, can be written as:

$$(5)\quad P_{ij} = \frac{\exp(Z_i'\beta_j)}{1 + \sum_{k=1}^{M-1} \exp(Z_i'\beta_k)}; \qquad j = (1,2,\ldots,M-1),$$

$$P_{iM} = \frac{1}{1 + \sum_{k=1}^{M-1} \exp(Z_i'\beta_k)}.$$

The relative odds of choices are expressed using the following MNL model:

$$(6)\quad \log\left(\frac{P_{ij}}{P_{iM}}\right) = Z_i'\beta_{jM}, \qquad j = (1,2,\ldots,M-1).$$

Equation (6) describes the logarithm of the likelihood of choosing technology $j$ relative to technology $M$. The $\beta_{jM}$ in this equation are vectors of the marginal effects of variables in $Z_i$ on the likelihoods ratio. By assuming that the $q$th regressor in $Z_i$ is size of the operation (proxied by the number of milking cows), testing the hypothesis that herd expansion influences technological adoption in the dairy industry is accomplished by testing the statistical significance of $\beta_{jMq}$. Furthermore, substituting $\beta_{jMq}$ and the remaining elements of the estimated vectors $\beta_{jM}$ for all $j$ ($j = 1,2,\ldots,M-1$) in equation (5) allows for estimation of all of the conditional probabilities ($\hat{P}_{ij}$) of technology adoption. The number of dairy farms adopting the $j$th technology is calculated using the sum of these estimated probabilities (i.e., $\sum_{i=1}^{N} \hat{P}_{ij}$). This information is useful in measuring the extent of milk supply response as producers consider the option of farm enlargement and technology adoption as a means of staying competitive.

Whether $\beta_{jMq}$ is found significant or not will determine if the adopted technology exhibits a scale-bias or scale-neutrality. Cochrane's (1979) treadmill theory examines scale-neutrality based on the pattern of a technology's diffusion from the time it is introduced until it is fully adopted. This dynamic perspective of scale-neutrality differs from the static perspective where technology is said to be scale-neutral only if it involves an inexpensive variable-cost input, unlike a scale-biased technology which is "lumpy," involves a fixed-cost input, and requires large capital investment (Kinnucan et al.). Cochrane's theory further suggests that technology adoption will lead to increased numbers of large scale operations, particularly if the pattern of adoption is such that larger units dominate the ranks of early adopters, and smaller units constitute the laggards. Accordingly, whether a technology is scale-dependent hinges on the pattern of diffusion, regardless of whether its cost is variable or fixed (Kinnucan et al.). In other words, a scale-bias is said to occur only if early adopters happen to be large scale operations, regardless of whether the cost of the adopted technology is small and variable (e.g., cost of DHI), or large and fixed (e.g., cost of advanced milking parlor).

## Data Issues and Model Specification

Data for the analysis are from the Dairy Version of the 1993 Farm Costs and Returns Survey, which in that particular survey year, included dairy producers in 15 States (figure 1).[3] Dairy farms in the North comprised 92% of the sampling coverage, dairies in the South and West accounted for 3% and 5%. The FCRS, which is conducted annually (but only every 5th year for a specific commodity) by the Economic Research Service and the National Agricultural Statistics Service, is a multiframe stratified survey with the sample being drawn from stratified list and area frames (U.S. Dept. Agr. 1994, p. 6). The survey design of the FCRS allows each sampled farm to represent a number of farms that are similar, the exact number of which is the survey expansion factor. This expansion factor, in turn, is defined as the inverse of the probability of the surveyed farm being selected (U.S. Dept. Agr. 1994a, p. 6). Consequently, these expansion factors are used to expand the data to derive estimates for the population of all farms producing the commodity. Excluding the 0.05% of farms organized as nonfamily corporations or cooperatives, the size of the sample used in the analysis was 680 which represented 102,785 dairy operations across the 15 states. In terms of annual average milk cow inventory, these operations held 7.977 million head, nearly 83% of the 1993 total cow inventory held by all milk producers (U.S. Dept. Agr. 1996b).

