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Breeding Technologies in U.S. Meat Goat Production: Who Are the Adopters and How Does Adoption Impact Productivity?

Jeffrey Gillespie, Berdikul Qushim, Narayan Nyaupane, and Kenneth McMillin

Adoption of advanced breeding technologies and management practices (BTMP) in U.S. meat goat production and their impact were examined. Adopters generally had larger-scale operations, used rotational grazing and/or dry lot systems, and sold larger percentages of animals for breeding and show purposes. Farmer demographics and farm variables also influenced adoption. Complementarity of adoption was found—adopters of one BTMP tended to adopt other BTMPs. Measures of productivity and profitability were not affected by adoption. Goat breed, farmer experience, production system used, and specialization influenced productivity, and farm size had the greatest influence on enterprise profitability.

***Key Words*:** meat goat, profitability, technology adoption, twinning

Advanced breeding technologies and management practices (BTMP) are widely used in today's animal agriculture to produce superior genetics, increase farms' output, and enhance farms' economic viability. One could argue that farmers have been adopting BTMPs since animals were first domesticated for food production, but advanced BTMPs developed over the past 75 years, such as artificial insemination (AI) in the 1940s and embryo transfer (ET) in the 1970s, have been instrumental in the ability of producers to gain access to superior genetic lines so that herd productivity can be improved faster. Among U.S. livestock producers, the dairy industry has adopted advanced BTMPs most rapidly, followed by the pork and, finally, the beef industries (Johnson and Ruttan 1997).

Meat goat production is a relative newcomer to the U.S. livestock industry. Recent increases in production have stemmed from several events: formation of trade associations such as the American Meat Goat Association in 1992 and the American Boer Goat Association in 1993; repeal in 1993 of the Wool Act of

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1954 and resulting lifting of wool and mohair incentives by 1995, which enticed many angora goat producers to switch to meat goat production; the 1998 U.S. tobacco settlement, which provided incentives for some former tobacco farmers to produce meat goats; and increased demand for goat meat spurred by growing populations of immigrants (Shurley and Craddock 2005). According to Shurley and Craddock (2005), the top three goat-meat-consuming groups in the United States were Muslims, Caribbean immigrants, and Hispanics. Coffey (2005) added Africans and Jewish people to the list of groups for which goat meat is a traditional food.

Because U.S. meat goat production is a new industry, little is known generally about the production practices used and specifically about how BTMPs may affect livestock productivity. Most of the work so far completed in economics has focused on consumption and marketing (Ekanem et al. 2011, Ibrahim 2011). A recent study by Gillespie, Nyaupane, and McMillin (2013) showed that producers viewed the high cost of production as one of the most important challenges facing the industry, a factor that can be partially addressed through development and adoption of technologies and best management practices.

In this study, we analyze rates of use of nine advanced BTMPs in the U.S. meat goat industry, the types of producers most likely to have adopted those BTMPs, complementarity in their adoption, and the impact of the BTMPs on farm productivity: AI, ET, doe flushing, examinations of the breeding soundness of bucks, exposing of noncycling females to sterile bucks to induce ovulation, controlled lighting systems to manipulate the breeding season, record-keeping, pregnancy checks, and use of breeding seasons.

Technology Adoption in Agriculture

The agricultural economics profession has devoted significant effort to understanding the dynamics of adoption of farm technologies. Technological advances typically are widely promoted to farmers and have been shown to increase productivity in many cases. By examining take-up rates and the types of farmers who adopt the technologies, insight can be gained into the types of farmers and industries to which extension efforts should be targeted, directions in which industry structures are heading, and the types of farms that will most likely yield productivity gains. Griliches (1957) was a particularly influential early study of adoption of farm technology that examined the diffusion of adoption of hybrid corn in the United States. The study showed that the diffusion of adoption follow an S-shaped pattern in which adoption accelerated at first and then decelerated as the technology approached an equilibrium level of use. Cochrane (1958) discussed the agricultural treadmill theory of adoption—early technology adopters generally benefited the most from adoption while others were forced to eventually adopt or exit production.

Much of the more recent work (after 1970) on adoption of technology has focused on who adopts innovations, including further examinations of diffusion of adoption and/or the impact of innovation on productivity and profitability. Feder, Just, and Zilberman (1985) analyzed much of the prior work on adoption of farm technologies in developing countries; they drew conclusions about the major drivers of technology adoption and provided a better understanding of the factors that affect adoption. In recent years, studies have increasingly used farm-level data to examine technology adoption and its impact on farm productivity and profitability (e.g., McBride, Short, and El-Osta 2004, Tauer 2009).

Breeding Technologies in Goat Production

In researching the nature of BTMPs and rates of uptake, it is useful to understand that goats are seasonal breeders. They tend to breed during late summer and early fall when days begin to be shorter. As the sun sets earlier and earlier, however, the goats typically become accustomed to shorter days and discontinue cycling (Wildeus 2005); the process varies somewhat by breed and individual animal. Thus, while the timing of goat breeding can be manipulated to some degree for marketing and/or production efficiency reasons, there is an underlying seasonal component.

Two common methods of manipulating breeding are AI and ET. AI is the process of introducing semen, usually from bucks that are genetically superior in production or phenotypic traits, manually into the females' reproductive tracts. Though training and practice are generally needed for effective AI, it is not capital-intensive; relatively little additional investment in facilities and equipment is required. ET involves transferring harvested embryos from a donor animal to a generally lower-value recipient animal. Wade (2005) described the procedures, equipment, and supplies needed for effective AI and ET in goats and noted that ET usually is performed by a veterinarian and tends to be cost-prohibitive for many meat goat farmers.

Flushing involves providing does with extra nutrition for several weeks before and during part of the breeding season to increase the number of ovulations and, thus, the incidence of twins and triplets. This practice was traditionally used by producers of angora goats and sheep and was later adapted to meat goats, and it may be beneficial for does with a poor body condition but likely is not for ones in better condition (Hart 2011).

Examination of bucks for breeding soundness occurs approximately one month before the breeding season begins and involves reviewing the goat's health history, inspecting for physical soundness, and sometimes conducting a semen evaluation (Wildeus 2005).

Exposure of noncycling females to intact and/or sterile bucks to induce ovulation through sight and smell is useful for initiating an early breeding season (Wildeus 2005). The breeding season also can be extended through controlled lighting in a light-proof barn (Wildeus 2005) and by chemically stimulating estrus using prostestagen and prostaglandin treatments (Wade 2005) in females for out-of-season breeding.

Good record-keeping is generally considered essential for successful livestock breeding because it provides data on the reproductive success of breeding stock for mating and culling decisions. Pregnancy checks allow one to identify open does, which also contributes to culling and other general management decisions (Wildeus 2005). Pregnancy detection methods for goats (Wade 2005) include examination of the vulva (generally by experienced producers), which is most effective later in the pregnancy; examination of the cervix to determine whether a "gray plug" has formed (as early as 30 days after conception); an ultrasound scan (this specialized equipment has become more feasible at the farm level), which is effective approximately one month after conception; blood and urine testing; and "bumping" to detect firmness within the abdomen, which Wade (2005) described as one of the least reliable pregnancy testing methods.

