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Market Participation Decisions, Commercialization Intensity, and Structural Transformation in Maryland's Goat Sector: An Empirical Analysis

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ABSTRACT

Although goat production accounts for a small share of the total U.S. livestock output, it plays a crucial role in diversified and small-scale farming systems. Despite representing less than 1% of the U.S. goat inventory and sales, Maryland provides valuable insights into the commercialization of small-scale livestock systems. However, limited empirical evidence exists on the drivers of goat commercialization at the state level, particularly in distinguishing between market growth driven by expansion within existing farms and that driven by the entry of new producers. This study examines the determinants of goat market participation and commercialization intensity using county-level panel data from the USDA Census of Agriculture for 2002–2022 (92 county–year observations). A Two-Way Fixed Effects (TWFE) and Poisson Pseudo-Maximum Likelihood (PPML) frameworks are employed to isolate within-county variation over time. Results show that increases in herd size are positively and significantly associated with goat sales (TWFE: $\beta = 0.844$, $p < 0.05$; PPML: $\beta = 1.204$, $p < 0.01$), while changes in the number of farms are not statistically significant. Although market participation increased until 2017 and declined by 2022, the overall pattern indicates emerging structural constraints in commercialization. These findings demonstrate that commercialization in small-scale goat production systems is primarily driven by intensification among existing producers rather than by new farm entry. By focusing on within-county variation, this study provides a clearer understanding of scale effects in small-scale livestock systems and contributes to the literature on structural transformation. The results suggest that policies focusing on improving market access, processing infrastructure, and support for herd expansion among existing farmers are more effective than policies aimed at increasing the number of producers.

INTRODUCTION

Goat production plays an important role in the U.S. livestock industry, particularly in areas dominated by small and diversified farms (Hart, Merkel, & Gipson, 2019; Miller & Lu, 2019; Lu & Miller, 2019). Goats are more adaptable to limited land areas and require comparatively less capital investment than cattle and hog industries (Monteiro *et al.*, 2017; Escareno *et al.*, 2012; Nair *et al.*, 2021). As a result, goats are raised as a complementary enterprise with crops and other livestock rather than as primary business (Kumar, 2007; Dubeuf *et al.*, 2004). Therefore, rather than a major increase in the number of farms (producing businesses), variations in goat sales are more likely to reflect changes in herd size on existing farms. Over the past two decades, the demand for goat meat in the U.S. has grown consistently (Sande *et al.*, 2005; Dubeuf *et al.*, 2004; Katuwal & Karki, 2026). This growth has been supported by demographic changes, the increase of specialty and ethnic food markets, and growing consumer interest in alternative protein sources (Sande *et al.*, 2005; Mazhangara *et al.*, 2019). However, responses from domestic suppliers have been inconsistent. In many areas, producers face limitations in land availability, limited slaughter and processing capacity, and unstable market access (Nguyen *et al.*, 2023; Alexandre & Mandonnet, 2005; Katuwal & Karki, 2026). Therefore, rather than widespread entry of new farms into goat farming, growth in goat sales may depend more on the capacity of current producers to scale up inventory (headcount).

Maryland provides an appropriate framework for analyzing these interactions. The state accounts for a small share of the national goat inventory; yet its goat industry exhibits substantial variation across counties in herd size, farm structure, and market engagement (USDA, 2022). Additionally, Maryland's proximity to major metropolitan markets contrasts with substantial land-use demands and inadequate small-ruminant processing infrastructure. As a result, variations in goat sales at the county level could originate from localized production variations rather than from structural changes at the state level. Understanding these intra-county dynamics is essential for assessing commercialization strategies in limited-land agricultural systems. Despite increasing demand and interest in the goat sector, research on the determinants of goat sales in the U.S. remains limited, especially at the county level. The majority of current studies rely on cross-sectional data or aggregate trends, making it difficult to distinguish location-specific differences from time-related changes. Similarly, an analytical approach that uses within-county variation facilitates more precise identification of the

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relationship between inventory scale, farm structure, and sales outcomes. Therefore, this paper analyzes county-level goat sales in Maryland using a two-way fixed-effects model that accounts for time-invariant county attributes. This approach provides more accurate insight into commercialization patterns within small-scale livestock systems.

LITERATURE REVIEW

The two-way fixed effects (TWFE) model is used to account for unobserved variation across cross-sectional units and time dimensions (Wooldridge, 2025; Kropko & Kubinec, 2020; Imai & Kim, 2021). The model includes unit-specific fixed effects to account for time-invariant features, like location, production structure, and agro-ecological conditions, which may affect outcomes but remain unobservable (Berisso, 2024). Simultaneously, temporal fixed effects provide uniform shocks across units, including policy alterations, macroeconomic factors, and industry-wide trends (Devicienti *et al.*, 2019). This approach leverages periodic within-unit variation to reduce omitted-variable bias when unobserved factors align with the explanatory variables. The TWFE model yields reliable and robust estimates in short-panel situations and is widely used in agricultural, resource, and applied microeconomic research that employs repeated census or survey data (Arkhangelsky *et al.*, 2024; Wu *et al.*, 2023). In this study, the two-way fixed effects (TWFE) framework is applied to county-level panel data to isolate within-county changes in goat market participation and offtake rates over successive census years.

Given the non-negative nature and skewed distribution of livestock sales outcomes, the empirical analysis further relies on Poisson-based estimators. Log-linear gravity models with ordinary least squares may yield skewed and inconsistent estimates in the presence of heteroskedasticity (Santos Silva & Tenreyro, 2006). Poisson Pseudo-Maximum Likelihood with fixed effects (PPML-FE) has become a widely used estimation method in applied economics, especially when the dependent variable is non-negative and exhibits heteroskedasticity (Llano-Verduras *et al.*, 2021; Chung, 2013). In contrast to log-linear OLS models, PPML-FE is estimated in levels, therefore avoiding bias from log transformation in the presence of heteroskedastic errors, while naturally accommodating zero outcomes without arbitrary modifications (Sorensen *et al.*, 2020; Melo & Portugal-Perez, 2013). Furthermore, the addition of fixed effects enables the model to account for unobserved, time-invariant heterogeneity among units and common temporal shocks, which is especially important in panel data contexts where structural differences among units can hinder causal inference (Millimet & Bellemare, 2023; Chiu *et al.*, 2025). As a result, PPML-FE has been extensively used in empirical research across trade, agricultural, energy, and development economics as a reliable substitute for linear fixed-effects estimators when outcome variables exhibit skewness or insufficient variation (Rashid, 2025). Westerlund and Wilhelmsson (2009) showed that the accuracy of log-linearized gravity models can be insufficient, leading to incorrect estimations. In contrast, they found that the Poisson maximum likelihood estimator performs well, characterized by little bias and higher accuracy in most cases. Accordingly, PPML-FE is well-suited for modeling livestock sales results in this study, where zero values and heteroskedasticity are prevalent across counties and census years.