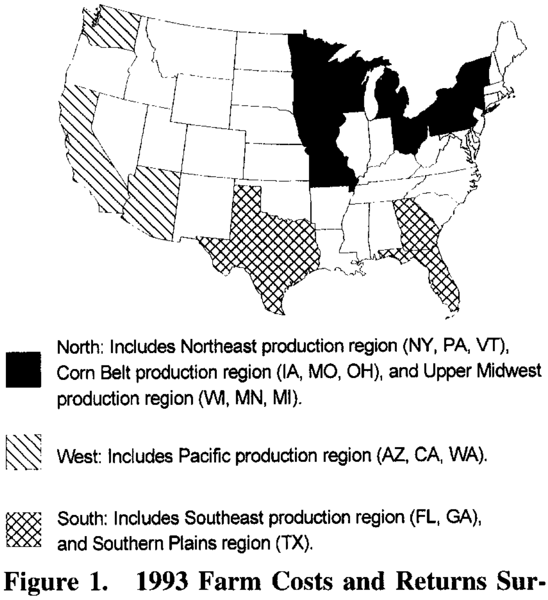


**Figure 1. 1993 Farm Costs and Returns Survey's Sampling Coverage of Milk Production by Milk-Producing Area**

The FCRS data for the 1989 and 1993 survey years document recent structural changes in the dairy industry. Even over that short period of time, dairy farms have become larger and more productive, and the dairy industry itself has become more concentrated. Increased concentration of the industry is noted as the group of large farms which comprises less than 1% of all dairy farms, those with 1,000 milking cows or more (also known as factory farms; see Warrick and Goodman and The Capital Times), owns 13% of the dairy stock and produces 15% of all marketed milk. In contrast, the group of small farms with less than 50 cows owns about one fifth of the cow inventory and produces one fifth of all milk sold yet this group constitutes more than half of dairy farms.

The fact that smaller dairy farms are not as productive as larger farms is not surprising since smaller dairies tend to produce milk using older equipment (e.g., tractors, trucks, pick-ups; milking equipment; feeding and waste handling systems) and older structures (e.g., housing and milking facilities, feed and manure storage). Based on data from the 1989 FCRS, figure 2 shows that dairy farms with less than 50 milking cows use equipment and structures that are nearly three times as old as those used by farms with 1000 cows or more (23.4 years versus 8.2 years for equipment and 34.9 years versus 11.8 for structure).[4] The use of newer, and in many cases costlier, capital inputs by larger farms contributes to their higher production per cow. This, however, should not be construed as saying that smaller dairy farms are not capable of achieving productivity levels that are similar to

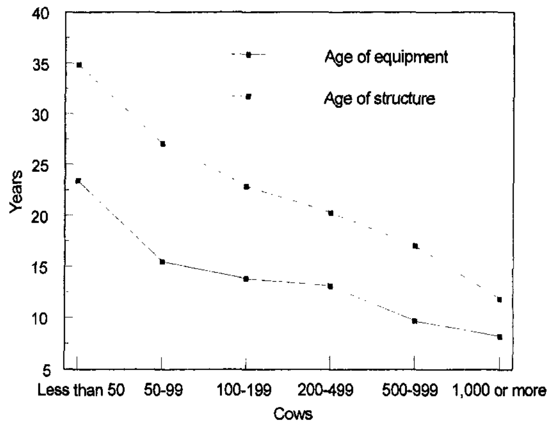


**Figure 2. Age of Equipment and Age of Structure in Dairy Production in the Milk-Producing Areas of the North, South, and West, 1989**

those of larger farms, even when using older equipment and older structures. A study by Barham et al. points to a push by many Wisconsin dairy farmers toward shifting from standard confinement to grass-based dairying, which reduces the need for farm equipment and storage and may lower per-unit production costs.

Table 1 uses data from the 1993 FCRS to illustrate the economics of choosing from among four types of selected technologies: *CIT*, a capital-intense technology which is an array of advanced milking parlors (e.g., herringbone, side opening, polygon, or carousel); *MIT*, a management-intense technology which is a Dairy Herd Improvement (DHI) production record keeping system; *CIT-MIT*, a choice that allows for the combined adoption of capital and management-intense technologies; and *NT*, which defines a no technological choice (e.g., usage of stanchions, barns with around the barn pipeline, or pail units/bucket milkers; and usage of farmer's own system of keeping records of breeding and production history).

Because per-unit costs are lower for farms with higher yields, dairy farms producing more output per cow based on their use of capital- and management-intense technologies, either separately or in combination, enjoy a significant cost advantage over non-users. For example, dairies using *CIT-MIT* technology have a per-unit economic cost advantage (i.e., cash and non-cash costs excluding interest paid) of \$6.30 (\$20.07–\$13.77) over the *NT* category. A major benefit of technology adoption appears in the form of improved labor efficiency, which in turn, is translated to savings in the cost of unpaid labor. The savings in the cost of unpaid labor when *CIT-MIT* is used instead of *NT* are dramatic, amounting to \$3.40 per unit of output. Only dairy operations with a *CIT-MIT* technology have a positive residual return to manage-