Methods

In this study, we conducted an initial survey by mail in July and August, 2012, of 1,600 U.S. meat goat producers to identify their production and marketing practices, perceptions of challenges facing the industry, preferences for breeding stock, and their demographic characteristics. The mailing list was constructed from an internet search for addresses of meat goat producers from websites of state industry associations, *www.eatwild.com*, and other sites identified as places at which the producers advertised their products. We sent a survey to all of the addresses identified from this search with a signed letter, a self-addressed postage-paid business-reply envelope, and a complementary pen on July 2, 2012, and followed that mailing with a postcard reminder one week later. Willimack et al. (1995) found that providing a pen as an unconditional incentive for an interviewer-administered survey increased responses. On July 23, 2012, we sent a second copy of the survey, signed letter, and business-reply envelope to those who had not responded to the first mailing and again followed with a postcard reminder one week later. This survey approach followed Dillman, Smyth, and Christian's (2009) tailored design method. In response, we received 584 usable surveys. After subtracting additional responses indicating a bad address or a farmer who was no longer producing goat meat, we find an adjusted response rate of 43 percent.

It is difficult to compare our sample to meat goat producers nationwide because the estimates from the agricultural census do not clearly identify the number of commercial meat goat farms in the United States. This is partly because many such farms are unlikely to be captured, a factor noted in a report by the U.S. Department of Agriculture's (USDA's) Animal and Plant Health Inspection Service (APHIS) (2005). According to APHIS, experts in the goat industry believed that the 2002 Census of Agriculture captured only 55–65 percent of the actual goat population. The 2012 Census of Agriculture (NASS 2012b) estimated that there were 100,910 goat farms (meat and other goats) and 2,053,228 goats (not including angora and milk goats), thus indicating that the inventory of the average meat goat farm was twenty goats. The Census of Agriculture included all farms that had $1,000 or more in total farm sales and one or more goats. Our sample farms had 61 goats on average for 2012, and between one and sixteen of those goats were breeds used for dairy, hair, or other purposes besides meat.

Further examination is needed, however, before arguing that the goat farms in our sample are larger than the average commercial meat goat farm. In analyzing data from the 2007 Census of Agriculture, APHIS (2011) showed that 52.4 percent of the goat farms represented had fewer than ten goats but accounted for just 9.1 percent of the total U.S. inventory. In those operations, the goats were kept primarily (72.4 percent) for other purposes (pets, livestock showing, brush control, and pack animals). As the size of farms increased, the percentage of goats kept for other purposes declined; goats for other purposes represented only 4.9 percent of the inventory for farms that had 100–499 goats (APHIS 2011). Thus, few meat goat farms that have less than ten goats can be considered commercial and the Census of Agriculture (2012b) average of twenty goats per farm would not represent commercial meat goat farms.

Though it is difficult to parse commercial meat goat operations (operations for which the primary goal is to produce and sell meat goats) from the census data, there is reason to believe that our sample reasonably represents the commercial segment of the industry since many of the small farms included in the census involve one or two goats kept as pets, for brush clearing, and as 4-H projects for children. The producers in our sample were engaged in commercial operations since they advertised meat goat products via the internet and/or were members of meat goat associations. Furthermore, our sample included farms from all but seven states (Alaska, Connecticut, Hawaii, Montana, Nevada, Rhode Island, and Wyoming) that collectively represented less than 3 percent of all meat goat farms in 2007 (NASS 2012a). We must recognize, however, that some commercial producers likely do not have a significant internet presence and that their rates of adoption of BTMPs could be different.

Table 1 presents the primary BTMP questions in the survey. Respondents were first asked about which of the following practices they used—AI, ET, flushing, examination of bucks for breeding soundness, exposing noncycling females to sterile bucks to induce ovulation, and controlled lighting systems to manipulate breeding. They were then asked whether they timed breeding so that the does would kid only during certain times of the year. Those who reported using timed breeding were asked to identify their main reasons for doing so from a set of options: market timing, efficient use of bucks, efficient use of facilities, efficient use of pastures, uniform kid weights at sale, and efficient use of AI/ET. Finally, they were asked how many breeding seasons they used.

The survey next asked respondents whether they maintained individual records for their goats to track offspring performance and whether they pregnancy-tested does. Those who did pregnancy test were asked to identify which of the following methods were used: vulva examination, cervical examination, ultrasound scanning, blood or urine tests, and bumping. All respondents were asked about the percentage of kidding in 2011 that produced twins or triplets. Additional questions dealt with the structure of their farms and their demographic characteristics.

The final question asked if the respondent was willing to participate in a four-page cost-and-return questionnaire designed to allow us to analyze the profitability of meat goat production. Those questions were not included in the initial survey because of the likelihood that such a lengthy survey asking for relatively sensitive information would significantly reduce the response rate. Of the 584 individuals who completed the first survey, 435 agreed to complete the second, which asked about revenue and expenses for the farm as a whole and for the meat goat enterprise. The questions closely followed the format of the cost-and-return questions included in USDA's Agricultural Resource Management Survey and allowed for a detailed cost and returns analysis for meat goat production. As with the first survey, we initially mailed a copy (in January 2013) and followed up with a second copy to nonresponders (in February 2013); 142 individuals completed and returned surveys. Of those, 124 had completely filled out the questionnaire and had also produced meat goats in 2011. After adjusting for nondeliverable surveys, the response rate was 30 percent.

Adoption Models

Farmers are assumed to maximize expected utility associated with alternative BTMPs as

$$\max_{Y=i} EU(\pi \mid \mathbf{X}) \tag{1}$$

Table 1. Primary Breeding Technology and Management Practice Questions and Percentages of Their Adoption

Question / Variable	Percent Adopted
Which of the following reproductive practices were used on your goat herd in 2011?	
Artificial insemination	11
Embryo transfer	7
Flushing does	17
Examine breeding soundness of bucks	24
Expose noncycling females to sterile bucks to induce ovulation	11
Controlled lighting to manipulate breeding season	1
Do you maintain individual records of your goats to track the performance of offspring? (percentage responding yes)	83
Do you time the breeding of your does such that goats will kid only during certain times of the year? (percentage responding yes)	87
If responded yes to timing breeding: What are your major reasons for timing breeding?	
Market timing	56
Efficient use of pastures	34
Efficient use of facilities	24
Uniform kid weight at sale	13
Efficient use of bucks	10
Efficient use of AI/ET	6
Other reason listed	35
If responded yes to timing breeding: How many defined breeding seasons do you use?	
One per year	66
Three every two years	6
Two per year	27
Other	2
How do you detect goat pregnancy?	
Ultrasound scans	17
Bumping to detect firmness in abdomen	14
Blood or urine test	7
Vulva examination	6
Cervical examination	0
Other means	9
I do not check goat pregnancy	62

Note: Each question was followed by “Circle All That Apply” unless otherwise noted.

where $i \in \{0,1\}$. A value of 0 represents nonadoption and a value of 1 represents adoption of a BTMP. The term $EU(\cdot)$ indicates expected utility, π is profit and equals $TR_i - TC_i$ (total revenue minus total cost), and **X** is a vector of farmer demographics and farm characteristics that affect adoption.

