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Can the use of digital technology improve the cow milk productivity in large dairy herds? Evidence from China's Shandong Province

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Introduction: Improving milk productivity is essential for ensuring sustainable food production. However, the increasing difficulty of supervision and management, which is associated with farm size, is one of the major factors causing the inverse relationship between size and productivity. Digital technology, which has grown in popularity in recent years, can effectively substitute for manual labor and significantly improve farmers' monitoring and management capacities, potentially addressing the inverse relationship.

Methods: Based on data from a survey of farms in Shandong Province in 2020, this paper employs a two-stage least squares regression model to estimate the impact of herd size on dairy cow productivity and investigate how the adoption of digital technology has altered the impact of herd size on dairy cow productivity.

Results: According to the findings, there is a significant and negative impact of herd size on milk productivity for China's dairy farms. By accurately monitoring and identifying the time of estrus, coupled with timely insemination, digital technology can mitigate the negative impact of herd size on milk productivity per cow.

Discussion: To increase dairy cow productivity in China, the government should promote both small-scale dairy farming and focus on enhancing management capacities of farm operators, as well as large-scale dairy farms and increase the adoption of digital technologies.

KEYWORDS

herd size, milk production, productivity, digital technology, large-scale farms, sustainable foods production

Introduction

Population growth, rising incomes, and urbanization are driving growth in demand for livestock-derived foods across the globe, including dairy (Lagrange et al., 2015). Global cow milk production must increase in response to the rising demand for dairy products. However, dairy farming is increasingly blamed for environmental and climatic damage because it emits greenhouse gases (GHGs) (Herron et al., 2022). Improving cow productivity can be an effective strategy for sustainable milk production (Kelly et al., 2020) while reducing the associated environmental impacts (Lamkowsky et al., 2021; Faverdin et al., 2022).

Driven by rapid growth and technological innovation, global dairy farming has experienced profound structural change over the past decades, including rapid growth in the average size of primary production units and a shift toward fewer and larger firms in many countries (FAO (Food and Agriculture Organization of the United Nations), 2010). Such changes have significant consequences for farming productivity. One of the most debated findings in agricultural economics is the inverse relationship (IR) between farm size and agricultural productivity (Helfand and Taylor, 2021; Julien et al., 2021). The inverse relationship, first discovered by Chayanov during his study of the Russian peasantry (Chayonov, 1966), was subsequently detected by Sen (1962) in crop production in India. Since then, the inverse farm size-land productivity relationship has been widely discussed in academia and supported by empirical studies in many developing countries (Rada and Fuglie, 2019). IR is mainly caused by the increasing difficulty of supervision and management along with the expanding scale of the operation (Feder, 1985; Ferreira and Féres, 2020), an imperfection in market factors (Sheng et al., 2018), and measurement errors and omitted variables (Deininger et al., 2018a). Other studies have found that the inverse farm size-agricultural productivity relationship has reversed due to new technology adoption and institutional arrangements (Otsuka et al., 2016; Deininger et al., 2018b). For example, the latest breeding, tillage, and information technologies make labor supervision easier and may attenuate diseconomies of scale for large-scale farmers (Deininger and Byerlee, 2012). Moreover, coupled with the development of non-farm employment, the emergence of new institutional arrangements such as farm machinery services facilitates the substitution of machines for labor, resulting in a reversal of the inverse farm size-agricultural productivity relationship (Wang et al., 2016; Yamauchi, 2016).

Though livestock breeding and crop production differ, both confront the increasing difficulty of supervision and management as the farm size expands, but the literature is less clear on the existence of IR. Most of the extant literature on the relationship between herd size and dairy cow yield is based on the descriptive statistical analysis method, which discovered that the larger the herd size, the higher the dairy yield (Lerman, 2008; Yu, 2012; Krpalkova et al., 2016). While some studies have found that larger herd size leads to higher dairy cow yield in the United States, there is no correlation between herd size and dairy cow yield outside of the Southern and Western regions (Weersink and Tauer, 1991). Some scholars have identified that milk production decreases with an increase in herd size (Brown and White, 1973), while others have empirically analyzed the determinants of dairy cow yield and concluded that herd size, in India, has a significantly positive impact on dairy cow yield (Kumar et al., 2020). Ma et al. (2019) found that with grazing dairy farms in New Zealand, an additional increase in stocking rate increased milk solids production per hectare by between 17 and 25% but decreased milk solids production per hectare cow by between 5 and 12%. They found that milking interval, dairy breed, farm labor, access to irrigation, and farm location were all important factors that increased milk solids production. Comparisons need to adjust as much for differences between farming systems (backyard, grazing, TMR) as access to critical inputs such as irrigation. Few studies have empirically analyzed the impact of herd size on dairy cow yield in China and so have missed the opportunity to identify potential causal relationships between herd size and cow yield.

To our knowledge, the role and impact of digital technology in improving cow yield and whether it differs in impact with herd size have not been well researched. Digital technology is a product or service included in or carried by information and communication technology (Lyytinen et al., 2016; von Briel et al., 2018) and comprises two main categories: precision farming technologies and software tools (Birner et al., 2021). In the dairy industry context, digital technology is known as Precision Dairy Farming or smart agriculture technology (Werkheiser, 2018; Eastwood et al., 2019). It may influence the dairy production process in two ways: First, digital technology automates operations and streamlines production steps and labor intensity, thus reducing the demand on operators' management abilities while increasing labor productivity (Barnes et al., 2019; Dela Rue et al., 2020; Yang et al., 2021). Second, digital technology collects data and automatically generates reports (Smith, 2020) to aid operators in decision-making (Huang et al., 2018; Parikoglou et al., 2022) and to improve management efficiency. However, the adoption of digital technologies remains relatively low in dairy farms around the world (Borchers and Bewley, 2015; Gargiulo et al., 2018). The barriers to adopting digital technologies include high initial investment costs and a lack of skilled labor (Pivoto et al., 2019; Bolfe et al., 2020). Compared to small-scale farmers, larger farmers are better able to adopt digital technologies (Lambert et al., 2015; Kolady et al., 2021) due to larger farmers needing more tools to manage their more complex production systems (Carrer et al., 2022) and economies of scale (Zhang et al., 2019; Mao et al., 2021). In China, digital technologies have gained popularity in dairy production systems incorporating TMR feeding (Cox, 2007). Such technologies include automatic cup removers and automatic teat cleaning with disinfection (Edwards et al., 2015), automatic temperature and weight recording devices, milk component monitoring and milk conductivity indicators (Bewley, 2010; Eastwood et al., 2012), wireless identification devices, automatic farm management software (Eastwood et al., 2012) and cow estrus detection tools (Mayo et al., 2019). Except for cow estrus detection, other technologies have either a high or low penetration rate among farms of various sizes (Dong, 2017; Li, 2017; Peng and Li, 2020) with little observed impact on the relationship between herd size and milk yield. Chinese farms of different sizes diverge in their adoption of estrus detection technology, which is more prevalent among farms of more than 1,000 heads and less popular on farms of less than 1,000 heads (Peng and Li, 2020).