Previous studies typically distinguish between market participation and commercialization intensity in the analysis of livestock and agricultural markets. Market participation is typically modeled using binomial logit-based generalized linear models (GLMs), with participation measured as the proportion of farms in a specific group or region that engage in sales. This methodology is frequently used because it allows the participation probability to be based upon farm characteristics while integrating time effect with fixed effects (Stephen *et al.*, 2022; Gbur *et al.*, 2012). Furthermore, logit models are appropriate when the dependent variable represents a limited proportion obtained from grouped data (Bowen & Wiersema, 2004). This approach has been widely used in research examining ownership structure, tenure status, and operator characteristics in agricultural markets (Arouna *et al.*, 2017; Mudiwa & Mudiwa, 2011).

However, participation alone does not indicate the extent of commercialization among selling farms. Therefore, numerous studies examine commercialization intensity using Poisson regression models that include an offset or exposure factor. This framework represents total sales relative to the number of farms participating, providing the interpretation of the result as sales per selling unit (Abate *et al.*, 2021; Mthethwa *et al.*, 2022). This methodology is especially suitable for counting data and rate-based outcomes and has been extensively utilized in agricultural, demographic, and development economics (Wajdi *et al.*, 2017; Lomi, 1995). Additionally, Poisson models with fixed effects are frequently used to account for time-specific shocks and unobserved variability (Weber *et al.*, 2012).

In addition to participation and intensity, recent studies show the significance of structural concentration and distributional outcomes among agricultural groups. Researchers often use fractional logit models when outcomes are expressed as shares constrained between 0 and 1, such as group-level inventory shares (Schwiebert & Wagner, 2015; Mullahy, 2010). This approach eliminates the limitations of linear models and ensures that predicted values remain within rational limits (Durham *et al.*, 2015). Moreover, overall concentration is frequently measured using indices, such as the Herfindahl–Hirschman Index (HHI) and the Theil index. The HHI analyzes market dominance and concentration (Peleckis, 2022; Evren *et al.*, 2021), whereas the Theil index measures inequality among groups and is sensitive to changes in distribution (Conceicao *et al.*, 2001; Malakar & Mishra, 2017). Overall, these indicators have been widely used to evaluate structural transformation and concentration trends in agricultural and livestock markets.

MATERIALS AND METHODS

Data Sources

This study uses data from the USDA Census of Agriculture and national inventory estimates from the USDA NASS. The Maryland analysis is based on county-level census data for all goats (inventory and sales) across five census periods: 2002, 2007, 2012, 2017, and 2022. After accounting for disclosure-related omissions, the final dataset consists of 92 county–year observations across Maryland counties for the five census periods included in the analysis. National descriptive tables, including sales class, ownership structure, operator tenure, and concentration, are also presented to provide an in-depth institutional background.

Maryland's Goat Inventory and Contribution to U.S. Goat Inventory

An analysis of Maryland goat inventories by production type was conducted using the 2022 USDA Census of Agriculture to evaluate the structural composition of the state's goat industry. As of January 1, 2022, inventory headcount was categorized according to USDA criteria into total goats (all types), meat and other goats, milk goats, and Angora goats. Shares of each category were computed relative to total inventory to enable comparison across production types and to identify areas of relative specialization.

Maryland's contribution to the U.S. goat inventory for each category is calculated as the ratio of Maryland's inventory to the total U.S. inventory, represented as a percentage.

$$\text{Maryland Share}_i=\frac{\text{Inventory}_{MD,i}}{\text{Inventory}_{US,i}}\times 100 \tag{1}$$

where:

i denotes the goat category. This analytical method provides a clear assessment of Maryland's position in the national goat industry.

Structural Characterization of Goat-Selling Operations in Maryland

Goat-Selling Operations by Farm Size

Data from the USDA Census of Agriculture for 2012, 2017, and 2022 are used to analyze goat-selling enterprises based on acreage classification (farm size). The selected census years use consistent farm-size classifications. To simplify analysis, farms are grouped into three size categories: less than 50 acres, 50–99.9 acres, and 100 acres or more. The 2002 and 2007 census data were excluded because of definitional inconsistencies.

Goat-Selling Operations by Economic Class

Goat-selling operations data are extracted from the 2012, 2017, and 2022 agriculture censuses and classified into three economic categories based on gross farm sales:

- Low revenue: < \$10,000
- Mid revenue: \$10,000–\$49,999
- High revenue: ≥ \$50,000

NAICS Classification of Goat-Selling Operations

Production orientation is evaluated by categorizing goat-selling operations by their primary North American Industry Classification System (NAICS) code, using Census data from 2012, 2017, and 2022. Operations are grouped into major production categories relevant to goat production, including sheep and goat farming, beef cattle ranching, poultry and egg production, and crop-based systems.

Variables and indicators

For each county c and year t, the variables were constructed using data from the Maryland Census of Agriculture for the corresponding year.

- $\text{InventoryFarm}_{ct}$: farms with goat inventory
- $\text{InventoryHead}_{ct}$: number of goats in inventory
- SalesFarms_{ct}: farms reporting goat sales
- SalesHead_{ct}: goats sold (head)

The study constructed two commercialization indicators as given by Kibona & Nyariki (2009) and Nyariki (2009):

$$\text{Market Participation } (MP_{ct})=\frac{\text{SalesFarms}_{ct}}{\text{InventoryFarms}_{ct}} \tag{2}$$

$$\text{Offtake Rate } (OR_{ct})=\frac{\text{SalesHead}_{ct}}{\text{InventoryHead}_{ct}} \tag{3}$$

Market participation is defined in the study as farmers' involvement in livestock sales, determined by the frequency of any sales during the period, while the degree of participation is measured by the quantity of animals sold (Kibona & Yuejie, 2021). Similarly, the offtake rate in the study is defined as the proportion of animals removed from a herd through sales, slaughter, or other exits during a given period (Tapson, 1990; Nyariki, 2009; Baldwin, 2008). In some counties, calculated participation and offtake rates exceed 100%. This occurs because the USDA Census reports point-in-time inventory and annual sales separately. Goats may be bought and sold multiple times within a year, or animals may be moved across counties for marketing purposes. As a result, the total number of goats sold during the year can exceed the inventory recorded at the census reference date. These values, therefore, reflect market turnover and animal movement rather than measurement errors.