**Table 1. Costs (per cwt) and Returns of Dairy Production by Type of Adopted Technology, 1993†**

| | | Means | | | |
|---|---|---|---|---|---|
| Item | All FCRS Sample | *CIT* | *MIT* | *CIT-MIT* | *NT* |
| Milk per cow (cwt) | 145 | 143[a] | 157[a] | 162[a] | 129 |
| Cows per farm | 78 | 106[a] | 63[a] | 238[a] | 43 |
| Total value of production | 14.34 | 14.57 | 14.52 | 13.93[a] | 14.55 |
| Economic (full ownership) costs: | | | | | |
| Variable cash expense | 10.90 | 11.08 | 10.94 | 10.41[a] | 11.56 |
| General farm overhead | 0.47 | 0.49 | 0.54 | 0.34[a] | 0.58 |
| Taxes and insurance | 0.25 | 0.24[a] | 0.30 | 0.16[a] | 0.35 |
| Capital replacement | 1.94 | 2.10[a] | 2.01[a] | 1.49[a] | 2.48 |
| Operating capital | 0.06 | 0.06 | 0.06 | 0.05[a] | 0.06 |
| Other nonland capital | 0.86 | 1.12 | 0.86[a] | 0.66[a] | 0.99 |
| Land | 0.01 | 0.01 | 0.00[a] | 0.00 | 0.01 |
| Unpaid labor | 1.95 | 1.50[a] | 2.30[a] | 0.65[a] | 4.05 |
| Total economic costs | 16.43 | 16.59[a] | 17.00[a] | 13.77[a] | 20.07 |
| Residual return to management and risk[1] | −2.09 | −2.03[a] | −2.49[a] | 0.16[a] | −5.51 |

†Source: USDA, Economic Research Service, Farm Costs and Returns Survey, 1993.

Note: The coefficients of variation (CV) of all estimates are below 25 percent (see Dubman for computation of CV). Differences in the means of estimates in the '*CIT*', '*MIT*', and '*CIT-MIT*' categories and those in the '*NT*' category are examined with the superscript [a] indicating that the respective means within each row are statistically different ($\alpha \geq .10$) from the means in the '*NT*' category. For example, the \$10.41[a] in the '*CIT-MIT*' category, when compared to that of \$11.56 in the '*NT*' category indicates that the mean variable cash expense for dairy operations with combined capital- and management-intense technologies is significantly lower than that for dairies where such technologies are not used.

[1]Residual return to management and risk is the difference between total value of production and total economic costs.

ment and risk ($0.16/cwt). This finding reflects the fact that farms in this group, in addition to being highly productive, are large, thus enabling them to fully utilize existing facilities and to spread costs of fixed inputs (e.g., machinery, buildings and equipment) over more units of output.

Explanatory variables used in the MNL model to explain technology adoption are those suggested by human capital theory and those that have been utilized in other related studies (see table 2). The source of these variables is the 1993 Farm Costs and Returns Survey (dairy version). Table 3 presents corresponding means by the type of adopted technology.

Haden and Johnson, Zepeda (1990a), and Batte et al. find age is negatively associated with technology adoption since older farmers have a shorter planning horizon and are more risk averse than young farmers. Accordingly, it is hypothesized here that age of the farm operator (*AGE*) and adoption of technology are negatively related. In contrast, because education improves the decision-making process by increasing the farmer's ability to acquire, decode and evaluate information pertaining to new technology, it is hypothesized that operators with higher levels of education (*EDUC*) will have a higher probability of adopting new technology than those with lower education levels.

Regional factors such as soil and climate variables, transportation, and processing infrastructure may impact the choice of technology (Negri and Brooks) although the direction of effect is difficult to discern *a priori*. Therefore, a regional dummy is included in the model as an independent variable.

Farm organization (*FARMORG*), expressed as a dummy variable, is also included as a possible determinant of technology adoption in dairy production. Specifically, it is expected that dairy farms where the operator is the sole proprietor would be less inclined to adopt new technology than farms under a different legal form of organization. The association between this structural variable and technology adoption is hypothesized to be negative because farm operators who are sole proprietors tend to be older with shorter planning horizon and less educated than their counterparts (Ahearn et al.).

Several other factors are also hypothesized to affect the probability of technology adoption. The proportion of owned land to total operated acres (*LAND*), average credit reserve of the farm business (*CREDRES*), and the size of the farm as measured by the average number of dairy cows (*COWS*) are expected to be positively associated with technology adoption. This is in line with Barlett's notion that larger and more resource-endowed farms are better able to take advantage of sophisticated, productivity-enhancing technology.

*DIVERSE* and *HOURS*, which are measured as the ratio of purchased feed cost to total feed cost,

**Table 2. Variables Used in MNL Regression**

| Variable | Definition | Hypothesized Direction of Effect |
|---|---|---|
| Operator Characteristics | | |
| *EDUC* | Educational level of the primary farm operator (years) | + |
| *AGE* | Age (years) of the primary farm operator | – |
| Farm and Enterprise Characteristics | | |
| | Region of the U.S. where dairy operation is located: | |
| *NORTH* | 1 if farm is in the Northern region (NY, PA, VT, IA, MO, OH, WI, MN, MI), 0 otherwise | ? |
| | Farm organization: | |
| *FARMORG* | 1 if farm is organized as sole proprietorship, 0 otherwise | – |
| *LAND* | Owned land as a proportion of total operated acres | + |
| *CREDRES* | Average credit reserves ($1,000) | + |
| *COWS* | Average number of milk cows during 1993 (both dry and milking) | + |
| *YIELD* | Milk per cow (hundredweight) | + |
| *DIVERSE* | Purchased feed cost as a proportion of total feed cost | + |
| *HOURS* | Paid on-farm labor hours as a proportion of total on-farm work hours | + |
| Categories of Response† | | |
| *CIT* | Capital-intense technology: Advanced milking parlors | NA |
| *MIT* | Management-intense technology: Dairy Herd Improvement (DHI) | NA |
| *CIT-MIT* | Capital-intense and management-intense technologies | NA |
| *NT* | Neither technologies | NA |

†NA = Not Applicable.