Furthermore, cow estrus monitoring is a crucial activity in dairy farming. In the event of a missed estrus, farmers require another estrous cycle (∼21 days), which delays the conception of the cows and, consequently, their milk supply (Gaude et al., 2021). Currently, methods for monitoring estrus in cows include manual and automated inspection. Manual inspection is labor-intensive, and a lack of management leads to missed estrus. Automatic estrus detection, on the other hand, is a type of wearable information monitoring technology in which sensors like pedometers and collars are worn on the legs or necks of cows. The daily step data collected by the sensors is automatically obtained *via* signal receivers and sent to computer software, which then performs statistical analysis to build an information system for dynamic monitoring of cow estrus. Implementing automatic estrus detection in dairy cows can assist management in improving the detection rate and reduce the incidence of missed estrus (Rorie et al., 2002; Steeneveld et al., 2015).

Therefore, this paper aims to extend previous research by analyzing the impact of herd size on dairy cow productivity in China and take estrus detection technology as an example to explore the impact of the interaction between herd size and digital technology adoption on dairy cow productivity. China is an interesting case for two reasons. First, driven by the "Dual Circulation" strategy (Lin and Wang, 2021; Guo et al., 2022), the Chinese dairy sector needs a new focus to meet the strong domestic demand for dairy products, with domestic production as the mainstay and domestic and international supply reinforcing each other. According to the forecast of China's Ministry of Agriculture and Rural Affairs, China's cow milk production and dairy consumption will reach 43.89 million tons and 69.33 million tons by 2030, with a production-demand gap of 25.44 million tons (MEWEC (Market Early Warning Expert Committee, Ministry of Agriculture and Rural Affairs), 2021). Domestic milk production would need to be boosted by 58% to meet the "Dual Circulation" requirements. Second, there are two ways to increase domestic milk production. One approach is to increase the stock of dairy cows.

From 2010 to 2020, the dairy cow numbers fell from 12.108 million heads to 10.43 million heads (HF (Holstein Farmer), and DC (dairy consultants), 2021). The main reason is that China's dairy production is shifting from backyard farming to larger-scale dairy farm production. Thus, despite the considerable decline in dairy cow stock, the average size of dairy farms is expanding significantly. From 2010 to 2020, the average number of dairy cows farmed in China increased from 5.24 to 20.37 head of stock/ dairy farming households at an average annual growth rate of 14.54% (CAHVYED (China Animal Husbandry Veterinary Yearbook Editorial Department), 2021). The other approach is to increase dairy cow productivity. In recent years, China's cow milk production growth has primarily depended on annual cow productivity increases.

Nevertheless, a gap remains in the level of dairy cow yield between China and developed countries. In 2020, China's dairy cow yield was 8.3 tons/year, compared to 10.785 tons/year in the United States, 11.924 tons/year in Israel, and 10.702 tons/year in Canada (HF (Holstein Farmer), and DC (dairy consultants), 2021) in housed, intensive, total mixed ration (TMR) dairy systems. Cow milk production is affected by genetic and managerial factors (Norring et al., 2012; Kato et al., 2022) and the system adopted. Chinese dairy farms have primarily introduced the world-recognized high-yielding breed, the Holstein, so the discrepancy between Chinese dairy yield and that of dairy-developed countries mainly stems from gaps in management among other aspects all else being equal.

This study makes the following marginal contributions: first, while most studies have focused on the impact of farm size on crop production (Aragón et al., 2022), few have paid attention to dairy farming in China (Xia et al., 2020). The negative relationship in crop plantation stems primarily from management supervision capacity and labor effort decrease as farm size increases (Feder, 1985; Ma et al., 2022), whereas dairy farming demands more refined management than crop production. This paper takes dairy farming as an example to fill the existing research gap. Second, it explores the impact of digital technology on the herd size-dairy cow productivity relationship, providing a new perspective for increasing dairy cow yield in China. Third, it empirically tests the impact of herd size on dairy cow productivity using the two-stage least squares(2SLS) regression model in an attempt to improve the accuracy and reliability of the estimation of the impact. In addition, it employs the quantile instrumental variable method for robustness testing.

Materials and methods

Research background

Changes in the size and structure of dairy production and dairy cow yield in China

Before the 1980s, dairy farming in China was concentrated in state-owned farms, with a breeding scale of about 1,000 heads (DAC (Dairy Association of China), 2002). With the development of the market economy and relevant policies, backyard farming evolved into the main pattern of dairy farming in China and remained unchanged for some time. After the Melamine incident in 2008, the Chinese government directed dairy farming toward large-scale, standardized, and intensive development, thereby changing the dominant production model of China's dairy sector (Mo et al., 2012). By 2016, the proportion of farming on a particular scale with an annual stock of more than 100 head exceeded 50%, indicating that the proportion of large-scale dairy farming in China surpassed that of backyard farming for the first time. After 2016, farming on a certain scale became China's primary production model for dairy farming. From 2016 to 2020, the proportion of dairy farms with an annual stock of more than 100 heads grew from 52.3 to 67.2% (DAC (Dairy Association of China), 2021), with an average annual growth rate of 6.9%.