To determine the drivers of adoption of BTMPs by meat goat producers, we use the following expression of a probit model, a limited dependent variable model used to analyze binary choice decisions (Green 2000):

(2) $$\text{Prob}(Y = 1) = \int_{-\infty}^{\beta' x} \phi(t)dt = \Phi(\beta' x)$$

where $\Phi(\cdot)$ denotes the standard normal distribution. While the signs on coefficients from probit models provide insight into the direction of any impacts, β estimates generally cannot be interpreted as marginal effects. The marginal effects for continuous variables are calculated as in Greene (2000):

(3) $$\delta E[y \mid x] \,/\, \delta x = \phi(\beta' x)\beta.$$

Marginal effects for the binary independent variables, d, also are calculated as in Greene (2000):

(4) $$\text{Prob}[Y = 1 \mid \bar{x}^{*}, d = 1] - \text{Prob}[Y = 1 \mid \bar{x}^{*}, d = 0]$$

where $\bar{x}^{*}$ refers to the means of all of the other independent variables in the model.

In addition to a probit model of adoption, we use a Poisson regression model to determine drivers that affect the extent of adoption using counts for all nine BTMPs. The Poisson regression method assumes a density function of

(5) $$\text{f}(y_i \mid x_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, y_i = 0, 1, 2, \ldots,$$

in which x_i represents the independent variables and μ_i is the expected number of technologies adopted:

(6) $$\mu_i = E[y_i \mid x_i] = \exp(X_i' \beta).$$

The Poisson regression model assumes an equal mean and variance of the dependent variable. In cases of unequal mean and variance, the negative binomial count-data model is more appropriate. Using the Lagrange multiplier test, we tested use of the Poisson versus the negative binomial model. The result was not significant ($P \leq 0.10$) and thus provided no evidence of overdispersion, making the Poisson model the more suitable choice (Greene 2000). Furthermore, the heterogeneity parameter α in the negative binomial model was not significant at $P \leq 0.10$, further supporting use of the Poisson model.

Table 2 presents the independent variables for goat breeds, farmer demographics, and farm structure, diversification, and region that were included in the probit and Poisson regression models. The two most frequently raised breeds were boer and kiko. We could find no prior research from which to predict the impact of breed on adoption so we included dummy variables for those breeds to determine whether producers of those breeds were more or less likely to use each BTMP.

The demographic variables included in the models are the farmer's age and level of education. *Age* is a continuous variable in 15-year increments, and *College* is a dummy variable indicating whether a producer had at least a

Table 2. Means of Independent Variables for Regression Analyses

Variable	Unit	Mean	Standard Deviation
Boer	0/1	0.56	0.44
Kiko	0/1	0.20	0.35
Age	1: 30 years or less 2: 31–45 years 3: 46–60 years 4: 61–75 years 5: 76 years or more	2.95	0.91
College	0/1: Producer has completed four-year degree (1 = yes, 0 = no)	0.45	0.50
Years farming	1: 10 years or less 2: 11–20 years 3: 21–30 years 4: 31–40 years 5: 41 years or more	1.58	0.83
Number of does	Number	35.72	50.62
Pastured not rotated	Percent /100	0.29	0.41
Extensive prod. system	Percent /100	0.11	0.28
Number of facilities	Number	5.39	1.72
Percent sales as breeders	Percent	30.38	29.76
Percent sales for show	Percent	16.18	25.37
Percent farm income from goats	1: 19 percent or less 2: 20–39 percent 3: 40–59 percent 4: 60–79 percent 5: 80 percent or more	2.52	1.71
Off-farm job	0/1	0.61	0.49
Southeast region	0/1	0.36	0.48
West region	0/1	0.20	0.40
Percent of twins and triplets produced	1: 19 percent or less 2: 20–39 percent 3: 40–59 percent 4: 60–79 percent 5: 80 percent or more	4.13	1.13
Profit per doe	Dollars	–325.45	642.39
Number of breeding technologies adopted	0–9	2.79	1.47

bachelor's degree. About 45 percent of the producers had completed a four-year college degree. Studies of AI use in dairy production (Howley, Donoghue, and Heanue 2012) and breeding-season manipulation and pregnancy testing in cow-calf production (Ward et al. 2008) have shown that older farmers tend not to adopt new technologies. Relatively educated producers, on the other hand, have been more likely to use AI, ET, and/or sexed semen (Pruitt et al. 2012) and pregnancy testing (Ward et al. 2008) in cow-calf production; AI and/or sexed semen (Khanal and Gillespie 2013) and record-keeping for individual cows in milk production (Zepeda 1994); and AI in hog production (Gillespie, Davis, and Rahelizatovo 2004).

A farm's structure may influence its use of technology. Operators of relatively large farms, for example, generally adopted advanced technologies and management practices in part because of economies of size associated with adoption. Larger-scale farms have more often used AI and ET and/or sexed semen in milk (Khanal, Gillespie, and MacDonald 2010) and cow-calf (Pruitt et al. 2012) production. Intensive breeding programs have been used in large-scale hog production (Gillespie, Davis, and Rahelizatovo 2004), and relatively frequent examinations of the breeding soundness of young bulls have been used in intensive cow-calf production operations (Ward et al. 2008). We include a variable for the number of each farm's does to indicate the size of the operation.

In the survey, producers reported the number of breeding-age goats for each of four systems: extensive range or a pasture/woods combination, pasture that was not rotated, pasture that was rotated, and dry lot. We included variables for the percentage of animals reported in the first two systems. Extensive range was defined in the survey as "Goats kept on large tracts of pasture or rangeland, mostly fending for themselves. Goats forage for food and care for young with minimal assistance." We expect producers who use less intensive systems to be less likely to adopt BTMPs. Farmers who use no-rotation pasturing are also expected to be less involved with their goats on a daily basis than farmers who regularly rotate the goats among pastures or frequently feed them in dry lots. Khanal and Gillespie (2013), for example, found that dairy farmers who grazed their cows were less likely than farmers who used intensive systems to adopt AI.

A third production-system variable represented the number of the following facilities used on each farm: working pens, breeding pens, kidding pens, working chutes, weaning pens, quarantine pens, scales, and sheds and barns. A large value for this variable suggests that the operation is relatively capital-intensive, which would be complementary with the capital-intensive (as opposed to labor-intensive) BTMPs such as AI, ET, and controlled lighting systems.

In terms of farm structure, the target market is an important factor. Producers reported percentages of sales of goats for slaughter/meat, breeding stock, and show, and we included variables for percent of sales for breeding and show in the models. We expect farmers who target those markets to pursue high-quality genetic lines and keep good records. A study of hog farmers raising breeding stock showed that such producers were less likely to farrow weekly (Gillespie, Davis, and Rahelizatovo 2004), and another study found that purebred cow-calf producers were more likely to use AI, ET, and/or sexed semen than other types of producers (Pruitt et al. 2012).