For econometric estimation, we apply logarithmic transformations to reduce skewness in the distribution of the variables. Because some county–year observations contain zero sales, a log-plus-one transformation was applied to preserve these observations while reducing skewness in the dependent variable.

$$\ln(\text{SalesHead}_{ct}+1), \ln(\text{InventoryHead}_{ct}+1), \ln(\text{InventoryFarms}_{ct}+1) \tag{4}$$

The log-plus-one transformation is applied because some county-year observations report zero goat sales. Taking the natural logarithm of sales plus one allows these observations to remain in the sample while reducing skewness in the distribution of the dependent variable.

Market participation was analyzed using a binomial generalized linear model (GLM) with a logit link. The model was computed as given by Buckley (2015).

$$y_{gt} \sim \text{Binomial}(n_{gt}, p_{gt}) \quad (5)$$

$$\log\left(\frac{p_{gt}}{1-p_{gt}}\right) = \alpha + \beta_1 \, \text{PartOwner}_g + \beta_2 \, \text{Tenant}_g + \beta_3 \, \text{OneOperator}_g + \lambda_t \quad (6)$$

where:

• full-owner and multi-operator farms form the baseline category,

• ygt denotes the number of farms reporting goat sales,

• ngt denotes the number of farms holding goat inventory for group g in the census year t,

• λ_trepresents year fixed effects.

• Commercialization intensity in the study was estimated by using a Poisson regression model with an offset.

where:

• ygt denote the total sales head,

• sgt denote the number of goat selling farms.

The model was computed based on Frome (1983).

$$y_{gt} \sim \text{Poisson}(\mu_{gt}) \quad (7)$$

$$\ln(\mu_{gt}) = \alpha + \beta_1 \, \text{PartOwner}_g + \beta_2 \, \text{Tenant}_g + \beta_3 \, \text{OneOperator}_g + \lambda_t + \ln(s_{gt}) \quad (8)$$

where:

The offset ln sgt captures sales per participating farm.

Structural concentration in the study was examined using a fractional logit model and computed based on Aditya & Acharyya (2011) and Misango *et al.* (2022), where the dependent variable is the group-level inventory share:

$$q_{gt} = \frac{\text{InventoryHead}_{gt}}{\sum_g \text{InventoryHead}_{gt}}, 0 < q_{gt} < 1 \quad (9)$$

To assess overall concentration across tenure groups, the Herfindahl–Hirschman Index (HHI) and Theil index were computed using inventory head and sales head shares.

where:

• skt denote the share of group k in year t,

• The indices are defined as given by Aditya & Acharyya (2011) and Conceicao *et al.* (2000).

$$HHI_t = \sum_{k=1}^{K} s_{kt}^2 \quad (10)$$

$$Theil_t = \sum_{k=1}^{K} s_{kt} \ln(K\, s_{kt}) \quad (11)$$

This analysis complements the county-level fixed-effects estimates by illustrating patterns of participation intensity and concentration across ownership and operator structures.

Econometric model specifications

Two-way fixed effects (TWFE-OLS)

To examine the relationship between herd size, farm numbers, and goat sales, the study employs a panel data framework with county fixed effects. The fixed-effects specification controls for time-invariant county characteristics such as geographic conditions, historical livestock specialization, and regional market access. This approach allows the analysis to focus on within-county changes over time, reducing potential bias from unobserved heterogeneity. We estimate a two-way fixed effects model following Blanc & Schlenker (2017) and Aguilar-Loyo, (2025):

$$\ln(\text{SalesHead}_{ct}+1) = \beta_1 \ln(\text{InventoryHead}_{ct}+1) + \beta_2 \ln(\text{InventoryFarms}_{ct}+1) + \alpha_c + \delta_t + \varepsilon_{ct} \quad (12)$$

where:

- α_cdenote county fixed effects,
- δ_tdenote year fixed effects.

Identification relies on within-county variation in goat inventory and farm counts over time. The log-plus-one transformation accommodates zero or low values while preserving interpretability.

Poisson Pseudo-Maximum Likelihood with fixed effects (PPML-FE)

Because SalesHeadct is a count variable that can take low values, we estimate a Poisson pseudo-maximum likelihood model with county and year fixed effects:

$$E[\text{SalesHead}_{ct}] = \exp\left(\beta_1 \ln(\text{InventoryHead}_{ct}+1) + \beta_2 \ln(\text{InventoryFarms}_{ct}+1) + \alpha_c + \delta_t\right) \quad (13)$$

In addition to the fixed-effects OLS specification, a PPML-FE is estimated as a robustness check. PPML is particularly appropriate for count data and is robust to heteroskedasticity. Estimating both models allows the study to assess whether the results are consistent across alternative econometric specifications. Both models use the available non-suppressed county-year observations, resulting in a regression sample of N=92 county-years.

Variance inflation factors (VIFs) for all explanatory variables were under 5, with a maximum VIF of 2.3. This indicates no significant multicollinearity. The PPML specification yields consistent estimates for count outcomes, even in the presence of heteroskedasticity, and effectively handles zero or low-valued observations.

Model Selection and Diagnostics

We estimated pooled ordinary least squares (OLS), random effects (RE), and fixed effects (FE) models using Maryland county-level data from the 2002 to 2022 Census years (see Table 1). The Breusch–Pagan Lagrange Multiplier (LM) test rejected the null hypothesis of no panel effects (LM = 28.41, $p < 0.001$), indicating the presence of unobserved county-level heterogeneity and that pooled OLS is unsuitable.