China's dairy cow yield has also witnessed growth as the country's dairy cow systems evolved from backyard-oriented to a large-scale operation. During the 2008–2020 period, the dairy cow yield grew from 4.575 tons/year to 8.3 tons/year nationwide, registering an average annual growth rate of 5.09%. Since 2004, the Ministry of Agriculture has classified dairy farming modes into four categories/systems by the average annual stock of dairy cows: (1) backyard breeding of a stock of fewer than ten heads; (2) small-scale breeding of an annual stock of 10–50 heads; (3) medium-scale breeding of an annual stock of 51–500 heads; and (4) large-scale breeding of an annual stock greater than 500 heads. From 2008 to 2020, dairy cow production of different scales registered yield growth: (1) The average yield of backyard dairy cows increased from 5.14 to 5.48 tons/year with an average annual growth rate of 0.54%; (2) The average yield of small-scale dairy cows increased from 5.16 to 5.61 tons/year with an average annual growth rate of 0.7%; (3) The average yield of medium-scale cows increased from 5.56 to 6.66 tons/year with an average annual growth rate of 1.52%; (4) The average yield of large-scale cows increased from 6.35 to 8.17tons/year, with an average annual growth rate of 2.12% (PDNDRC (Price Department of National Development Reform Commission), 2021).

Shandong is one of the most critical dairy farming provinces in China. From 2016 to 2020, cow milk production in this province occupied about 7% of the total milk nationwide and ranked fourth in China, and its dairy cows accounted for about 8.5% of the national stock and ranked fifth in the country. In the past five years, the dairy herd size and cow yield have been improving rapidly in the province. The proportion of farms with more than 100 heads showed an average annual growth rate of 31.57%, ranking fourth nationwide, and the average annual growth rate of dairy cow yield was 15.04%, ranking second across China.

Use of estrus detection technology in dairy cows

The reproductive performance of dairy cows is critical to the profits of a farm because it affects the time interval between the parity of cows, which in turn affects cow milk production (Reith and Hoy, 2018). The estrus cycle of Holsteins generally lasts 18–23 days, with 21 days on average. The duration of estrus within each cycle is short, lasting 1.7–30.7 h (Dobson et al., 2008). Cows

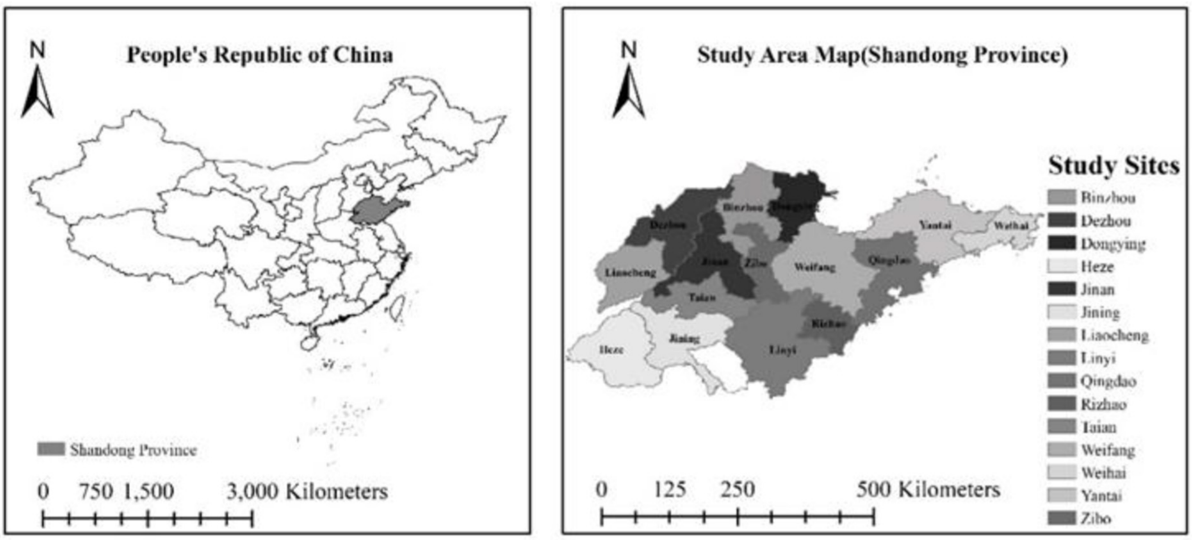

FIGURE 1
Map of the study area.

TABLE 1 Descriptive statistics results of model variables.

Variable name	Definition of variable	Mean value	SD	Minimum value	Maximum value
Dairy cow yield	Average daily milk production per cow (kg/head/day)	28.119	3.545	20	38
Herd size	Whole herd stock (head)	580.902	811.577	88	6,700
Adoption of digital technology	Adopted estrus detection technology = 1; Not adopted = 0	0.258	0.438	0	1
Proportion of hired workers	The proportion of hired workers to total workers (%)	0.763	0.216	0	1
Education level	Years of education (years)	10.766	3.006	0	19
Age	Age of operator (years)	47.912	8.386	22	76
Farming experience	Years of dairy farming (years)	15.207	6.233	3	40
Gender	1 = male; 0 = female	0.901	0.299	0	1
Fixed assets input	Depreciation of fixed assets (Yuan/head/day)	0.774	0.475	0.027	3.193
Amount of concentrated feed input	Daily concentrate feed input per cow (kg/head/day)	9.75	2.172	4	20
Labor input	Daily costs of employed labors and family laborers per cow (Yuan/head/day)	3.472	1.694	0	12.359
Breeding density	Land area per cow (mu/head)	0.178	0.204	0.01	2.381
Parity	Average years of usage per cow (years)	3.893	1.178	1.5	8.5
Breeds	The proportion of heads of Holstein breed cows to the whole herd (%)	0.961	0.112	0	1
Jiaodong area	Qingdao = 1; Dongying = 1; Linyi = 1; Weihai = 1; Rizhao = 1; Weifang = 1; Yantai = 1; otherwise = 0	0.586	0.493	0	1
Central area	Jinan = 1; Taian = 1; Jining = 1; Zibo = 1; Binzhou = 1; otherwise = 0	0.329	0.471	0	1
Western area	Dezhou = 1; Liaocheng = 1; Heze = 1; otherwise = 0	0.085	0.279	0	1