Income diversification also can influence adoption of technologies. On one hand, a greater diversification of income could allow one enterprise to subsidize another, particularly if the enterprises are technically complementary, which is often the case with cograzed goats and cattle. On the other hand, greater diversification into other enterprises could reduce the effort devoted to the goat enterprise. Khanal and Gillespie (2013) found that specialized dairy farmers were more likely than other farmers to use AI while producers who worked off-farm were less likely to use AI, ET, and/or sexed semen. Gillespie, Davis, and Rahelizatovo (2004) found that U.S. hog farmers who had a greater number of enterprises were less likely to use weekly farrowing. In a study of Oklahoma cow-calf producers, Ward et al. (2008) found that farmers who obtained a larger percentage of net household income from the beef cattle operation were more likely than other producers to implement breeding seasons, pregnancy tests, and examinations of bull soundness, and Howley, Donoghue, and Heanue (2012) found that Irish dairy farmers who had off-farm jobs were less likely than farmers who did not to adopt AI. These studies suggest that on-farm diversification and off-farm employment tend to dampen adoption of BTMP. We thus include two variables to represent the degree of income diversification: percentage of farm income from the meat goat enterprise and a dummy variable that indicates whether the farmer had off-farm employment.

Adoption of BTMP could vary regionally so we include two regional dummy variables. *Southeast* is composed of Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. *West* is composed of Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, New Mexico, Nevada, Oklahoma, Oregon, Texas, Utah, Washington, and Wyoming. The baseline was all other states.

Complementarity of Adoption

Past studies have suggested that adopters of one BTMP also adopt other BTMPs (Khanal, Gillespie, and MacDonald 2010, Pruitt et al. 2012). This can be related to two technologies being technically complementary (adoption of one increases the marginal physical productivity associated with the other, as with AI and ET) or occur simply because some producers are more prone than others to adopt technologies. We tested for differences in the proportion of the sample that adopted BTMP 1 by the proportions that did and did not adopt BTMP 2 using Fisher's exact test (Zar 1984). For example, we separated producers who were and were not AI adopters and tested to see whether the rate of adoption of ET differed between them. This method is similar to the one used to test for complementarity of technology adoption in Khanal, Gillespie, and MacDonald (2010) and Pruitt et al. (2012).

The Impact of Breeding Technologies on Farm Productivity

To determine whether BTMP use affected farms' productivity, we estimated the impact of the number of BTMPs used and of the farms' characteristics on two measures of farm productivity: the percentage of does that bore twins and triplets and the percentage of the farm's profit per exposed doe.

For the percentage of twins and triplets produced, we used an interval regression analysis. In the first survey, participants were asked "Of your does that kidded during January–December, 2011, what percentage had twins or triplets (circle one)?" The options provided were 0–19 percent, 20–39 percent, 40–59 percent, 60–79 percent, and 80–100 percent. Wooldridge (2009) showed that the dependent variable in the interval regression model (w) is defined as

$$w = 0 \text{ if } y \leq r1$$
$$w = 1 \text{ if } r1 < y \leq r2$$
$$\vdots$$
$$w = J \text{ if } y > rJ \tag{7}$$

where $r1 < r2 < \ldots < rJ$ denotes the interval limits. Maximum-likelihood estimation is used for the interval regression, and we assume a homoskedastic normal population distribution (Wooldridge 2009). Thus, the parameter estimates can be interpreted directly as marginal effects.

To determine the impact of BTMPs on farm profitability, we use ordinary least squares regression, and farm profitability is calculated on a goat-enterprise-level basis. Revenue includes farm sales of meat goats and goat meat.

Costs associated with meat goat enterprises include purchasing goats, renting and/or purchasing land, producing and/or buying feed; renting, building, purchasing, and maintaining structures and other facilities; medical supplies; veterinary care; acquiring and maintaining machinery and vehicles; improvements and repairs; marketing services and equipment such as boxes; wages, taxes, and benefits for labor; contracted custom work; and noncash expenses associated with personal expenses, professional advice, and conservation. The cost-and-return survey asked producers to indicate the portion of expenses that could reasonably be segregated by enterprise for the meat goat operation. For the rest (e.g., farm supplies, marketing containers, hand tools, and shop power equipment), we had data only on whole-farm expenditures. We estimated the portion of those expenditures attributable to the meat goat enterprise by first calculating how much of the producer's total return was attributable to the meat goat enterprise (total return from meat goats divided by the total return for the farm) and then multiplying the whole-farm expense by that ratio.

Several studies of adoption of livestock technologies have found that adopters generally adopt more than one technology, which can lead to difficulty in identifying the impacts of individual technologies (Pruitt et al. 2012, Khanal, Gillespie, and MacDonald 2010). We therefore include counts of the number of the BTMPs adopted by each farm as an independent variable. A positive and significant coefficient would suggest that adoption of one additional BTMP would increase the farm's productivity. Since endogeneity is a potential concern when productivity or profitability and BTMP adoption are determined simultaneously, we test for endogeneity of the number of BTMPs adopted using the Hausman (1978) test for both profit per doe and percentage of twins and triplets using the variables for farmer's age and number of facilities as instruments for the number of BTMPs adopted. No endogeneity was found.

To isolate the impact of a BTMP on the productivity measure of interest, we included an independent variable for the goat breed (boer and kiko) in the model of the percentage of twins and triplets (it was not included in the profitability equation due to the lack of significance) to identify relationships between breed and incidence of twins and triplets. Other independent variables were the number of years the producer had been in business as a measure of experience; number of does as a measure of farm size; production system (no-rotation pasturing (not included in the profit equation due to lack of significance) and extensive pasturing); percent of goat sales for breeding/showing as a measure of the impact of different target markets; percent of farm income attributable to the goat operation as a measure of farm specialization; level of education; off-farm job holders as an indicator of income diversification; and regions (southeast and west) to account for potential geographic differences in farm productivity. While our results should reflect the commercial segment of the meat goat industry, our sample size for the profitability analysis (124 observations) is nonetheless rather small, raising a concern about consistency in estimating the farm profit model. Therefore, we used Monte Carlo (MC) simulation to investigate the sample-size properties of the data. We refer readers to Kennedy (2003), Cameron and Trivedi (2009), and Kiviet (2012) for additional information regarding MC simulation.

We conducted an empirical MC simulation and considered the following data-generation process:

$$
\begin{aligned}
(8)\quad \textit{Profit per Doe}_i = {} & 1 + 2 \times \textit{No. Breed Tech Adopt}_{1i} + 3 \times \textit{Percent TwinsTriplets}_{1i} \\
& + 4 \times \textit{Years Farming} + \textit{No. Does}_{1i} + 4 \times \textit{Extensive}_{1i} \\
& + 2 \times \textit{Percent Sale Breeders}_{1i} + 3 \times \textit{Percent Sale Show}_{1i} \\
& + 4 \times \textit{Percent Farm Income Goats}_{1i} + \textit{Off-farm Job}_{1i} \\
& + \textit{Southeast}_{1i} + \textit{West}_{1i} + \nu_i,\ i = 1, \ldots, N
\end{aligned}
$$

where $\nu_i \sim N(0,1)$, the error term is drawn from a standard normal random (*rnormal* (0,1)) variable, and N is the number of observations in the survey data for the farm profit model. We performed 250, 500, and 1,000 replications for the empirical MC simulation. For all of the analyses (probit, ordinary least squares, and interval regression), the variance inflation factors were checked for multicollinearity and no factor exceeded 4.0, indicating that multicollinearity is not a problem for our model. Robust standard errors also were estimated to correct for unobserved heteroskedasticity.