**Table 3. Means of Variables Used in MNL Regression by Type of Adopted Technology, 1993†**

| | Means | | | | |
|---|---|---|---|---|---|
| Variable | All FCRS Sample | *CIT* | *MIT* | *CIT-MIT* | *NT* |
| Dependent | | | | | |
| *CIT* | 0.118 | 0.118 | | | |
| *MIT* | 0.396 | | 0.396 | | |
| *CIT-MIT* | 0.099 | | | 0.099 | |
| *NT* | 0.387 | | | | 0.387 |
| Explanatory | | | | | |
| *EDUC* | 12.14 | 11.95 | 12.38[a] | 13.24[a] | 11.67 |
| *AGE* | 48 | 48 | 47[a] | 49 | 50 |
| *NORTH* | 0.92 | 0.77[a] | 0.98[a] | 0.69[a] | 0.96 |
| *FARMORG* | 0.83 | 0.78 | 0.83 | 0.65[a] | 0.89 |
| *LAND* | 0.66 | 0.48[a] | 0.67[a] | 0.56[a] | 0.74 |
| *CREDRES* | 40.21 | 51.68[a] | 35.35[a] | 119.49[a] | 21.33 |
| *COWS* | 78 | 106[a] | 63[a] | 238[a] | 43 |
| *YIELD* | 145 | 143[a] | 157[a] | 162[a] | 129 |
| *DIVERSE* | 0.50 | 0.61[a] | 0.49 | 0.52[a] | 0.47 |
| *HOURS* | 0.20 | 0.22 | 0.19[a] | 0.39[a] | 0.14 |
| Expanded number of farms | 102,785 | 12,115 | 40,656 | 10,216 | 39,798 |

†Source: USDA, Economic Research Service, Farm Costs and Returns Survey, 1993.
Note: The coefficients of variation (CV) of all estimates are below 25 percent (see Dubman for computation of CV). Differences in the means of estimates in the '*CIT*', '*MIT*', and '*CIT-MIT*' categories and those in the '*NT*' category are examined with the superscript [a] indicating that respective means within each row are statistically different ($\alpha \geq .10$) from the means in the '*NT*' category.

and as paid on-farm labor hours to total on-farm work hours are expected to be positively associated with technological adoption. This hypothesis is based on the premise that a dairy farm where most inputs are purchased tends to be more specialized in dairy production than another farm with most of the inputs being contributed by the farm. Thus, the specialized dairy production farm is more likely to use its investment capital to obtain yield-enhancing technologies that are specific to milk production.

Animal productivity, denoted here as *YIELD*, and the probability of adoption are expected to be positively related. This positive association likely reflects a tendency by operators of productive cows to try new technology in order to induce even greater productivity gains. Because technology affects productivity, using *YIELD* directly as an explanatory variable in equation (5) produces inconsistent parameter estimates due to simultaneous equation bias (Zepeda, 1994). The problem is avoided here by first regressing *YIELD* on operator's age and education, and state corn prices (U.S. Dept. Agr., 1994b), and then, by using the resulting expected yield (*EXPYIELD*) as an instrumental variable for *YIELD* in equation (5).[5]

## Empirical Results

The MNL model depicted in equation (6) was estimated using maximum-likelihood methods. Table 4 shows the regression coefficients along with their corresponding t-statistics.[6] The reference technology category for the MNL regression is *NT* reflecting the decision of no technological adoption. Accordingly, the estimated coefficients $\beta_j$ ($j = 1, \ldots, M-1$) measure the marginal effect of the regressors in vector $Z_i$ (see equation (6)) on the likelihood of being in category *CIT*, *MIT*, or *CIT-MIT* relative to *NT*. A positive regression coefficient means that an increase in the explanatory variable is associated with increased probability of a category $j$ (i.e., *CIT*, *MIT*, or *CIT-MIT*) relative to category $M$ (i.e., *NT*).