begin to produce milk only after timely and accurate detection of cows in estrus, timely breeding, the conception of cows, and successful delivery of calves. Farmers need to wait for the next estrus cycle (21 days on average) if they fail to detect the estrus, and the increased inputs during cows' missed conception will result in the farm incurring economic losses. Therefore, detecting estrus is a crucial management factor affecting the reproductive performance of dairy cows (Dolecheck et al., 2015; Endo, 2022).

Historically, cow estrus monitoring was accomplished mainly through manual labor, such as external observations of cow activity and rectal and vaginal examinations. These methods, which rely on the experience of farmers, are time-consuming and labor-intensive with a high human cost. In addition, cow estrus frequently occurs at night, when observers are most fatigued, making manual monitoring difficult and possibly resulting in missed estrus. Manual monitoring has become even more challenging as herd sizes grow, with detection accuracy often falling below 50% (Roelofs et al., 2010). Since then, automatic estrus detection has gradually replaced manual detection (Homer et al., 2013). Automatic estrus detection is designed on the principle that cow activity increases when a cow is in estrus. The adult cow will wear a pedometer to identify its number and track its movement. When approached by a cow, the sensor automatically collects data about it and transmits it to a computer, which sends the movement data to a computerized estrus monitoring and analysis system to generate a report. Breeders schedule timely breeding according to the estrus report form. Pedometer estrus monitoring can be as accurate as 80%—90% or even 100% (Stevenson et al., 2014).

Small and medium-sized farms in China still detect cow estrus manually, whereas large-scale farms have utilized cow estrus monitoring systems (Liu et al., 2019). The Chinese self-designed automated estrus monitoring system is still in its early stages, and companies such as Afimilk and SCR from Israel, Delaval from Sweden, and Nadap from The Netherlands have all developed market-ready products (Cao et al., 2013).

TABLE 2 Empirical results on the impact of herd size on the dairy cow yield.

Variable	(1) OLS		(2) 2SLS First stage		(3) 2SLS Second stage	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Average size of county-level farms in 2017	–	–	0.179***	0.044	–	–
Herd size	0.032**	0.013	–	–	−0.197**	0.078
Adoption of digital technology	0.052***	0.015	0.338***	0.075	0.130***	0.033
Proportion of hired workers	0.080***	0.03	1.211***	0.118	0.387***	0.114
Years of education	0.050*	0.027	0.274**	0.112	0.102**	0.044
Age	−0.031	0.042	−0.122	0.181	−0.069	0.07
Breeding experience	0.024	0.015	0.002	0.07	0.028	0.02
Gender	−0.015	0.023	0.036	0.11	0.023	0.028
Fixed assets input	0.050***	0.012	−0.123**	0.058	0.021	0.021
Feed input	−0.018	0.033	0.074	0.149	0.019	0.043
Labor input	0.049***	0.016	−0.249***	0.067	−0.029	0.032
Breeding density	−0.029**	0.011	−0.085	0.053	−0.039*	0.02
Parity	0.013	0.024	−0.319***	0.114	−0.075	0.049
Breeds	0.023	0.049	0.665**	0.306	0.223**	0.092
Western area	0.043*	0.024	0.319	0.207	0.170**	0.086
Jiaodong area	0.059***	0.015	−0.049	0.073	0.031	0.026
Constant term	2.999***	0.22	5.307***	0.946	4.516***	0.646
Observed value	284					
R^2	0.338					

SE, standard errors.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

However, the imported estrus monitoring systems are costly and necessitate specific computer skills on the part of the breeders (Luo et al., 2019).

Econometric model

To examine the impact of herd size on dairy cow yield, we developed the following econometric model.

$$\ln y_i = \beta_0 + \beta_1 \ln size_i + \gamma X_i + \varepsilon_i \quad (1)$$

In model (1), we denote cow yield by the explained variable y_i, referred to as daily milk production per cow for farm i. The $size_i$ is herd size, referring to a farm's total cow numbers. X_i refers to other factors that influence cow yield. We choose basic characteristics of operators and farming features as control variables based on extant research. These include the operator's age; years of education; years of farming; gender; the proportion of hired workers, expressed as the ratio of the number of hired workers to the total number of workers; fixed asset input; feed input per cow; farming density; cow parity; breed, expressed as the proportion of the number of Holsteins to the entire number of cows; the economic region where the farm is located. The ε_i in Equation (1) is a random disturbance term whereas β_0, β_1 and γ are model parameters to be estimated. Our focus is β_1,and a negative and statistically significant $\beta_1$would suggest the existence of an inverse herd size-dairy cow yield relationship.

To further test the role of digital technology on the impact of herd size on dairy cow yield, this paper creates an interaction term of herd size and whether digital technology is applied based on model (1) and constructs the model as follows.

$$\ln y_i = \alpha_0 + \alpha_1 \ln size_i + \alpha_2 DT_i * \ln size_i + \alpha_3 DT_i + \delta X_i + \mu_i \quad (2)$$

In model (2), DT_i is a dummy variable for 'whether digital technology is applied'. Value is taken as 1 when digital technology is applied and 0 when not applied. μ_i is a random disturbance term. α_0, α_1, α_2, $\alpha_3$and δ are model parameters to be estimated. α_1, α_2, $\alpha_3$are the parameters of our interest. A positive and statistically significant α_2 indicates the dairy cow

TABLE 3 Empirical results on the impact of digital technology adoption on the relationship between herd size and dairy cow yield by OLS.