Results

Table 1 provides the means and standard deviations of use of each BTMP. The most frequently used BTMP was breeding season (by 87 percent of respondents). Their most frequently cited reason for using it was market timing (56 percent). After market timing, respondents cited efficient use of pastures, 34 percent; efficient use of facilities, 24 percent; uniform kid weight at sale, 13 percent; efficient use of bucks, 10 percent; efficient use of AI/ET, 6 percent; and other reasons, 35 percent, for using a breeding season. Most, 66 percent, used one defined breeding season per year, followed by two per year (27 percent). In sum, the majority of producers used one breeding season, mostly for market timing purposes.

The second most frequently used BTMP was also used by a large share of respondents: individual animal record-keeping (83 percent).

The third most frequently used BTMP, pregnancy checks, was used by far fewer producers (38 percent). Methods cited were ultrasound scan, 17 percent; bumping, 14 percent; blood/urine tests, 7 percent; vulva exams, 6 percent; and other means, 25 percent.

The remaining BTMPs were reported as examining breeding soundness of bucks, 24 percent; flushing, 17 percent; AI, 11 percent; exposing noncycling females to sterile bucks, 11 percent; ET, 7 percent; and controlled lighting, 1 percent. We have found no previous estimates for meat goat producers to use to compare to our results, but our estimates exceed those of Pruitt et al. (2012) for U.S. cow-calf producers for AI, ET, and individual record-keeping.

Table 2 reports means for the independent variables. Of the survey respondents, 56 percent raised boer goats and 20 percent raised kiko goats; the average producer was 52 years of age and had been farming for 11 years; 45 percent held a four-year college degree; 61 percent held off-farm jobs; the average number of does on a farm was 36; 29 percent of the goats were pastured and 11 percent were raised under extensive systems; 30 percent of sales were for breeding and 16 percent were for show; 36 percent of farms were in the southeast; and 20 percent were in the west. The average percentage of twins and triplets was 63 percent. The average profit per doe was –$325 and there was a rather large standard deviation of $642. Approximately 21 percent of respondents reported a profit. The average number of BTMPs adopted by farmers was 2.8.

The probit results are reported in Table 3. We find that a farmer who raised boer goats had a 0.015 greater probability of using ET and a 0.101 greater probability of using exposure of females to induce ovulation. For farmers who raised kiko goats, the probability of using flushing decreased 0.117 and the probability of keeping individual records increased 0.128. These results suggest that breed type had a modest impact on the propensity to adopt BTMPs, but we cannot identify a general direction for BTMP adoption behavior by breed type.

Older farmers generally made less use of BTMPs; each additional 15 years of age reduced the probability of adoption of ET, flushing, controlled lighting, and pregnancy checks by 0.001, 0.036, 0.004, and 0.069, respectively. The results of the Poisson regression indicate that an additional 15 years of age decreased the number of BTMPs used by 0.208. These results are consistent in sign with previous studies of BTMP adoption for other animal agriculture enterprises (Ward et al. 2008, Khanal and Gillespie 2013) and suggest that, as new producers (who are ostensibly younger) enter the industry, diffusion of the technologies will continue.

Larger-scale farmers were more likely to adopt BTMPs. An additional ten breeding-age does increased the probability of use of AI, ET, flushing, and exposure of females to sterile bucks by 0.005, 0.002, 0.007, and 0.005, respectively, and increased the number of BTMPs used by 0.032. These results are also consistent in sign with earlier studies of BTMPs in other animal agricultural enterprises (Ward et al. 2008, Pruitt et al. 2012) and reflect either economies of size associated with BTMPs or simply a generally greater tendency for larger-scale producers to adopt them.

Farmers who used no-rotation pasture systems had a greater probability of 0.015 of adopting ET and a smaller probability of 0.120 of using pregnancy checks relative to farmers who produced no animals under a no-rotation pasture system. Furthermore, use of no-rotation pasturing reduced the number of BTMPs adopted by 0.098. Farmers who used extensive systems were less likely to keep individual records for goats (0.179) and to use a breeding season (0.076) relative to farmers who used other pasturing systems.

The number of types of facilities included on a farm had a strong positive impact on BTMP adoption. For each additional facility, the probability of

Table 3. Probit Results for Adoption of Breeding Technologies and Management Practices

Variable	β	Standard Error	Marginal Effect	Std. Error Marg. Effect
Artificial Insemination				
Constant	–2.8300***	0.5527	—	—
Boer	0.2339	0.3126	—	—
Kiko	0.1060	0.4279	—	—
Age	–0.1382	0.1087	—	—
College	0.2410	0.1786	—	—
Number of does	0.0045**	0.0018	0.0005**	0.0002
Pastured not rotated	–0.1845	0.2123	—	—
Extensive system	0.2605	0.3389	—	—
Number of facilities	0.1500***	0.0545	0.0171***	0.0006
Percent sales for breeders	0.0100***	0.0034	0.0011***	0.0004
Percent sales for show	0.0180***	0.0035	0.0020***	0.0004
Percent farm income goats	–0.1488***	0.0562	–0.0169*	0.0063
Off-farm job	0.1103	0.1918	—	—
Southeast region	0.3444*	0.1868	0.0421	0.0260
West region	0.2080	0.2279	—	—
Observations 496				
Wald χ^2 62.05***				
Pseudo R^2 0.2235				
Embryo Transfer				
Constant	–3.6777***	0.9308	—	—
Boer	0.6031**	0.2987	0.0146*	0.0086
Kiko	—	—	—	—
Age	–0.4129***	0.1377	–0.0010*	0.0054
College	0.1624	0.2354	—	—
Number of does	0.0063***	0.0021	0.0002***	0.0001
Pastured not rotated	0.6233***	0.2352	0.0151**	0.0075
Extensive system	—	—	—	—
Number of facilities	0.1718**	0.0786	0.0042**	0.0020
Percent sales for breeders	0.0204***	0.0045	0.0005***	0.0002
Percent sales for show	0.0221***	0.0046	0.0005***	0.0002
Percent farm income goats	–0.0690	0.0661	—	—
Off-farm job	–0.2984	0.2559	—	—
Southeast region	0.2235	0.2567	—	—
West region	0.4156	0.2862	—	—
Observations 496				
Wald χ^2 68.96***				
Pseudo R^2 0.3405				

Table 3 (continued)