The F-test comparing pooled OLS and fixed effects was statistically significant ($F = 7.36$, $p < 0.001$), indicating county fixed effects are collectively non-zero

Table 1: Panel model selection and diagnostic tests

Test	Statistic	p-value	Null Hypothesis	Decision	Interpretation
Breusch–Pagan LM test (Pooled OLS vs RE)	LM = 28.41	< 0.001	No panel effects	Reject H_0	Significant county-level heterogeneity exists; pooled OLS is inappropriate
F-test (FE vs Pooled OLS)	F = 7.36	< 0.001	All county fixed effects = 0	Reject H_0	County fixed effects are jointly significant; FE required
Hausman test (FE vs RE)	$\chi^2 = 12.87$	0.0016	RE estimator is consistent	Reject H_0	Regressors correlated with county effects; FE preferred over RE
Wooldridge test (Serial correlation)	F = 6.42	0.014	No first-order serial correlation	Reject H_0	Serial correlation present; cluster standard errors

Notes: FE = Fixed Effects; RE = Random Effects.

and must be incorporated in the model. The Hausman specification test rejected the random-effects assumption ($\chi^2 = 12.87$, $p = 0.0016$), suggesting that the explanatory variables are related to unobserved county-specific characteristics. This finding indicates that the random effects estimator is inconsistent and that the fixed effects estimator is preferable. The Wooldridge test for first-order serial correlation rejected the null hypothesis of no autocorrelation ($F = 6.42$, $p = 0.014$). To ensure correct inference in the presence of serial correlation and heteroskedasticity, the fixed-effects estimates are reported with standard errors clustered at the county level. These diagnostic tests validate the use of a two-way fixed effects model with fixed effects for both county and year as the primary empirical specification.

RESULTS AND DISCUSSION

Goat inventory type in Maryland, 2022

Results show that Maryland's goat inventory in 2022 totaled 12,830 heads. The majority of goats, 9,329 (72.7%), were meat and other goats. Milk goats constituted the second-largest category, 3,041 heads (23.7%), with Angora goats accounting for 460 heads (3.6%). Although meat production is the main focus of Maryland's goat industry, the significant number of milk goats indicates a distinct dairy-oriented feature compared to other smaller production categories. Overall, these trends indicate that Maryland's goat industry is primarily oriented toward meat production, as meat and other goats account for nearly three-quarters of the state's total inventory. However, the notable presence of milk goats also suggests that dairy goat production represents an important secondary component of the state's goat sector.

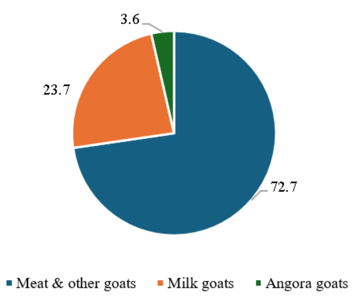

Figure 1: Goat inventory type in Maryland, 2022 (%). *Source: USDA Census of Agriculture (2022); USDA NASS January 1 Inventory Survey.*

Comparison of Maryland goat inventory to total U.S. goat inventory

Table 2: Comparison of Maryland goat inventory with total U.S. goat inventory

Category	U.S. Total Inventory (Head)	Maryland Inventory (Head)	Maryland Share of U.S. (%)
Total Goats (All Types)	2,570,000	12,830	0.50
Angora Goats	110,000	460	0.42
Meat & Other Goats	2,040,000	9,329	0.46
Milk Goats	420,000	3,041	0.72

Table 2 shows that Maryland accounts for less than one percent of the total U.S. goat inventory in 2022. Despite this small overall contribution, Maryland shows a relatively stronger presence in the dairy goat sector compared with the national average. Milk goats represent 0.72% of the U.S. milk goat inventory, which is higher than Maryland's overall share of 0.50% of total U.S. goats. In contrast, Maryland's share of meat and other goats (0.46%) and Angora goats (0.42%) remains slightly below its overall share. This suggests that while meat goats dominate within Maryland, the state is relatively more specialized in dairy goat production compared with the national distribution.

Statewide trends in Maryland goat inventory and sales

Table 3 provides an overview of goat inventory and sales in Maryland from 2002 to 2022. The number of goat farms increased from 702 in 2002 to a peak of 1,163 in 2007 (+65.7%) and then stabilized at around 1,000 farms in subsequent censuses (903 in 2012; 1,085 in 2017; 1,023 in 2022). Goat inventory increased significantly from 9,601 in 2002 to 16,889 in 2007 (75.9% increase), before declining to 12,830 head by 2022.

Market participation (sales farms) increased from 282 in 2002 to 507 in 2017 (+79.8%), before declining to 394 farms in 2022. The proportion of inventory farms involved in sales rose from 40.2% in 2002 to 46.7% in 2017, then decreased to 38.5% in 2022.

Sales volume (head sold) increased from 3,914 in 2002 to 7,264 in 2017 (+85.6%) and then declined to 4,654 in 2022. Overall sales grew from $723,000 in 2012 to $1.088 million in 2017 and remained relatively stable at $1.080 million in 2022. This stability occurred despite a decline in sales volume in 2022, indicating that higher unit prices offset the reduction in quantities sold. Statewide trends show rapid growth from 2002 to 2007, increased commercialization through 2017, followed by a decline in market participation and sales volume after 2017.

Table 3: Goat inventory and sales in Maryland (state totals), 2002–2022

Year	Inventory farms	Inventory head	Number of farms sold	head sold	Sales value ($1,000)
2002	702	9,601	282	3,914	NA
2007	1,163	16,889	470	7,216	NA
2012	903	10,745	400	5,134	723
2017	1,085	13,833	507	7,264	1,088
2022	1,023	12,830	394	4,654	1,080

Source: Author's calculations based on Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

County-level descriptive patterns in goat production and sales

Table 4 shows the wide variation in goat production and commercialization across Maryland counties. In 2002, market participation rates ranged from 19.0% in Howard County to 68.8% in Cecil County, while offtake rates ranged from 21.8% in Caroline County to 148.6% in Prince George's County. These initial differences indicate inconsistent participation in commercial markets, even with moderate statewide averages.

dispersion expanded more in 2007. Market participation ranged from 20.4% in Cecil County to 75.0% in Talbot County, while offtake fluctuated from 13.9% in Dorchester County to 173.5% in Kent County, indicating that certain counties experienced unusually high turnover relative to existing inventories. In 2012, participation ranged from 23.7% in Harford County to 82.4% in Howard County, while offtake ranged from 15.4% in Harford County to 103.9% in Howard County, showing a partial comeback in commercialization following the post-2007 decline in average inventory and sales.