Variable	Coefficient	SE
Herd size	0.036**	0.016
Herd size *adoption of digital technology	−0.009	0.017
Adoption of digital technology	0.109	0.106
Proportion of hired workers	0.075**	0.032
Years of education	0.050*	0.027
Age	−0.033	0.042
Breeding experience	0.025	0.015
Gender	−0.015	0.023
Fixed assets input	0.050***	0.012
Feed input	−0.017	0.033
Labor input	0.049***	0.016
Breeding density	−0.028**	0.011
Parity	0.013	0.024
Breeds	0.021	0.05
Western area	0.044*	0.024
Jiaodong area	0.060***	0.015
Constant term	2.978***	0.228
Observed value	284	
R^2	0.339	

SE, standard errors.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

yield gap between small and larger farms diminishes when digital technology is used.

The key explanatory variables of herd size in models (1) and (2) are theoretically endogenous variables that may lead to endogenous problems and estimate bias in the model. We use the two-stage least squares (2SLS) regression model to solve endogenous problems. We chose the "average size of county-level farms in 2017" as the instrumental variable. This variable meets the necessary condition for being an instrumental variable for the herd size: the average size of county-level farms in 2017 directly influences the size of a single farm in the county in 2020 but does not directly affect the dairy cow yield on a single farm in the county. In equation (2), for the interaction term between digital technology and herd size, we take the interaction term between digital technology and "average size of county-level farms in 2017" as the instrumental variable. In the empirical process, the model underwent the endogenous test and the validity test of the instrumental variables.

To ensure the reliability of the estimation, we adopt two methods for the robustness tests. The first is to change the dependent variable. We transformed the dependent variable of the average daily cow yield in 2020 into the average daily cow yield in spring and winter in 2020. That is because cows dislike heat, and milk production is generally low in summer and autumn, while the average daily yield is high in spring and winter. The second is to change the estimation method. We use the instrumental variable quantile regression method.

Data sources and variable definitions

This paper incorporates data from a survey of dairy farms in Shandong Province in 2020 for empirical research. Due to the dispersed distribution of dairy farms in each county, we gathered the managers/owners of dairy farms to the animal husbandry station of each county and recruited the trained graduate students as enumerators to conduct one-on-one interviews with them. The interview lasted about an hour, and the enumerators filled out questionnaires covering the basic characteristics of the farm manager/owner as well as the farm's cost and benefits in 2019 and 2020, including total milk production, price and quantity of milk sold, cost of feeding the entire herd of cows, amount of feed input, depreciation of fixed assets, labor input and adoption of digital technology, in particular estrus detection technology.

We first used stratified random sampling in the survey and selected 15 cities with relatively more large-scale dairy farming households, considering regional distribution and development disparities. Then, based on the number of dairy farming households of each county in the 15 cities, we selected 1–5 counties with more farming households and conducted a census of dairy farming households in each of these counties. The 15 cities selected in Shandong Province are shown in Figure 1. Zaozhuang is excluded due to relatively few dairy farmers in the city. The survey obtained a total of 361 samples, of which 324 were valid, accounting for 89.75% of all samples.

The most important three variables used in this analysis are cow yield, herd size, and adoption of digital technology. Cow yield is measured in daily milk production per cow reported by farm manager/owner. We define herd size as the highest number of cows per farm during the year. Many studies use the number of milking cows to define herd size (Huettel and Jongeneel, 2011; Dong et al., 2016). However, this is not the case in China. Our definition of herd size follows China Agricultural Product Cost-Benefit Complication, published by the National Development and Reform Commission. The adoption of digital technology is a dummy variable equal to one if the farm adopts dairy cow estrus detection technology and zero otherwise, directly reported by manager/owner. The analysis also controls for a large number of farm characteristics. The labor input includes hired labor and family labor expressed as daily costs per cow. The cost of family labor is reported by the farm manager/owner. The proportion of hired workers and breeds are expressed

TABLE 4 Empirical results on the impact of digital technology adoption on the relationship between herd size and dairy cow yield by 2SLS.

Variable	(1)		(2)		(3)	
	First stage Herd size		Herd size *adoption of digital technology		Second stage Dairy cow Yield	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Average size of county-level farms in 2017	0.168***	0.051	−0.041	0.037	–	–
Average size of county-level farms in 2017* adoption of digital technology	0.036	0.088	0.312***	0.064	–	–
Herd size	–	–	–	–	−0.235**	0.092
Herd size *adoption of digital technology	–	–	–	–	0.133*	0.079
Adoption of digital technology	0.127	0.522	4.467***	0.377	−0.693	0.477
Proportion of hired workers	1.216***	0.119	0.194**	0.086	0.412***	0.123
Years of education	0.273**	0.113	0.191**	0.081	0.086*	0.045
Age	−0.115	0.182	−0.220*	0.131	−0.036	0.066
Breeding experience	0.003	0.070	0.068	0.050	0.02	0.021
Gender	0.032	0.110	0.079	0.080	0.009	0.028
Fixed assets input	−0.127**	0.059	−0.039	0.042	0.017	0.022
Feed input	0.077	0.150	0.050	0.108	0.018	0.043
Labor input	−0.249***	0.067	−0.073	0.048	−0.029	0.033
Breeding density	−0.086	0.053	0.026	0.038	−0.047**	0.019
Parity	−0.316**	0.115	−0.100	0.083	−0.071	0.048
Breeds	0.665**	0.307	0.146	0.221	0.229***	0.088
Western area	0.325	0.208	−0.119	0.150	0.205**	0.097
Jiaodong area	−0.050	0.074	0.010	0.053	0.027	0.026
Constant term	5.331***	0.949	0.600	0.685	4.668***	0.69
Observed value	247		247		247	

SE, standard errors.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

in percentages. Fixed assets input includes total mixed ration (TMR), milking machines, feeding machines and some transport machines, measured by the depreciation. Education is expressed as the manager's years of school and farming experience as the number of years the manager has raised dairy cows. We define breeding density as the total raising land area divided by total cow numbers. The amount of concentrated feed is expressed in quantity. Parity is expressed as the average years the milking cows used. We also controlled the regional difference and expressed in dummy variables.