The MNL results point towards the heterogeneity in the set of significant regressors across adoption categories. Findings show that education (*EDUC*) increases the likelihood of adopting a management-intensive technology, either alone or in conjunction with a capital-intensive technology. The fact that *EDUC* is important to the adoption of a management-intensive and not to adoption of a capital-intensive technology may suggest, as was noted by Zepeda (1990b), that a management-intensive technology requires more knowledge to implement. This is in contrast to a capital-intensive technology, which in terms of its effective use is more self-evident (Zepeda, 1990b), and as such, does not require higher levels of educational attainment. The finding that educational attainment is important to choice of technology may suggest

**Table 4. MNL Estimates of Technology Choice, 1993†**

| | *CIT* | | *MIT* | | *CIT-MIT* | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | t-Statistic | Coefficient | t-Statistic | Coefficient | t-Statistic |
| *INTERCEPT* | −14.451 | −2.43[b] | −1.698 | −0.39 | −15.299 | −2.64[c] |
| *EDUC* | 0.014 | 0.09 | 0.275 | 2.36[b] | 0.462 | 3.30[c] |
| *AGE* | 0.310 | 1.93[a] | 0.054 | 0.68 | 0.267 | 2.37[b] |
| *AGE*$^2$ | −0.003 | −1.87[a] | −0.001 | −0.91 | −0.002 | −2.21[b] |
| *NORTH* | −0.540 | −0.60 | 1.073 | 1.55 | −0.672 | −0.91 |
| *FARMORG* | 0.115 | 0.22 | −0.057 | −0.14 | −0.330 | −0.72 |
| *LAND* | −1.815 | −2.47[b] | −0.378 | −0.87 | −1.421 | −2.55[b] |
| *CREDRES* | 0.006 | 1.59 | 0.005 | 1.35 | 0.007 | 1.77[b] |
| *COWS* | 0.019 | 3.15[c] | 0.016 | 2.78[c] | 0.019 | 3.26[c] |
| *EXPYIELD* | 0.026 | 0.83 | −0.029 | −1.03 | 0.004 | 0.10 |
| *DIVERSE* | 3.338 | 2.25[b] | 0.205 | 0.26 | 1.077 | 1.15 |
| *HOURS* | −0.105 | −0.11 | 0.114 | 0.16 | 1.405 | 1.70[a] |
| McFadden's $R^2$ | 0.172 | | | | | |
| Log-Likelihood | −103431 | | | | | |
| Restricted Log-Likelihood | −124958 | | | | | |
| $\chi^2$ | 127.7 (33, ∞)[c] | | | | | |

†Estimated coefficients here are $\beta_{jM}$ (see eq. 5) and denote the impact of changes in the explanatory variables on the odds of the *j*th versus *M*th technology (i.e., category *NT*).
[a]Significant at 10% level. [b]Significant at 5% level. [c]Significant at 1% level.

that more and more dairy farms, due to the continuing rise in the number of U.S. farm operators with higher education, will be characterized by technological advances. For example, while only 10% of the operators had attended or graduated from college (including graduate education) in 1964, the number rose to nearly 35% in 1988 (Bellamy).

The age of the farm operator is significant in terms of adopting a capital-intensive technology alone or in association with a mangement-intensive technology, but not in terms of adopting a management-intensive technology. The positive and significant coefficient of *AGE* along with the negative and significant coefficient of *AGE*$^2$ implies that although the likelihood of adopting a capital-intensive technology increases with age, it starts to decline after it reaches its maximum at age 52. The relationship between age and the likelihood of adopting a combination of capital- and management-intensive technologies follows a similar pattern, except that the likelihood of adoption reaches its maximum at a much later age, at 67. That the likelihood of adoption peaks at a later stage in the life of the operator when a management-intense technology is combined with a capital-intense technology is perhaps due to the fact that management-intense technologies are inexpensive and less risky, thus increasing the planning horizon of the operator.

The results show that while dairy operations in the North are less likely to adopt a capital-intensive technology, they are more likely to adopt a management-intensive technology. The weak but negative association between dairy farms in the North and the likelihood of adopting a capital-intensive technology may be explained by the fact that dairy farms in that region are more apt to invest in extensive housing facilities or in insulated barns due to colder climate (McClelland, Perez), than to invest in *CIT*, which, as defined, refers only to advanced milking parlors. A strong negative correlation appears to exist between ownership of land and the adoption of *CIT* or *CIT-MIT*. This finding suggests that dairy farmers who adopt expensive capital inputs tend to lease rather than own their land, a strategy which in itself allows for freeing of financial resources and for the option of increasing investments in capital inputs.

The variable *CREDRES* which measures the farm's credit reserves is positively related with adoption of both technologies. This result suggests that financially endowed dairy farms are more likely to produce milk using a combination of advanced milking parlors and production record keeping systems, such as DHI. Size of dairy operation (*COWS*), which is of primary interest in the analysis, is consistently significant and has the expected positively signed coefficient across *CIT*, MIT and *CIT-MIT*. This result supports the hypothesis that larger farms are more likely to adopt capital- and management-intense technologies, which indicates a scale-bias toward technology adoption. In a study on the determinants of profitability of commercial dairy farms, El-Osta and Johnson examined the relationship between the size of the dairy operation and the likelihood of adopting advanced milking parlors in combination with DHI. Findings indicated that the probability of adoption increases in a linear fashion as size increases, but only in the non-traditional milk producing states (Florida, California, Washington, Texas, Arizona). In contrast, the relationship between size and technology adoption in the traditional milk-producing states (Minnesota, Michigan, Wisconsin, Pennsylvania, New York, Vermont) appeared quadratic, with maximum likelihood of adoption occurring at a size of operation equivalent to 650 milking cows.