County-level differences peaked in 2017, coinciding with the highest average levels of commercialization. Market participation ranged from 14.3% in Prince George's County to 116.7% in Worcester County, while offtake ranged from 10.4% in Baltimore County to 395.2% in Worcester County. These extremes highlight significant regional variations in herd shifts, marketing intensity, and census-year dynamics across counties.

By 2022, commercialization had diminished and become increasingly inconsistent. Market participation ranged from a minimum of 7.0% in Baltimore County to a maximum of 100.0% in Dorchester County. Offtake rates declined significantly, ranging from 5.2% in Baltimore County to 60.9% in Wicomico County. These patterns suggest that county-level goat commercialization improved until 2017 but declined significantly by 2022, showing large and persistent cross-county differences.

County-level concentration in goat production and farms

Goat sales are concentrated in a relatively small number of counties, while many counties contribute only a small share of statewide sales. This pattern suggests persistent regional specialization in goat marketing activity (Table 5). In each census year, the county with the highest presence accounts for about 12–15% of the total goat inventory and 11–13% of goat farms, whereas the smallest counties contribute less than 1%, indicating a highly uneven geographical distribution of production capacity.

Larger production hubs have remained dominant over the years. Counties such as Frederick County consistently show the highest percentages of farms and often lead in

Table 4: County-level descriptive statistics and dispersion in commercialization (%) by census year (All goats)

Year	Inventory number (mean)		Sales number (mean)		Mean market participation (%)	County market participation (%)		Mean offtake (%)	County offtake (%)	
	Farm	Head	Farm	Head		Min	Max		Min	Max
2002	34	484	15	221	43.2	19.0 (Howard)	68.8 (Cecil)	44.2	21.8 (Caroline)	148.6 (Prince George's)
2007	55	734	21	322	43.3	20.4 (Cecil)	75.0 (Talbot)	48.9	13.9 (Dorchester)	173.5 (Kent)
2012	32	401	14	179	45.5	23.7 (Harford)	82.4 (Howard)	43	15.4 (Harford)	103.9 (Howard)
2017	48	601	22	347	55.2	14.3 (Prince George's)	116.7 (Worcester)	64.2	10.4 (Baltimore)	395.2 (Worcester)
2022	45	608	17	242	40.8	7.0 (Baltimore)	100.0 (Dorchester)	31.2	5.2 (Baltimore)	60.9 (Wicomico)

Notes: County coverage varies by census year. Data for 2002 is available for 18 counties, whereas data for all 23 counties are available for subsequent census years. Percentages are means across counties with available (non-suppressed) values.
Source: Author's calculations based on the Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

inventory, with Washington County standing out as the primary contributor to inventory in 2022. Conversely, smaller counties, such as Talbot County and Dorchester County, typically have the lowest proportions of farms or livestock.

Furthermore, these percentage trends remain stable despite variations in statewide totals (as shown in the table), indicating that changes in overall inventory and farm counts are driven primarily by growth or decline within established hubs rather than by convergence across counties. The percentage-based evidence supports the previously reported mean trends, confirming that Maryland's goat production is structurally concentrated, which affects market access, processing infrastructure, and the focus of extension and policy interventions.

Table 5: County-level concentration in goat production and farms (% of state total), by census year (All goats)

Year	**Metric**	**Minimum (% of state total)**	**County (Minimum)**	**Maximum (% of state total)**	**County (Maximum)**
2002	Inventory farms	0.7	Allegany	8.3	Frederick
	Inventory head	1.1	Queen Anne's	12.2	Garrett
2007	Inventory farms	0.3	Talbot	11.6	Carroll
	Inventory head	0.3	Kent	14.9	Frederick
2012	Inventory farms	0.4	Kent	12.2	Carroll
	Inventory head	0.6	Talbot	13.7	Frederick
2017	Inventory farms	0.2	Talbot	13.1	Frederick
	Inventory head	0.2	Worcester	14.4	Frederick
2022	Inventory farms	0.1	Dorchester	12.1	Frederick
	Inventory head	0.1	Talbot	13.8	Washington

Notes: Percentages are calculated as each county's share of the statewide total in the corresponding census year, using only goats and excluding suppressed (D) observations.
Source: Author's calculations based on Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

Land-size structure of goat inventory farms in Maryland

Table 6 shows the distribution of goat farms by landholding size across several census years. This sector is mainly comprised of small farms. In 2002, farms with 1–49 acres accounted for approximately 70% of all goat farms. This proportion continued to increase steadily, exceeding 75% in 2012 and reaching 76.4% in 2022. In contrast, medium-sized farms (50–179 acres) held a significantly smaller share, declining from 24.1% in 2002 to 18.3 percent in 2017, before rising moderately to 20.5 percent in 2022.

Table 6: Goats by size of farm (acres): All inventory (farms), Maryland, 2002–2022

Farm size (acres)	2002	2007	2012	2017	2022
1–49	69.8	69.2	78.2	76	76.4
50–179	24.1	21.9	24	18.3	20.5
180–449	8.7	9.7	9.1	4.6	(D)
500–999	1.9	0.9	2.1	0.6	0.8
1,000–4,999	2	0.6	0.3	0.6	(D)
5,000+	(D)	0.2	0.2	0.2	(D)

Note: (D) indicates disclosure suppression.
Source: Author's calculations based on Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

During this period, farms larger than 180 acres were relatively uncommon. The percentage of farms in the 180–449 acre range peaked at 9.7% in 2007, then dropped to 4.6% by 2017, with values remaining low in 2022. Moreover, farms larger than 500 acres consistently made up less than 2% of goat farms across all years, indicating the minimal presence of large-scale farmers in the industry. Overall, these patterns suggest a stable small-farm structure, with goat farming in Maryland primarily occurring on small landholdings despite changes in the total number of farms over time.

Goat inventory and sales by legal/organizational status

Figure 2 illustrates the ownership structure of goat farms in Maryland. During this period, family and individual operations dominated the industry. In 2002, they represented 91.4% of all goat farms. This percentage declined to 87.5% in 2012 but rebounded to 90.6% in 2017 and 91.0% in 2022. Conversely, partnerships maintained a small and relatively stable share, fluctuating between 3.0% and 3.8% across all census years.