The definitions and descriptive statistics of the variables used in this paper are shown in Table 1. On average, the milk production per cow is 28.119 kg /day. The average herd size is 580 cows. 25.8% of dairy farms have adopted digital technology, 76.3% have hired workers, and 90.1% of the operators are male. The operators' average age, education level and dairy farming experience are 47.912 years of age, 10.766 years of education and 15.207 years of dairy farming, respectively. In terms of expenditures, the daily depreciation of fixed assets per cow is 0.774 yuan (0.112 US dollars; 2019 dollars). In terms of variable costs, a milking cow receives 9.75 kg of concentrate feed per day. Furthermore, the daily wage for employed and family laborers is 3.472 yuan per cow. The land area per cow is 0.178 Mu (1 Mu = 1/15th of a hectare). The average parity of the cows is 3.893 gestations per cow, and 96.1% of dairy farms use Holstein cows. Furthermore, 32.9% of the farms are located in the central area, 8.5% in the western area, and 58.6% in the Jiaodong area.

Results and discussion

The impact of herd size on the dairy cow yield

Column (1) in Table 2 reports the ordinary least squares (OLS) estimation results of model (1). The coefficient of Herd size is positive and significant at a 1% level, and a 1% increase in herd size increases the dairy cow yield by 3.2%, suggesting that small farms will increase dairy cow yield by

TABLE 5 Robustness test: the impact of herd size on the dairy cow yield by change the dependent variable.

Variable	(1) 2SLS First stage		(2) 2SLS Second stage	
	Coefficient	SE	Coefficient	SE
Average size of county-level farms in 2017	0.178***	0.044	–	–
Herd size	–	–	−0.194**	0.08
Adoption of digital technology	0.331***	0.076	0.109***	0.034
Proportion of hired workers	1.206***	0.119	0.385***	0.116
Years of education	0.287**	0.115	0.106**	0.045
Age	−0.114	0.182	−0.046	0.073
Breeding experience	−0.001	0.07	0.029	0.021
Gender	0.035	0.11	0.025	0.025
Fixed assets input	−0.123**	0.058	−0.001	0.022
Feed input	0.087	0.151	0.033	0.046
Labor input	−0.246***	0.067	−0.014	0.033
Breeding density	−0.08	0.053	−0.041*	0.021
Parity	−0.310***	0.115	−0.08	0.05
Breeds	0.652**	0.307	0.198**	0.09
Western area	0.322	0.208	0.145*	0.08
Jiaodong area	−0.053	0.074	0.005	0.031
Constant term	5.226***	0.96	4.442***	0.643
Observed value	245		245	

SE, standard errors.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

enlarging their herd size in China. The coefficients on the adoption of digital technology (estrus detection technology), Proportion of hired workers, Years of education, fixed asset input, and labor input are all positive and significant, indicating that implementing these practices could also increase dairy cow yield. The coefficient of breeding density is significantly negative, consistent with Ma et al. (2019). In addition, dairy cow yields were higher on farms in the western and Jiaodong areas.

It should be noted that there is a causal relationship between herd size and cow yield but that using the OLS estimation may lead to biased results. Therefore, we used the two-stage least squares (2SLS) regression model. Before doing so, we first tested the validity of the instrumental variables. The Hausman test results reported that the null hypothesis is rejected at a 1% level of significance, indicating that the herd size is considered an endogenous variable. We further conducted weak instrumental variable tests. The Cragg-Donald Wald F-statistic was 14.527, significantly greater than the threshold for the weak instruments test formalized by Stock and Yogo (2005). The above results proved that the model does not have a weak instrumental variable problem. Therefore, the instrumental variable selected in this paper, namely "average size of county-level farms in 2017", is reasonable.

Column (2) of Table 2 presents the first stage regressions of the 2SLS model (1). The estimated effect of the average size of county-level farms in 2017 on herd size is positive and significant. This implies that the larger the average size of county-level farms in 2017, the larger the herd size. As for the magnitude, a 1% increase in average size of county-level farms in 2017 is associated with a 0.181% increase in herd size.

Column (3) of Table 2 reflects the second stage estimation results of 2SLS model (1), which reveal that herd size contributes negatively and statistically significantly to dairy cow yield. When controlling for other factors, a 1% increase in herd size reduced the dairy cow yield by a 19.7%. This indicates that under current conditions where technology, fixed input, and factor input are constant, expanding herd size will result in a decline in the average dairy cow yield in China. That is because management ability and practices are primary milk production determinants (Bewley et al., 2001b). Most large-scale farms evolved from small-scale farms in China, while the large-scale farmers' managerial ability did not improve simultaneously

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TABLE 6 Robustness test: the impact of digital technology adoption on the relationship between herd size and dairy cow yield by change the dependent variable.

	(1)		(2)		(3)	
	First stage Herd size		Herd size *adoption of digital technology		Second stage Dairy cow yield	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Average size of county-level farms in 2017	0.167**	0.049	−0.041**	0.020	–	–
Average size of county-level farms in 2017* adoption of digital technology	0.035	0.096	0.308**	0.104	–	–
Herd size	–	–	–	–	−0.235**	0.094
Herd size *adoption of digital technology	–	–	–	–	0.145*	0.083
Adoption of digital technology	0.127	0.557	4.473***	0.613	−0.785	0.501
Proportion of hired workers	1.210***	0.151	0.183**	0.067	0.413***	0.125
Years of education	0.287**	0.101	0.208**	0.080	0.087*	0.045
Age	−0.107	0.194	−0.212	0.148	−0.011	0.072
Breeding experience	0.000	0.069	0.062	0.053	0.021	0.022
Gender	0.031	0.093	0.078	0.082	0.01	0.025
Fixed assets input	−0.126**	0.057	−0.037	0.039	−0.005	0.023
Feed input	0.090	0.121	0.067	0.078	0.03	0.046
Labor input	−0.246**	0.095	−0.066	0.050	−0.014	0.034
Breeding density	−0.081	0.065	0.035	0.053	−0.051**	0.021
Parity	−0.307**	0.132	−0.087	0.097	−0.076	0.049
Breeds	0.652**	0.221	0.127	0.181	0.206**	0.089
Western area	0.328	0.262	−0.114	0.106	0.183**	0.091
Jiaodong area	−0.054	0.077	0.003	0.058	0.001	0.031
Constant term	5.248***	1.042	0.501	0.752	4.612***	0.677
Observed value	245		245		245	