As operations grow in size, a higher level of mechanization with its subsequent need for more skilled labor relative to total labor becomes more important if the business is to remain solvent and competitive. This notion is supported by the finding that dairy production units that use more paid labor, which are predominantly larger farms, are more likely to adopt *CIT-MIT*, as indicated by the positive and significant coefficient of *HOURS*.

Of the remaining variables, only *FARMORG* which measures whether the farm operator is the sole proprietor of the dairy operation and *EXPYIELD* are consistently not important (using a two-tailed test at the 10% significance level) to technology adoption.

The last panel of table 4 presents descriptive statistics regarding the predictive ability of the MNL model. The model's goodness-of-fit is evaluated using McFadden's $R^2$. Although this measure is suitable for binary choice models, it is nevertheless analogous to the coefficient of determination $R^2$ used in linear regression.[7] The McFadden's $R^2$ value of 0.172 indicates a reasonably good fit. The reported $\chi^2$-statistic indicates that the explanatory variables (except for the intercept) when considered as a group, are significant in predicting technology adoption.

## Model Simulation

Estimated MNL coefficients from table 5 and individual observations of the explanatory variables are used (see equation (5)) to simulate the effect of farm expansion on the likelihood of technological adoption. Specifically, the simulation attempts to quantitatively determine how doubling or tripling farm size, while holding all else equal, affects the pattern of technological adoption. When farms are contemplating herd expansion, doubling or tripling are scenarios that many dairy farms consider, since to expand the size of operation requires more than just a few cows. For example, if expansion for Minnesota and Wisconsin farms with herds of 50 to 99 cows is to occur, it will require some multiple of the 50 to 99 cow herd (Hammond).

**Table 5. Actual and Simulated Probabilities of Technology Adoption: The Role of Farm Expansion, 1993**

| | Actual unconditional probabilities¶ | Simulated conditional probabilities† | |
|---|---|---|---|
| | Size of farm: 78 cows | Size of farm: 156 cows | Size of farm: 254 cows |
| Adoption: | | | |
| $P_1$: (*CIT*) | 0.118 | 0.151 | 0.178 |
| $P_2$: (*MIT*) | 0.396 | 0.459 | 0.490 |
| $P_3$: (*CIT-MIT*) | 0.099 | 0.129 | 0.155 |
| $P_4$: (*NT*) | 0.387 | 0.261 | 0.177 |
| Total | 1.000 | 1.000 | 1.000 |
| Use: | | | |
| *CIT* | 0.217 | 0.270 | 0.333 |
| *MIT* | 0.495 | 0.588 | 0.645 |

¶Actual unconditional probabilities are proportions derived from the survey.

†Simulated conditional probabilities of adopting *CIT*, *MIT*, *CIT-MIT*, and *NT* are computed as: $P_j = \sum_{i=1} P_{ij}/n$ $(j = 1,2,3,4)$ and are based on MNL coefficients and individual characteristics of farms in the full FCRS sample. Actual unconditional and simulated conditional probabilities of using *CIT* and *MIT* are computed as $P_1 + P_3$ and $P_2 + P_3$, respectively (see Zepeda, 1990b).

Table 5 presents the results of the simulated mean conditional probabilities along with the actual mean unconditional probabilities. Based on the 1993 FCRS sample of dairy farms, changes in the pattern of technology adoption seem to occur when the size of an operation is doubled or tripled. For example, if operators were to double their herd size, the probability of adoption changes from 0.118 to 0.151 for a capital-intense technology (*CIT*), from 0.396 to 0.459 for a management-intense technology (*MIT*), from 0.099 to 0.129 for a combined capital- and management-intense technologies (*CIT-MIT*), and from 0.387 to 0.261 for neither types of technologies (*NT*). If operators were to triple the size of their farms, the probabilities of adopting *CIT*, *MIT*, *CIT-MIT*, and *NT* change even more dramatically, to 0.178, 0.490, 0.155, and 0.177, respectively.

While a sizable increase in farm size will tend to moderately increase the likelihood of adopting a capital- or a management-intense technology, either singly or in combination, it will significantly lower the probability of adopting a technology where neither a capital- nor a management-intense technology is used. For some farms, herd size expansion remains feasible even when no new milking facilities are built. For example, evidence from Minnesota suggests that some DHI farms are able to grow to a size equivalent to over 150% of barn capacity by using calf hutches, by housing dry cows separately from the milking cows, and by milking in shifts, etc. (Conlin).