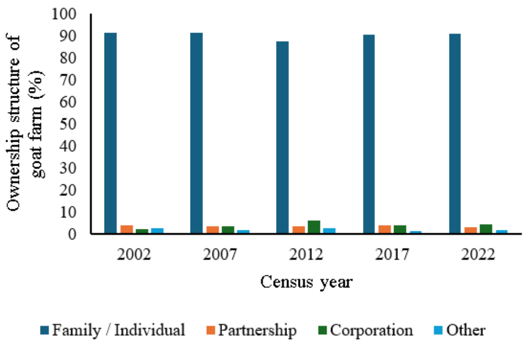

Figure 2: Ownership structure of goat farms in Maryland, 2002–2022.
Source: Author's calculations based on Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

Meanwhile, corporate ownership increased from 2.1% in 2002 to a peak of 6.3% in 2012, showing a gradual shift towards more formal organizational structures. However, this upward trend did not persist, and the corporate share decreased to 4.1% in 2017 and slightly increased to 4.4% in 2022. Other ownership types remained below 2.7% at the minimal level. Overall, these patterns indicate limited structural change, with family ownership continuing to be a key feature of Maryland's goat farming industry.

Goat inventory and sales by operator tenure and number of operators

Table 7 illustrates the tenure status and operational structure of goat farms in Maryland. Throughout all census years, full ownership is the dominant tenure type. In 2002, fully owned farms accounted for 75.6% of goat farms. This share increased steadily, reaching a peak of 82.2% in 2017, before decreasing to 79.4% in 2022. Conversely, partial ownership declined from 20.4% in 2002 to 15.5% in 2017 before slightly increasing to 16.8% in 2022. Tenant-operated farms have always been a small part of the sector, declining from 4.1% in 2002 to 2.2% in 2017, before rising again to 3.9% in 2022.

The operator or operational structure indicates a clear move towards multi-operator farms. In 2002, farms operated by a single operator made up 45.5% of goat farms. After that, its share fell significantly to 34.3% in 2007 and remained below 42% in the following years, reaching a low of 32.1% in 2022. Meanwhile, farms operated by multiple operators increased steadily, rising from 54.5% in 2002 to 67.9% in 2022. Overall, these trends suggest a gradual shift towards shared management responsibilities, alongside a dominant role for full ownership. While land tenure remains mainly stable, goat farming is becoming more collaborative over time.

Table 7: Goat inventory by operator tenure and number of operators in Maryland

Year	**Full owner**	**Partial owner**	**Tenant**	**One operator**	**Multiple operators**
2002	75.6	20.4	4.1	45.5	54.5
2007	75.8	18.7	5.5	34.3	65.7
2012	77.9	18	4	40.6	59.4
2017	82.2	15.5	2.2	41.3	58.7
2022	79.4	16.8	3.9	32.1	67.9

Source: Author's calculations based on Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

Table 8: Tenure status and operator structure of goat sales farms (%)

Year	**Full owner**	**Partial owner**	**Tenant**	**One operator**	**Multiple operators**
2002	72.4	22	5.6	51.6	48.4
2007	67.5	24.3	8.2	49	51
2012	73.8	22.6	4.2	43.7	56.3
2017	62.9	35.8	1.3	33.4	66.6
2022	66.9	27.7	5.3	36.3	63.7

Source: Author's calculations based on Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

Table 9: Distribution of goat-selling operations by farm size in Maryland (2012–2022)

Farm size category	2012 (%)	2017 (%)	2022 (%)
< 50 acres	67.8	76.9	77.2
50–99.9 acres	18.3	11.2	12.5
≥ 100 acres	14.0	11.8	10.3
Total	100.0	100.0	100.0

Source: Author's calculations based on Maryland Census of Agriculture (2012, 2017, and 2022).

Table 8 presents the tenure status and operator structure of farms involved in goat sales in Maryland. Similar to the overall goat farm structure, full ownership remained the most common tenure type among sales farms, although its share fluctuated over time. In 2002, fully owned farms accounted for 72.4% of sales farms. This share declined to 67.5% in 2007, increased to 73.8% in 2012, and then fell to 62.9% in 2017 before slightly recovering to 66.9% in 2022. Partial ownership showed greater variability, increasing from 22.0% in 2002 to 35.8% in 2017, before declining to 27.7% in 2022. Tenant-operated farms consistently represented a small proportion of sales farms, ranging between 1.3% and 8.2%.

The operator structure also shows a shift toward collaborative management. Farms operated by a single operator accounted for 51.6% of sales farms in 2002 but gradually declined to 36.3% in 2022. In contrast, farms with multiple operators increased from 48.4% in 2002 to 63.7% in 2022. These results suggest that goat marketing activities are increasingly associated with farms that rely on shared management and labor arrangements. Compared with the overall goat farm structure presented in Table 7, goat-selling farms show slightly lower shares of full ownership and a stronger reliance on multi-operator management structures. This suggests that farms engaged in market sales tend to rely more on collaborative management arrangements.

Table 9 shows the distribution of goat-selling operations in Maryland, categorized by farm size for the years 2012, 2017, and 2022. The findings indicate a clear and persistent shift toward smaller-scale goat production systems over the study period.

In 2012, farms smaller than 50 acres accounted for 67.8% of goat-selling farms. However, this share increased to 76.9% in 2017 and reached 77.2% in 2022. This trend indicates that the growth in the Maryland goat market has mainly been driven by small farms, rather than the growth of larger operations.

The proportion of large farms (≥ 100 acres) consistently decreased, from 14.0% in 2012 to 11.8% in 2017, and further to 10.3% in 2022. Medium-sized farms (50–99.9 acres) declined from 18.3% in 2012 to 11.2% in 2017, then recovered slightly to 12.5% in 2022. Still, this slight recovery did not offset the continuing dominance of small-scale enterprises.

Overall, these trends indicate that Maryland's goat industry is increasingly defined by small-scale producers, suggesting that goat production operates as a complementary or niche enterprise rather than a land-intensive business. Therefore, efforts to improve the performance of the goat sector in Maryland are likely to yield greater returns if they prioritize market access, collaboration, and value-chain coordination for smallholders rather than simply focusing on scale expansion.