SE, standard errors.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

(Hu et al., 2019). In recent years, dairy cow farming has scaled up very quickly in China, while dairy farmers have also not improved their management capacity despite expanding herd size (Liu et al., 2018), resulting in farms growing in size but attenuating their cow productivity. This is consistent with previous findings, suggesting that milk production decreases with an increase in herd size (Brown and White, 1973). The drop in milk production is greatest for those rapidly expanded farms. The reasons for this drop included lack of production ability and incorrect management practices (Speicher et al., 1978). In addition, other control variables which significantly impact dairy cow yield include the adoption of digital technology, the proportion of hired workers, years of education, breeds and the economic region where the farm is located still present a positive and significant influence on dairy cow yield. Breeding density has a negative and significant influence on dairy cow yield.

Moderating effect of digital technology

To verify that the adoption of digital technology reduces the demand for management capacity and improves management efficiency, as well as to mitigate the inverse herd size-cow yield relationship further, we empirically analyze the impact of technology adoption on the herd size-cow yield relationship based on model (2). The estimated results are presented in Tables 3, 4. Table 3 reports the OLS estimation results, which indicate that herd size positively contributes to dairy cow yield.However, according to these results, neither digital technology adoption has a significant impact on the dairy cow yield nor does the adoption of digital technology significantly impact the herd size-dairy yield relationship. To address the endogenous problem of the model, we further develop a two-stage least squares (2SLS) regression model. Before that, it was necessary to pass the endogeneity test of herd size and

TABLE 7 Robustness test: influence of herd size on cow yield at different quartiles.

	25*th* Coefficient	SE	50*th* Coefficient	SE	75*th* Coefficient	SE
Herd size	−0.254**	0.11	−0.248**	0.117	−0.241*	0.141
Adoption of digital technology	0.147***	0.039	0.140***	0.052	0.134*	0.081
Proportion of hired workers	0.517***	0.197	0.467***	0.168	0.413***	0.154
Years of education	0.126**	0.059	0.107*	0.058	0.088	0.076
Age	0.028	0.088	−0.05	0.071	−0.133	0.081
Breeding experience	0.023	0.03	0.024	0.024	0.025	0.026
Gender	−0.035	0.04	0.001	0.032	0.039	0.038
Fixed assets input	0.033	0.027	0.006	0.033	−0.022	0.05
Feed input	0.017	0.057	0.045	0.054	0.074	0.073
Labor input	−0.038	0.042	−0.043	0.042	−0.048	0.046
Breeding density	−0.070***	0.024	−0.043**	0.02	−0.016	0.022
Parity	−0.056	0.05	−0.1	0.07	−0.146	0.113
Breeds	0.201	0.165	0.229*	0.121	0.259	0.168
Western area	0.147	0.105	0.185	0.125	0.226	0.198
Jiaodong area	0.052*	0.029	0.028	0.033	0.003	0.049
Constant term	4.321***	0.701	4.751***	0.795	5.207***	1
Observed value	247		247		247	

SE, standard errors.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

the weak instrumental variable test. The Hausman test results showed that the null hypothesis is rejected at a 1% significance level; the Cragg-Donald Wald F-statistic was 7.069, significantly higher than the threshold of the Stock-Yogo weak instrumental variable. According to the results of the above tests, the herd size is an endogenous variable, and the instrumental variables selected in this paper are reasonable.

Columns (1) and (2) in Table 4 report the results for the first stage regression [model (2)]. Column (1) shows that the average size of county-level farms in 2017 positively and significantly impacts herd size. Column (2) shows a positive and significant effect of the interaction between the average size of county-level farms in 2017 and the adoption of digital technology on the interaction between herd size and adoption of digital technology. The results suggest that the average size of county-level farms in 2017 increased the herd size.

Table 4 column (3) reports the second stage estimates of the 2SLS model (2). The regression shows that herd size significantly negatively affects dairy cow yield, and 1% increase in herd size leads to a reduction of 23.5% in dairy cow yield. The negative impact of herd size on dairy cow yield diminishes with the adoption of digital technology. As mentioned above, the reason for the negative effect of herd size on dairy cow yield is that dairy farmers have expanded herd size but have not improved their managerial ability. However, as herd size increases, herd management is the biggest challenge (Bewley et al., 2001a). The adoption of digital technology can help to reduce the requirements for managerial ability and improve managerial efficiency (Eastwood et al., 2012, 2016; Cabrera et al., 2020). Farmers operating larger farms are more likely to adopt digital technology (Läpple et al., 2015; Min et al., 2020) to take advantage of economies of scale (Pierpaoli et al., 2013; Tamirat et al., 2018). Therefore, the adoption of digital technology can attenuate the negative impact of herd size on dairy cow yield. This is supported by the literature, which indicates that larger farms adopting new technologies or management practices can increase milk production (Khanal et al., 2010) due to a scale-bias toward technology adoption (Abeni et al., 2019). China is experiencing a rapid digital transformation of agriculture (Cui et al., 2022; Shen et al., 2022). Large-scale farms have advantages in adopting digital technology (Xie et al., 2021). These suggest that the impact of herd size on dairy milk yield may change as China transforms.