Finding that the pattern of technology adoption is sensitive to the doubling or tripling of herd size affirms earlier MNL results, namely, that a scale-bias in technology adoption exists. Multiplying the actual mean unconditional probabilities of adoption (table 5) by the total number of dairy farms determines the actual number of dairy farms in each of the four technology categories. Multiplying the simulated mean conditional probabilities by the total number of dairy farms (or alternatively summing individual estimated probabilities, i.e., $\sum_{i=1}^{N} \hat{P}_{ij}$) provides an estimate of number of dairy farms in each of the four technology categories. Multiplying further the resulting number of farms in each technology category, based on actual farm size or simulated farm size, by the corresponding average per-cow yield and average per-farm number of milking cows determines the total amount of milk produced.

Table 6 shows the effect of the changes in the pattern of technology adoption resulting from herd size expansion on total milk production. If all operations expand the size of their herds by 100%, assuming all else held constant, proportionate changes in the number of adopters of *CIT*, *MIT*, *CIT-MIT*, and those in the *NT* category will result in total milk production increasing by 127%, or by 152,750 million pounds. In the case of all operations enlarging their size by 200%, total milk production increases by 272%, or by 326,885 million pounds. The significant impact of herd expansion on milk production centers around the presence of a scale-bias towards technology adoption.

**Table 6. Actual and Simulated Total Milk Production: Scale-Bias Scenario of Technology Adoption, 1993**

| | Actual milk production (mil. lb.)¶: | Simulated milk production (mil. lb.)†: | |
|---|---|---|---|
| | Based on average size of farm (78 cows) | Average size of farm is doubled (156 cows) | Average size of farm is tripled (254 cows) |
| Adoption: | | | |
| *CIT* | 18,363 | 47,161 | 83,239 |
| *MIT* | 40,213 | 93,375 | 149,312 |
| *CIT-MIT* | 39,388 | 102,615 | 183,998 |
| *NT* | 22,076 | 29,642 | 30,376 |
| Total | 120,040 | 272,794 | 446,925 |
| Change in total production (%) | 0.00 | 127.25 | 272.31 |

¶Based on total number of farms in each of the four categories of technology adoption, corresponding average per-cow yeild, and corresponding per-farm average number of milking cows.
†Based on simulated total number of farms (i.e., based on simulated probabilities of adoption as shown in table 5), corresponding average per-cow yield, and corresponding twofold and threefold per-farm average number of milking cows, respectively.

## Conclusions and Implications

Findings based on data from the 1993 FCRS point to increased concentration in milk production. Farms with 1,000 or more cows produce fifteen percent of all marketed milk using only thirteen percent of the dairy inventory. Farms with less than 50 cows comprise about 50% of all dairy farms. Their production based on 23% of the cow inventory is one fifth of all marketed milk. The disproportionate contribution of larger farms to total production reflects their higher per-cow productivity due mainly to their higher utilization of capital- and management-intense technologies. Differentials in the rates of technology adoption between small and large farms (see table 5) provide a viable explanation to why some smaller farms are at an economic disadvantage, compared to larger farms.

Empirical results from the MNL model of technology adoption identified age of operator, size of operation, and specialization in dairy production as important in increasing the likelihood of adopting advanced milking parlors. The MNL regression results identified educational attainment and size of operation as important in explaining the usage of DHIA record keeping system. Operator's human capital, availability of credit reserves, specialization in dairy production, size of farm, and increased dependence on hired labor are found important in increasing the probability of adopting advanced milking parlors in conjunction with a DHIA record keeping system.

An interesting implication from the MNL model of technology adoption pertains to the effect higher technology adoption rates attributed to increased levels of educational attainment might have on the allocation of human labor in agriculture. Specifically, as farm operators become more educated, the results have pointed to potential increases in the adoption rates of management-intensive technologies either alone or in conjunction with capital-intensive technologies. For the adopting dairy farm operator, this might mean a reduction in the amount of human labor required to produce a given level of output (see Albrecht and Murdock, p. 92). For the multi-enterprise operator who is operating a small-sized dairy operation, Matulich argues that milking parlor automation for this type of operator might be beneficial in that it causes a release of milker labor to alternative tasks. Additionally, for the large highly specialized dairy operator, increased efficiency in milk production will allow for release of personal milker labor to non-farm activities. In the case of hired milker labor, increased milking efficiency due to technological adoption, as suggested by Matulich, may mean the loss of farm employment and the crowding-out of available off-farm job opportunities.

A study by the Office of Technology Assessment (U.S. Congress, pp: 195–6) examined the projected relationship between the adoption of biotechnology and farm structure. Findings from the study suggest that dairy farmers who opt for technological adoption will be able to increase milk production per cow, and accordingly will be able to achieve reductions in the real cost of producing milk, a finding confirmed here in the case of adopters of capital- and management-intense technologies. In consequence, these farmers will be able, in the longer run, to remain profitable even with lower milk prices, and because of their productivity gains, they will be able to stay competitive and financially solvent. In contrast, non-adoptors will likely become financially insolvent and may be forced to exit farming. To the extent that 39% of the dairies in the study are non-adoptors of either a capital- or a management-intensive technology, either separate or combined, this suggests that a large number of dairy farmers might not be able to remain competitive. Increased volatility in milk prices following passage of the 1996 farm bill will likely only exacerbate the plight of the non-adopters thus accelerating the likelihood of their farm exit.