Table 10: Distribution of goat-selling operations by economic class in Maryland (2012–2022)

Economic class	**2012 (%)**	**2017 (%)**	**2022 (%)**
< $10,000	72.0	72.8	67.3
$10,000–$49,999	16.8	21.7	29.1
≥ $50,000	11.3	5.5	3.6
Total	100.0	100.0	100.0

Source: Author's calculations based on Maryland Census of Agriculture (2012, 2017, and 2022).

Table 10 shows the distribution of goat-selling operations in Maryland, categorized by economic class, from 2012 to 2022. Throughout all census years, the goat industry was characterized by low-revenue farms. In 2012, farms generating less than $10,000 accounted for 72.0% of goat-selling operations, a proportion that rose slightly to 72.8% in 2017 before falling to 67.3% in 2022.

The percentage of mid-revenue farms generating between $10,000 and $49,999 increased steadily, rising from 16.8% in 2012 to 21.7% in 2017 and reaching 29.1% by 2022. The proportion of high-revenue farms (≥ $50,000) decreased significantly, falling from 11.3% in 2012 to 5.5% in 2017, and further to 3.6% in 2022.

Overall, the findings indicate that goat farming in Maryland is primarily characterized by small-scale operations. These results suggest that mid-revenue farms may be gradually increasing their level of commercialization.

NAICS-Based Structure of Goat-Selling Operations

Table 11 shows that goat-selling farms in Maryland were primarily classified under Sheep and Goat Farming (NAICS 1124) across all census years. In 2022, this group conducted 189 operations, representing 48.0% of all goat-selling farms. A similar dominance was observed in previous years, with 48.3% in 2017 and 44.5% in 2012, indicating a consistent structural core focused on specialized small-ruminant production.

A portion of goat sales occurred on farms primarily engaged in other agricultural activities rather than sheep and goat rearing. In 2022, Poultry and Egg Production (NAICS 1123) represented 11.9% of goat-selling farms, and Beef Cattle Ranching (NAICS 112111) included 7.6%. Similarly, crop-oriented systems—comprising Other Crop Farming (NAICS 1119) and Mixed Crop Farming (NAICS 11193–11199)—accounted for around 18.3% of operations, underscoring the significance of goats as a supplementary enterprise within diverse agricultural systems.

Temporal comparisons show small yet significant shifts in production orientation. In 2017, beef cattle-oriented farms accounted for a slightly larger share (11.6%) than in 2022, whereas mixed animal production systems (NAICS

Table 11: Distribution of goat-selling operations by NAICS classification in Maryland (%)

NAICS classification	Description	2012 (%)	2017 (%)	2022 (%)
1124	Sheep & goat farming	44.5	48.3	48.0
112111	Beef cattle ranching	13.5	11.6	7.6
1125 & 1129	Other animal production	15.0	12.2	—
1123	Poultry & egg production	4.5	—	11.9
1119	Other crop farming	11.3	7.9	9.4
11193–11199	Mixed crop farming	—	—	8.9
Other NAICS	Remaining categories	11.3	19.9	14.2
Total		100	100	100

Source: Author's calculations based on Maryland Census of Agriculture (2012, 2017, and 2022).
Notes: "—" indicates that the category was not separately reported in that census year and was included under "Other NAICS."

1125 and 1129) were more significant in 2012 (15.0%). Despite these changes, the residual "Other NAICS" category typically represented between 11% and 20% of operations, indicating ongoing variability in agricultural structures.

The analysis based on NAICS indicates that, although specialized sheep and goat farms form the foundation of Maryland's goat industry, a significant share of goat sales originates from multi-enterprise farms that produce both livestock and crops. This structure highlights the integrated nature of goat farming within larger farm operations rather than functioning as a separate commercial operation.

Econometric evidence: within-county determinants of goat sales

Table 12 presents the estimates of county and year fixed effects with standard errors clustered at the county level. All coefficients vary within counties to account for county- and year-specific effects and influences. In the TWFE-OLS model, the coefficient for ln(Inventory head + 1) is positive and statistically significant (β = 0.844, SE = 0.353; $p < 0.05$), indicating that within a county, increases in goat herd size correlate with higher sales volumes. The coefficient on goat inventory is positive and statistically significant, indicating that counties with larger goat populations tend to record higher levels of market sales.

Table 12: County and year fixed effects estimates (All goats)

Variable	TWFE-OLS: ln(Sales head + 1)		PPML-FE: Sales head	
	Coefficient	SE (clustered by county)	Coefficient	SE (clustered by county)
ln(Inventory head + 1)	0.844**	0.353	1.204***	0.319
ln(Inventory farms + 1)	−0.017	0.354	0.039	0.392
County fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
Observations (county–years)	92		92	
R^2 (within)	0.41			
Pseudo R^2	0.36			

*Notes: SE clustered by county. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*
*TWFE-OLS estimates employ the natural logarithm of sales head plus one as the dependent variable. PPML-FE estimates use the levels of sales head and are robust to heteroskedasticity and zero outcomes. Standard errors are clustered at the county level. * $p < 0.10$. R^2 reports the within R^2 from the fixed-effects OLS model. Pseudo R^2 corresponds to the McFadden pseudo R^2 from the Poisson fixed-effects model.*
Source: Author's calculations based on Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

Because the dependent variable is specified as ln(sales + 1), the coefficient can be interpreted as an approximate elasticity for larger values of sales. The results, therefore, suggest a strong positive association between herd size and goat marketing activity. Conversely, the coefficient for ln(Inventory farms + 1) is small and statistically insignificant (β = −0.017, SE = 0.354), indicating that fluctuations in the number of goat farms, when total inventory remains constant, do not independently contribute to sales head. Similar results are found with the PPML-FE estimates: ln(Inventory head + 1) is positive and highly significant (β = 1.204, SE = 0.319; $p < 0.01$), while ln(Inventory farms + 1) remains insignificant. The similarity in sign and significance between TWFE-OLS and PPML-FE models indicates that the findings are robust to different functional forms and distributional assumptions.

Group-level econometric results for Maryland goat operation: participation, intensity, structure, and concentration

Tables 13–16 present the group-level econometric results for goat operations in Maryland based on Census of Agriculture data from 2002 to 2022. The analysis examines how farm ownership structure and operator organization influence market participation, commercialization intensity, inventory concentration, and overall structural distribution within the Maryland goat sector. These models use aggregated group-level observations constructed from Maryland census data across tenure and operator categories, allowing the analysis to capture structural differences among farm types over time.