Robustness tests

Tables 5, 6 present the results of the two-stage least squares (2SLS) regressions for the first robustness tests. Column (1) of Table 5, and columns (1) and (2) of Table 6 report the first-stage estimation results. Column (1) of Table 5 and column (1) of Table 6 shows that the average size of county-level

TABLE 8 Robustness test: Influence of digital technology adoption on the relationship between herd size and dairy cow yield at different quartiles.

	25*th*		50*th*		75*th*	
	Coefficient	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Herd size	−0.224**	0.089	−0.237***	0.088	−0.252**	0.108
Herd size *adoption of digital technology	0.207***	0.067	0.223***	0.071	0.242***	0.093
Adoption of digital technology	0.105***	0.034	0.067***	0.024	0.024	0.028
Proportion of hired workers	0.411***	0.141	0.392***	0.117	0.370***	0.114
Years of education	0.087*	0.046	0.056	0.041	0.02	0.047
Age	0.048	0.071	−0.01	0.062	−0.077	0.079
Breeding experience	0.006	0.027	0.007	0.022	0.008	0.022
Gender	−0.025	0.047	−0.014	0.036	−0.002	0.038
Fixed assets input	0.042*	0.022	0.014	0.023	−0.019	0.035
Feed input	−0.01	0.06	0.037	0.047	0.091*	0.054
Labor input	−0.018	0.032	−0.022	0.03	−0.027	0.037
Breeding density	−0.056**	0.022	−0.037**	0.017	−0.014	0.02
Parity	−0.039	0.04	−0.067	0.045	−0.099	0.073
Breeds	0.128*	0.077	0.217**	0.095	0.318	0.207
Western area	0.146**	0.074	0.201*	0.111	0.265	0.194
Jiaodong area	0.051*	0.028	0.017	0.028	−0.021	0.041
Constant term	2.875***	0.32	3.253***	0.278	3.685***	0.33
Observed value	247		247		247	

SE, standard errors.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

farms in 2017 positively and significantly impacts herd size. Column (2) of Table 6 shows that the interaction between average size of county-level farms in 2017 and the adoption of digital technology has a positive and significant impact on the interaction between herd size and the adoption of digital technology. These results are consistent with the above results, indicating that our results are robust.

The regression result in column (2) of Table 5 shows significantly negative coefficients for herd size, implying that statistically significant negative impact of herd size on dairy cow yield corroborating the regression results above and indicating that the research conclusions are robust. The regression result in column (3) of Table 6 shows that herd size significantly influences dairy cow yield, with digital technology significantly attenuating the negative impact of herd size on dairy cow yield, which is consistent with the previous empirical results, indicating the robustness of our findings. In addition, we performed an endogeneity test of herd size and the weak instrumental variable test. The results of the Hausman test indicated that the null hypotheses should be rejected for all models. The Cragg-Donald Wald F-statistic exceeds the threshold for the weak instrumental variable test formalized by Stock and Yogo, indicating our estimations do not suffer from weak instrumental variable problems.

Tables 7, 8 present the estimation results for the second robustness test. Table 7 reports the regression results of the quantile instrumental variables method for the influence of herd size on dairy cow yield. The impact of herd size on dairy cow yield is significantly negative at different quantiles, once again confirming that the main results of this paper are robust. In addition, Table 8 reports the regression results of the quantile instrumental variable method for the influence of digital technology adoption on herd size and dairy cow yield. First, the regression results show that herd size has a significantly negative impact on dairy cow yield, and the adoption of digital technology can significantly mitigate the negative impact of herd size on dairy cow yield, indicating that the above research findings are robust. Second, the regression coefficient of the interaction term of herd size and technology adoption was the largest at the 75th quantile and showed a increasing trend as the quantile increased, indicating that the digital technology adoption on farms with high cow yield had a greater mitigating effect on the negative impact of herd size on dairy cow yield.

Conclusions

Increasing cow milk productivity is essential for ensuring sustainable milk production. However, the impact of herd size on milk productivity is complicated. Based on research data from dairy farms of certain scales in Shandong Province in 2020, this paper used a two-stage least squares (2SLS) regression model to explore the influence of herd size on dairy cow yield and further discussed the impact of digital technology adoption on the herd size-dairy cow yield relationship, citing dairy cow estrus monitoring technology as an example. The main findings are as follows: first, herd size significantly negatively impacts dairy cow yield; second, the adoption of digital technology can attenuate the negative impact of herd size on dairy cow yield.

According to the findings of this paper, our estimates are in line with previous studies that found a negative influence of farm size on land productivity in developing countries. However, the government has provided a series of large-scale oriented subsidies for dairy farms since 2008, resulting in the rapid development of scale in China's dairy sector. The large-scale farms that grew fast from small-scale farms have not upgraded their management and other aspects, resulting in stagnation in China's milk production. Thus, a possible policy option would be to promote small-scale dairy farming to enhance dairy cow yield. Furthermore, the results of this paper also show that the adoption of digital technology can mitigate the negative impact of herd size on dairy cow yield. This is consistent with extant studies that new technologies may change the negative influence of farm size on land productivity. It means large-scale farms' managerial ability could be offset by adopting digital technologies. The role of digital technologies in improving dairy yield is important. As a result, the government should encourage large-scale farms rapidly expanding from small-scale farms to use digital technologies to boost their dairy cow yields. Further research suggestions prompted from the conclusion of this paper include using continuous multi-period panel data to explore the impact of herd size on dairy cow yield. This paper uses cross-sectional data, so the author will extend this work and conduct a follow-up survey on dairy farms to analyze the dynamic influence of herd size on dairy cow yield. Also, while estrus monitoring was chosen as an example for digital technology, the influence of the adoption of different digital technologies on the herd size-cow yield relationship can be compared in further studies.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

Conceptualization and investigation: YQ and JH. Data curation, formal analysis, methodology, visualization, and writing—original draft: YQ. Funding acquisition, project administration, and resources: JH. Supervision: JH and NS. Validation: NS and QZ. Writing—review and editing: JH, NS, and QZ. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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