Variable		β	Standard Error	Marginal Effect	Std. Error Marg. Effect
Flushing Does					
Constant		−1.1975***	0.4661	—	—
Boer		−0.2481	0.2384	—	—
Kiko		−0.5282*	0.3118	−0.1171*	0.0685
Age		−0.1630*	0.0883	−0.0361*	0.0196
College		0.0799	0.1433	—	—
Number of does		0.0033**	0.0016	0.0007**	0.0004
Pastured not rotated		0.1466	0.1753	—	—
Extensive system		0.2345	0.2950	—	—
Number of facilities		0.1034**	0.0454	0.0229**	0.0101
Percent sales for breeders		0.0045*	0.0026	0.0010*	0.0006
Percent sales for show		0.0045	0.0032	—	—
Percent farm income goats		−0.0442	0.0451	—	—
Off-farm job		−0.0666	0.1662	—	—
Southeast region		0.0901	0.1585	—	—
West region		−0.1506	0.2053	—	—
Observations	496				
Wald χ^2	27.32**				
Pseudo R^2	0.0688				
Examine Breeding Soundness of Bucks					
Constant		−1.4010***	0.4125	—	—
Boer		−0.0482	0.2116	—	—
Kiko		−0.1980	0.2521	—	—
Age		−0.1125	0.0763	—	—
College		0.0536	0.1309	—	—
Number of does		0.0012	0.0013	—	—
Pastured not rotated		0.0019	0.1618	—	—
Extensive system		0.2871	0.2522	—	—
Number of facilities		0.1182***	0.0430	0.0361***	0.0130
Percent sales for breeders		0.0040*	0.0023	0.0012*	0.0007
Percent sales for show		0.0051*	0.0028	0.0016*	0.0009
Percent farm income goats		0.0056	0.0390	—	—
Off-farm job		0.3007**	0.1481	0.0893**	0.0424
Southeast region		−0.0300	0.1443	—	—
West region		0.0008	0.1748	—	—
Observations	496				
Wald χ^2	24.37**				
Pseudo R^2	0.0497				

Table 3 (continued)

Variable		β	Standard Error	Marginal Effect	Std. Error Marg. Effect
Expose Noncycling Females to Sterile Bucks					
Constant		–2.0832***	0.4706	—	—
Boer		0.5946**	0.2812	0.1014**	0.0468
Kiko		0.5109	0.3409	—	—
Age		–0.0713	0.0988	—	—
College		–0.1722	0.1527	—	—
Number of does		0.0028**	0.0014	0.0005**	0.0002
Pastured not rotated		–0.0774	0.2003	—	—
Extensive system		0.1189	0.3350	—	—
Number of facilities		0.0767	0.0519	—	—
Percent sales for breeders		–0.0022	0.0029	—	—
Percent sales for show		0.0034	0.0032	—	—
Percent farm income goats		–0.0120	0.0442	—	—
Off-farm job		0.2373	0.1774	—	—
Southeast region		0.1007	0.1717	—	—
West region		–0.0526	0.2271	—	—
Observations	496				
Wald χ^2	20.08				
Pseudo R^2	0.0564				
Controlled Lighting System to Manipulate the Breeding Season					
Constant		–2.5783***	0.7895	—	—
Boer		0.0928	0.5835	—	—
Kiko		—	—	—	—
Age		–0.4340***	0.1224	–0.0042*	0.0022
College		0.0716	0.3063	—	—
Number of does		–0.0029	0.0032	—	—
Pastured not rotated		0.1162	0.3664	—	—
Extensive system		0.1204	0.4090	—	—
Number of facilities		0.1165	0.0802	—	—
Percent sales for breeders		0.0102	0.0066	—	—
Percent sales for show		0.0159***	0.0031	0.0002*	0.0001
Percent farm income goats		–0.0292	0.0906	—	—
Off-farm job		–0.0275	0.3546	—	—
Southeast region		—	—	—	—
West region		—	—	—	—
Observations	496				
Wald χ^2	75.17***				
Pseudo R^2	0.1900				

Table 3 (continued)

Variable		β	Standard Error	Marginal Effect	Std. Error Marg. Effect
Record-keeping					
Constant		0.8846**	0.4424	—	—
Boer		–0.1301	0.2371	—	—
Kiko		0.5529*	0.2954	0.1278*	0.0676
Age		–0.1328	0.0834	—	—
College		–0.0492	0.1461	—	—
Number of does		–0.0014	0.0015	—	—
Pastured not rotated		–0.2759	0.1768	—	—
Extensive		–0.7739***	0.2571	–0.1789***	0.0586
Number of facilities		0.1136***	0.0441	0.0263**	0.0104
Percent sales for breeders		0.0069***	0.0026	0.0160***	0.0006
Percent sales for show		0.0040	0.0034	—	—
Percent farm income goats		0.0003	0.0443	—	—
Off-farm job		–0.1170	0.1536	—	—
Southeast region		–0.3488**	0.1572	–0.0844**	0.0392
West region		0.3431	0.2145	0.0708*	0.0390
Observations	493				
Wald χ^2	50.55***				
Pseudo R^2	0.1136				
Pregnancy Checks					
Constant		–0.4231	0.3911	—	—
Boer		0.3139	0.2005	—	—
Kiko		–0.3319	0.2548	—	—
Age		–0.1862**	0.0741	0.0686**	0.0273
College		0.1842	0.1233	—	—
Number of does		–0.0021	0.0013	—	—
Pastured not rotated		–0.3246**	0.1537	–0.1196**	0.0565
Extensive system		–0.1417	0.2523	—	—
Number of facilities		0.0750*	0.0403	0.0277*	0.0148
Percent sales for breeders		0.0025	0.0021	—	—
Percent sales for show		0.0049*	0.0026	–0.0018*	0.0010
Percent farm income goats		0.0182	0.0365	—	—
Off-farm job		–0.1384	0.1375	—	—
Southeast region		0.0421	0.1357	—	—
West region		0.1535	0.1644	—	—
Observations	496				
Wald χ^2	47.87***				
Pseudo R^2	0.0838				

Table 3 (continued)

Variable	β	Standard Error	Marginal Effect	Std. Error Marg. Effect
Breeding Season				
Constant	0.9191**	0.4683	—	—
Boer	0.1228	0.2643	—	—
Kiko	0.1244	0.2504	—	—
Age	−0.0401	0.0872	—	—
College	0.1296	0.1488	—	—
Number of does	0.0011	0.0014	—	—
Pastured not rotated	−0.2243	0.1948	—	—
Extensive system	−0.4370*	0.2555	−0.0759*	0.0443
Number of facilities	0.0399	0.0492	—	—
Percent sales for breeders	0.0006	0.0025	—	—
Percent sales for show	0.0152***	0.0057	0.0026***	0.0009
Percent farm income goats	−0.0509	0.0464	—	—
Off-farm job	0.2541	0.1668	—	—
Southeast region	−0.1712	0.1617	—	—
West region	−0.1771	0.2133	—	—
Observations 493				
Wald χ^2 50.55***				
Pseudo R^2 0.1136				

Note: There are various pseudo R-squared measures for binary response models. We used McFadden's (1974) pseudo R-squared measure, which is $R^2 = 1 - \hat{L}(M_F) / \hat{L}(M_I)$ in which $\hat{L}(M_F)$ is the log-likelihood function for the estimated model with predictors and $\hat{L}(M_I)$ is the log-likelihood function for the estimated model with only an intercept.

adoption increased 0.017 for AI, 0.004 for ET, 0.023 for flushing, 0.036 for examining breeding soundness of bucks, 0.026 for keeping individual records, and 0.028 for pregnancy checks. Generally, with the exception of the estimates for ET and no-rotation pasture, the results for these three variables suggest that producers who use more capital-intensive systems and who use management-intensive grazing operations are greater BTMP users. These results are generally as expected given the greater hands-on managerial requirements of dry lot and rotated pasture systems relative to no-rotation pasturing and extensive systems, as well as the complementarity of capital-intensive facilities and some of these BTMPs.