Panel A

Initially, Panel A of Table 13 presents the results of the binomial generalized linear model for market participation. Compared with the baseline category of full-owner and multi-operator farms, part-owner farms are positively correlated with participation, but the association is statistically insignificant. By contrast, tenant farms show a negative coefficient, indicating a lower probability of market participation but are associated with significant uncertainty. Likewise, the coefficient for single-operator farms is approximately zero, indicating no significant variation in involvement after controlling for tenure and temporal factors. These findings suggest that ownership alone does not strongly influence whether farms participate in goat markets. Instead, market participation appears broadly distributed across ownership types, reflecting the small-scale and diversified nature of Maryland's goat sector.

Table 13: Ownership and operator structure effects on market participation (binomial GLM)

Variable	Coefficient	Robust SE (HC1)
Part owner vs full owner	0.397	0.257
Tenant vs full owner	−0.351	0.41
One operator vs multi operator	0.007	0.086
Year fixed effects	Yes	
Observations	25	

*Notes: Estimates are derived from a binomial generalized linear model with market participation as the dependent variable. The baseline category is full-owner, multi-operator farms. Robust standard errors (HC1) are shown in parentheses. All specifications (models) incorporate year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Panel B

Table 14 estimates of commercialization intensity from a Poisson regression with an offset for the number of selling farms, thereby capturing sales per participating farm. Relative to full-owner farms, both part-owner and tenant farms show positive coefficients, indicating higher sales intensity conditional on market participation. In contrast, single-operator farms show a negative and statistically significant coefficient, indicating substantially lower sales per selling farm than in multi-operator operations. Thus, the ownership structure shows limited and insignificant associations with commercialization intensity, whereas operator organization emerges as a more salient determinant of sales intensity among participating farms.

Table 14: Ownership and operator structure effects on commercialization intensity (Poisson model with offset)

Variable	Coefficient	Robust SE (HC1)
Part owner vs full owner	0.413	0.198
Tenant vs full owner	0.316	0.33
One operator vs multi operator	−0.299***	0.042
Year fixed effects	Yes	
Observations	25	

*Notes: Estimates are from a Poisson regression model with an offset equal to the logarithm of the number of farms selling. The dependent variable is the number of goats sold (head). Coefficients are reported in logs. Robust standard errors (HC1) are shown in parentheses. The baseline category is full-owner, multi-operator farms. All specifications include year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Panel C

Panel C analyzes structural composition using a fractional logit model, with the dependent variable being the share of total goat inventory held by each ownership and operator category. Relative to the baseline group of full-owner, multi-operator farms, both part-owner and tenant farms show large, statistically significant negative coefficients, indicating a substantially lower share of total inventory. Single-operator farms also hold a significantly smaller share of inventory compared to multi-operator operations. These results suggest that goat inventory is disproportionately concentrated among fully owned and multi-operator farms, indicating structural inequality in inventory ownership across production arrangements.

Table 15: Ownership and operator structure effects on inventory concentration (fractional logit model)

Variable (baseline: full owner / multi-operator)	**Coefficient**	**Robust SE (HC1)**
Part owner vs full owner	−2.801***	0.081
Tenant vs full owner	−4.471***	0.137
One operator vs multi-operator	−0.848***	0.116
Year fixed effects	Yes	
Observations	25	

*Notes: Estimates are from a fractional logit model with inventory head share as the dependent variable. Coefficients are reported on the log-odds scale. The baseline category is full-owner, multi-operator farms. Robust standard errors (HC1) are shown in parentheses. All specifications include year fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 16 presents goat inventory and sales concentration across different tenure groups, using the Herfindahl–Hirschman Index and the Theil index. Both measures indicate that goat inventory became more concentrated from 2002 to 2017, with a slight decline in 2022. In contrast, sales heads' concentration levels are consistently lower than those of the inventory head in all years. This pattern suggests that goat ownership is concentrated among certain tenure groups, whereas selling activity is more evenly distributed across farms. These results align with earlier findings in Tables 12–14, which show that full-owner and multi-operator farms hold larger inventories, whereas market participation and sales intensity are more widespread among various tenure and operator types. As a result, goat inventory is mainly concentrated among full-owner and multi-operator farms. However, commercialization outcomes are more evenly distributed across tenure groups.

Table 16: Concentration of goat inventory and sales across tenure groups

Year	Inventory concentration		Sales concentration	
	HHI	Theil	HHI	Theil
2002	0.61	0.43	0.58	0.37
2007	0.61	0.42	0.52	0.29
2012	0.64	0.47	0.59	0.40
2017	0.70	0.56	0.52	0.38
2022	0.66	0.49	0.53	0.32

Notes: The Herfindahl–Hirschman Index (HHI) and Theil index are calculated across tenure categories using inventory head and sales head, respectively. Higher values indicate greater concentration. Source: Author's calculations based on the Maryland Census of Agriculture (2002, 2007, 2012, 2017, and 2022).

CONCLUSION

The findings show that goat commercialization rose rapidly in the early 2000s, continued to grow through 2017, and then declined by 2022. This reduction is primarily due to declines in market participation and sales volume, despite relatively stable inventory and sales value. Significant heterogeneity remains across counties, indicating an important geographical concentration of production. The econometric results show that increases in goat herd size are positively and significantly associated with goat sales within counties, whereas fluctuations in the number of goat farms show little independent influence after inventory is accounted for. The findings indicate that goat commercialization in Maryland is primarily driven by increases in production on established small, family-run, and diversified farms, rather than by increases in the number of new farmers.

Therefore, policy and development initiatives should aim to support herd growth among current producers by enhancing improved breeding stock, veterinary services, feed management, and short-term financing options. Additionally, investing in small-ruminant slaughter, processing, and coordinated marketing channels is essential to reversing the decline in market participation seen since 2017. With production and sales concentrated in specific regions, targeted efforts at the county level are likely to be more effective than uniform statewide efforts and strategies. Ultimately, given the increasing number of small-acreage and low-revenue generating farms, measures that encourage partnerships, infrastructure, and value-chain connectivity will be more suitable than those focusing solely on large-scale expansion.

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