Results from simulating the effect of farm expansion on the probability of technology adoption reveal changes in the pattern of adoption. Specifically, in doubling the size of operation, the percentage of non-adopters falls significantly, from 39 to 26%. In tripling the size of the operation, the percentage of non-adopters falls even more, to 18%.

Herd expansion allows for the full utilization of newly adopted capital equipment and for improved labor efficiency, thus ameliorating farmers' returns and competitive position (see table 1). However, while this strategy for financial survival is the choice of many dairy experts, its success depends on farmers themselves having greater control or access to substantial captial resources. Although the federal price support program for milk is to be eliminated in its current form, the government could continue to play a role in supporting the dairy industry by indirectly helping farmers to expand and to adopt new technologies. This could be achieved by increasing credit availability (Title VI of the 1996 farm bill delineates credit programs, lending policies of the Farm Service Agency, and eligibility [see U.S. Dept. Agr. 1996a, pp. 63–70]), and/or by lowering the cost of borrowed funds (via lowering reserve requirements as was described in one of the titles in the Depository Institutions Deregulation and Monetary Control Act of 1980 [see Barry; Dixon, Ahrendsen, and Barry]). The easier access to credit and the decrease in the cost of borrowing may work also at increasing the willingness and the ability of the farmers to invest in newer capital equipment. This is in accordance with Lamm's finding that the cost of capital has a statistically significant negative effect on real farm investment.

Simulation results pertaining to the effect of farm expansion on total milk production show that an increase in farm size will increase production by a larger proportion. The sizeable increase in total milk production resulting from the change in adoption patterns in response to the doubling or the tripling of herd size is likely to exert a downward pressure on the price of milk. When this finding is evaluated based on the knowledge that the demand for milk is price inelastic (see Kinnucan et al.) implying that not all milk produced at a lower price will be cleared by demand, any incentive for dairy farmers to expand, with its attending impact on technological adoption as a way of improving their competitive edge, is likely to be foreshadowed by the likelihood of lower returns. The implication of this is that dairy operators have the predicament of exerting financial stress on their operations if, in their effort to stay competitive, they implemented the strategy of farm expansion coupled with the adoption of capital- and management-intensive technologies. Although fundamentally correct, this strategy has the potential to create large surpluses, which, without programs to enhance exports or to control supplies, are detrimental to the whole dairy industry. Benefits from farm expansion and technology adoption remain possible as long as their purpose is to lower per-unit costs through enhanced production efficiency rather than solely for increasing per-cow yields.

The results obtained here are based on an adoption model that does not incorporate the dairy farm operator's perference towards risk. Thus, the exact pattern of adoption among the capital- and the management-intensive technologies based on size of farm cannot be discerned precisely. This, and the social and welfare implications that might arise due to the predicted demise of dairy farms—particularly smaller operations—that will not or cannot adopt any of the technologies considered in the analysis must be the subject of future research.

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## Notes

1. As in Zepeda (1990b), a capital-intensive technology is defined as one for which the largest single cost share for its implementation is capital cost. A management-intensive technology is defined likewise.

2. While not considered in this paper, the vector $Z_i$ may also contain attributes of the technology.

3. The Dairy version included only farms that were in business the entire calendar year.

4. The same data also show that smaller farms tend to operate with about 3.5% of the credit reserves (i.e., the difference between the dollar amount of farm's credit capacity and farm's debt) available for larger farms ($22,701 versus $648,826).

5. It should be noted that of all the explanatory variables used in the adoption model, only *EDUC*, *AGE*, *NORTH*, and *EXPYIELD* are truly exogenous. An argument could be made that the remaining variables may be jointly determined with the adoption decision. Attempts at creating additional instruments to remedy this problem produced singularity in the matrix of explanatory variables, and thus were abandoned. As a result, all remaining variables are assumed to be exogenous.

6. To account for the complexity of the survey design that underlies FCRS data, estimation of the MNL models is carried using PC CARP (see Fuller et al.), a specialized statistical package designed specifically for probability-based data as in the FCRS.

7. The McFadden $R^2 = [1 - \text{Log } L(\underline{\beta})/\text{Log } L(\beta_0)]$, where Log $L(\beta_0)$ is the maximum value of the log-likelihood function subject to the constraint that all regression coefficients except the intercept term are zero, Log $L(\underline{\beta})$ is the maximum value of the log-likelihood function without constraints, and $\underline{\beta}$ is the estimated vector of parameters (Amemiya, p. 1505; Maddala, p. 39). McFadden $R^2$ will equal 0 (indicating poor fit) if the model predicts technology adoption no better than a simple flip of coin, and will be equal to 1 if the model predicts technology adoption perfectly.