The market for which meat goats were being produced strongly influenced BTMP use. We find positive and significant coefficients for five of the probit models for percent sales of breeders and for six of the probit models for percent sales for show; the Poisson results are also significant. An additional 10 percent of sales for breeding stock increased the probabilities of use of AI by 0.011, ET by 0.005, flushing by 0.010, examination of breeding soundness by 0.012, and individual animal record-keeping by 0.160 and increased the number of BTMPs adopted by 0.082. With an additional 10 percent of sales for show, the probability of use increased 0.020 for AI, 0.005 for ET, 0.016 for examination of breeding soundness, 0.002 for controlled lighting, 0.018 for pregnancy checks, and 0.026 for a breeding season and resulted in use of 0.137 additional BTMPs. These results are consistent in sign with studies of BTMP adoption for other animal agricultural enterprises (Gillespie, Davis, and Rahelizatovo 2004, Pruitt et al. 2012) and were expected given that farmers who produce for breeding and showing are likely to manage breeding of their goats more closely.

Diversification of income had only a limited impact on BTMP use. A 20 percent increase in the percent of income derived from the goat enterprise decreased the probability of AI usage by 0.017. This result was unexpected. It may suggest that other enterprises on the farm are complementary with AI use, which is plausible if the other enterprises are livestock-related. An off-farm job increased the probability of examining breeding soundness by 0.089.

Region also had a limited impact on BTMP use; southeastern producers were more likely to adopt AI and less likely to keep individual animal records while western producers were more likely to keep individual animal records.

The Fisher exact test to examine complementarity of adoption among the BTMPs showed strong evidence that adopters of one BTMP also adopted other BTMPs (Table 4). For 68 of the 72 comparisons (9 BTMPs and 8 comparison BTMPs), the adoption rate of one BTMP was numerically greater for adopters of another BTMP. In 45 of the comparisons, the difference was significant at $P \leq 0.10$ and adopters of a BTMP more often adopted another BTMP, suggesting that there is strong complementarity of adoption among the BTMPs. Table 4 shows the results when adoption of one BTMP showed greater adoption of a second BTMP, and the differences were 15 percentage points or more. For example, only 10.6 percent of nonadopters of controlled lighting adopted AI whereas 37.5 percent of adopters of controlled lighting also adopted AI. The BTMPs that were generally relatively highly correlated with other BTMPs were exposing females to sterile bucks, ET, and AI; each had adoption rate spreads of 15 percent or more for at least five other BTMPs. These results suggest that, in the productivity regressions, caution is warranted when including a single BTMP since it would be problematic to sort out the impact of that BTMP from impacts from the other correlated BTMPs. Using a count of the number of BTMPs adopted is likely to be a more appropriate measure to address the intensity of BTMP adoption.

We find no evidence to suggest that adoption of BTMPs had any impact on farm productivity (Table 5); the coefficient for number of breeding techniques adopted was not significant in the models of profit per doe or percent of twins and triplets. Several factors may explain these results. The simplest is that BTMPs do not generally affect the productivity of meat goats. But that is unlikely given evidence that they do increase the productivity of the goats and results of studies of other agricultural animals (i.e., profitability results of Khanal and Gillespie (2013) for AI in dairy cows and pounds weaned per exposed female by Ramsey et al. (2005) for breeding season length in cow-calf production). There could be too much variability in the dependent variable (particularly in the profit-per-doe measure, which has a large standard deviation (Table 1)) to discern differences in this independent variable, or there could be opposing differential impacts of individual BTMPs on productivity so that a simple conglomerate measure shows no impact.

To check whether individual BTMPs change the results, we replaced the variable for number of breeding technologies adopted with a dummy variable

Table 4. Estimates of Adopters and Nonadopters Who Adopted Other Breeding Technologies and Management Practices

Breeding Technology or Management Practice	Percent of Nonadoption	Percent of Adoption
Artificial Insemination		
Embryo transfer	2.5	45.3
Flushing does	12.2	53.1
Examine breeding soundness of bucks	21.9	45.3
Expose noncycling females to sterile bucks	8.1	31.3
Checking pregnancy	33.1	75.0
Embryo Transfer		
Artificial insemination	6.5	69.1
Flushing does	10.8	92.9
Examine breeding soundness of bucks	22.5	50.0
Expose noncycling females to sterile bucks	8.4	40.5
Checking pregnancy	34.7	76.2
Flushing Does		
Artificial insemination	6.2	35.1
Embryo transfer	0.6	40.2
Checking pregnancy	34.9	51.6
Examining Breeding Soundness of Bucks		
Checking pregnancy	32.1	54.9
Exposing Noncycling Females to Sterile Bucks to Induce Ovulation		
Artificial insemination	8.5	32.3
Embryo transfer	4.8	27.4
Flushing does	14.5	35.5
Examine breeding soundness of bucks	22.5	40.3
Checking pregnancy	33.9	69.4
Controlled Lighting to Manipulate Breeding Season		
Artificial insemination	10.6	37.5
Record-keeping		
Checking pregnancy	22.0	41.1
Checking Pregnancy		
Artificial insemination	4.4	21.9
Embryo transfer	2.8	14.6
Breeding Season		
Checking pregnancy	21.3	39.9

Notes: The table reports results with a difference of 15 percentage points or more. All are significant at $P \leq 0.10$.

Table 5. Results of Additional Regression Analyses

	Number of Breeding Technologies Adopted – Poisson Regression				Profit per Doe – Ordinary Least Square Regression		Percent of Twins and Triplets – Interval Regression	
Variable	**β**	**Standard Error**	**Marginal Effect**	**Std. Error Marginal Effect**	**β**	**Standard Error**	**β**	**Standard Error**
Constant	1.0267***	0.1171	—	—	–442.17	297.27	61.21***	4.51
No. breeding tech. adopted	—	—	—	—	–88.54	53.75	–0.03	0.78
Percent of twins/triplets	—	—	—	—	–31.40	43.24	—	—
Boer	0.0653	0.0723	—	—	—	—	7.64**	3.60
Kiko	–0.0760	0.0885	—	—	—	—	7.00*	4.11
Age	–0.0775***	0.0265	–0.2076***	0.0711	—	—	—	—
Years farming	—	—	—	—	90.60	54.87	2.08**	1.05
Number of does	0.0012**	0.0006	0.0032**	0.0016	5.95***	2.28	–0.02	0.02
Pastured not rotated	–0.2613*	0.1369	–0.0975*	0.0512	——	2.65	2.43	
Extensive system	–0.1391	0.1208	—	—	–166.46	182.18	–11.32**	5.05
Percent sale for breeders	0.0031***	0.0009	0.0082***	0.0021	2.37	2.37	0.04	0.04
Percent sale for show	0.0051***	0.0009	0.0137***	0.0024	–4.31	2.79	0.03	0.05
Percent farm income goats	–0.0164	0.0135	—	—	28.74	30.84	1.84***	0.61
College	0.0351	0.0450	—	—	—	—	–0.15	2.15
Off-farm job	0.0107	0.0503	—	—	188.46	168.48	–3.24	2.20
Southeast region	0.0050	0.0491	—	—	0.04	140.92	–2.70	2.30
West region	0.0483	0.0602	—	—	–17.15	158.41	–1.56	3.01
/lnsigma	—	—	—	—	—	—	3.06***	0.04
Sigma	—	—	—	—	—	—	21.28	0.88
Observations	495				114		475	
Wald χ^2	98.11***				—		41.05***	
F	—				2.00**		—	
R^2	—				0.1777		—	
Pseudo R^2	0.0360				—		—	

for each BTMP (one regression per BTMP). In only one case was a BTMP significant at $P \leq 0.10$: negative for examining the breeding soundness of bucks. This seems contradictory since adopters of this BTMP also adopt other BTMPs, but examining the breeding soundness of animals is not easy to conduct, requires expertise to evaluate semen, and may not provide useful enough results to justify the effort and expense.

The percent of twins and triplets was positively affected by use of the boer breed (7.64 percent) and of the kiko breed (7.00 percent). An additional ten years of experience in farming increased the percentage of twins and triplets produced by 2.08 percent, and an additional 20 percent of farm income from goats increased the percentage of twins and triplets by 1.84 percent. Farmers who used extensive production systems had an 11.32 percent lower rate of twins and triplets.

The only factor that consistently affected profit per doe was the number of does, suggesting a significant economy of size in the meat goat industry. The scale of the parameter estimate is striking; each additional breeding doe increased the profit per doe by $5.95. As reported in Table 2, there otherwise was significant variability in profit per doe, and the model explained only about 18 percent of that variability. The modest goodness-of-fit is not surprising and is likely explained by the wide range of production systems used by meat goat farmers, differential production conditions faced by producers, and the relative sparseness of research and extension information in the industry recommending specific management strategies.

For the profit equation, the results of the empirical MC simulation with 250, 500, and 1,000 replications showed that the means of the point parameter estimates were very close to the true values, the standard deviations of the parameter estimates were close to the means of the standard errors, and the rejection rates were lower than the nominal size of the test. We also used t-tests ($P \leq 0.05$) to determine whether the parameter estimates were equal to the true parameters and found a lower likelihood of rejecting the null hypothesis with increasing replications. These results indicate that there was no significant bias and that the asymptotic distribution approximated the finite-sample distribution well for the data-generating process with the sample size of 124. Thus, we are confident that our profit model produced consistent estimates.

Conclusions

The meat goat producers who responded to the survey in this study were members of meat goat associations and/or advertised via the internet and thus operated commercial meat goat farms. It is likely, therefore, that the survey respondents were generally more likely than meat goat producers in general to have adopted advanced BTMPs since many noncommercial operations are small in scale (less than ten goats) and use meat goats for other purposes. This sample was also more likely than not to time breedings so kids would be produced primarily during certain times of the year and to maintain records on individual goats.

About 38 percent checked the pregnancy status of their does, but a number of methods were being used with none emerging as the standard of the industry. Flushing and examining breeding soundness were conducted by 17 percent and 24 percent of producers, respectively, followed by 11 percent or less for exposure of noncycling females to sterile bucks, AI, controlled lighting, and ET. Clearly, as with cow-calf production, many different combinations of breeding technologies are being used in the meat goat industry.

We find that a number of factors have a positive effect on adoption of BTMPs. The farmers who were relatively likely to use BTMPs in general produced boer goats, had relatively large-scale operations and extensive facilities, were younger, and produced a greater percentage of their stock for sale as breeders or for show. When comparing adoption of two BTMPs, producers who used extensive systems were less likely to adopt two BTMPs. An increase in the percentage of farm income from goats reduced adoption of one BTMP while holding an off-farm job increased adoption of one BTMP. Factors that had mixed impacts depending on the breeding technology or management practice used are farmers who produce kiko goats and use of no-rotation pasturing.

From these results, it is apparent that efforts to encourage greater adoption of BTMPs to advance the industry will require educational programs for producers who raise less common breeds of goats and who have smaller-scale operations. Furthermore, recognition that adopters of one BTMP are likely to adopt other BTMPs is significant for future studies since it is likely to be difficult to design models that can single out the impact of a single BTMP on productivity.

We find no evidence that adoption of multiple BTMPs increases the incidence of twins and triplets or the farm's profit. Drivers of more frequent twins and triplets were breed type, experience raising goats, use of a relatively intensive production system, and the importance of the meat goat enterprise to the farmer's income. Three of those drivers—experience, production system, and importance of the goat enterprise—speak directly to the importance of management in improving this productivity measure. Producers with greater experience can manage their systems in ways that result in greater productivity while those who use extensive systems in which the goats are left essentially to fend for themselves should not expect strong results. Producers for whom the goat enterprise is a primary focus are likely to obtain more goats from each doe.

The sole driver of profitability was farm size, which is not too surprising given the large range of the size of the operations—from less than 5 does to more than 600—and significant economies of size that would be expected over this range. Furthermore, there was extensive variability in profit per doe, which is consistent with a relatively new industry since many of the producers currently have limited experience and research and extension efforts are not as extensive as they are for other animal industries such as beef, dairy, poultry, and swine. In addition, like cattle production, goat production uses unconfined systems that cannot be fully controlled. What is apparent is that further research is needed to determine the minimum size for a meat goat operation at which economies of size can be realized and the conditions under which use of specific BTMPs is likely to result in greater profit, particularly given the negative mean net return found for farms in this sample. Some of the farms were profitable, but of fourteen reasons for choosing to enter into meat goat production in a survey by Dunn et al. (2015), "goat production is profitable" was ranked twelfth behind lifestyle reasons and other reasons having to do primarily with how well the goat enterprise fit with other enterprises on the farm.

The fact that we found no evidence of impact of adoption of BTMPs on productivity measures does not lead to a conclusion that no impact exists (a potential type II error). While it is possible that there is no impact from BTMPs on productivity, perhaps because the BTMPs' additional costs are not offset by additional revenue, the more likely explanations are (i) that the large amount of variation in profitability among farms is related to management rather than to production practices so only the major profitability drivers will be significant and (ii) that differentials in the impacts of BTMPs sometimes offset one another when summed. Further research on BTMPs and follow-up extension programs to guide producers in using them effectively are warranted in this relatively new industry.

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