USDA Economic Research Service
U.S. DEPARTMENT OF AGRICULTURE

Economic Research Report Number 356

January 2026

Precision Dairy Farming, Robotic Milking, and Profitability in the United States

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Economic Research Service
U.S. DEPARTMENT OF AGRICULTURE

Economic Research Service

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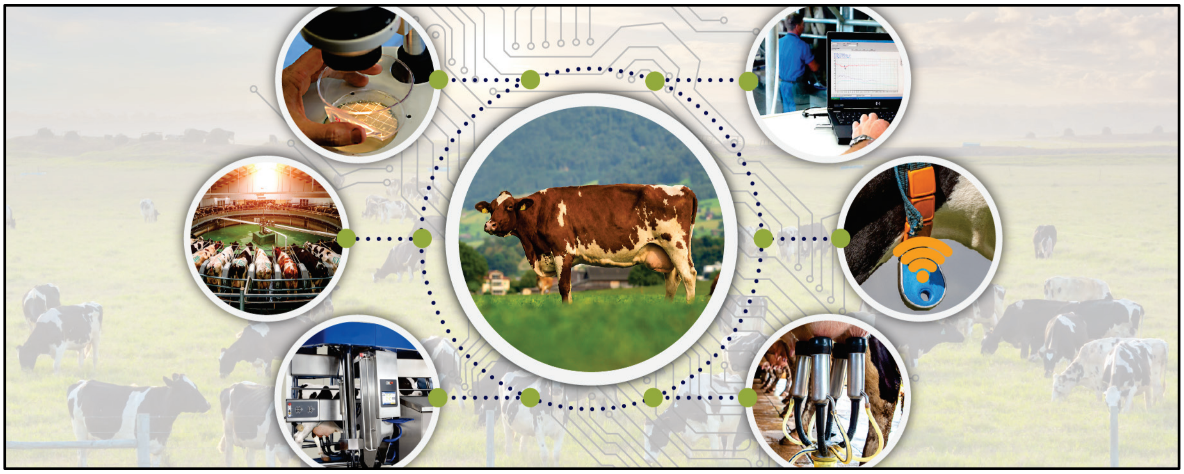
Recommended citation format for this publication:

McFadden, J., & Raff, Z. (2026). *Precision dairy farming, robotic milking, and profitability in the United States* (Report No. ERR-356). U.S. Department of Agriculture, Economic Research Service.



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Abstract

Modern precision dairy farming, including a wide array of sensors, data analytics, and automation technologies, help operators implement cow level—rather than herd level—management practices. Use of one or more of these technologies can reduce average costs and increase milk yields per cow. USDA's Agricultural Resource Management Surveys show that U.S. adoption of precision dairy technologies increased steadily between 2000 and 2021. This report provides aggregate estimates using detailed data from a representative sample of U.S. dairy farms to understand the profitability impacts of adopting precision dairy technologies. We overview and classify precision dairy equipment into three sets of technologies (non-robotic milking, breeding, and data systems), as well as robotic milking, while documenting their increasing use relative to conventional technologies and the characteristics of operators and farms that use them. Building on this information, we develop a model to estimate the impacts of precision technologies on dairy profitability, controlling for farm size and infrastructure, demographics, high speed internet access, and other factors. This analysis is the first to quantify how the adoption of more than one class of precision dairy technologies, including robotic milking, affects dairy net returns.

Keywords: Precision dairy, profitability, digital agriculture, robotic milking, individual cow management

Acknowledgments

The authors thank Brent Hueth, David Donaldson, Jeffrey Gillespie, and Thomas Worth of USDA, Economic Research Service (ERS), as well as Krishna Paudel and James MacDonald (formerly of USDA, ERS) for providing feedback on this research report. We would also like to thank the following individuals for their insights in discussions: Eric Njuki (USDA, Economic Research Service); Lizzy French (USDA, Agricultural Research Service); Nigel Key, Ann Stapleton, Diane Wray-Cahen, Matthew Branan (formerly of USDA); Victor Cabrera and Doug Reinemann (University of Wisconsin-Madison), Marcia Endres (University of Minnesota); Jared Hutchens (University of Illinois Urbana-Champaign); Larry Tranel (Iowa State University); Christopher Wolf

(Cornell University); Katie Meier (Lely Industries); and Jason French and Grant Peissig (DeLaval). Finally, the authors wish to thank Grant Wall for editorial support and Adele Wilcoxen for design help in producing this report.

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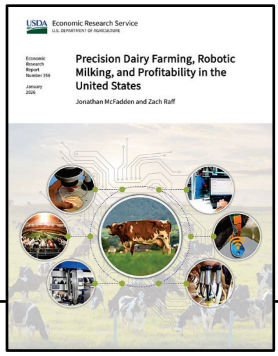


Precision Dairy Farming, Robotic Milking, and Profitability in the United States

Jonathan McFadden and Zach Raff

Key Points

- USDA's Agricultural Resource Management Surveys show that U.S. adoption of precision dairy technologies related to milking, breeding, and data systems increased steadily between 2000 and 2021.
- Precision dairy technologies and robotic milking adoption rates vary substantially by technology, geography, and herd size.
    - We examine in-depth the following 10 precision dairy technologies and practices: holding pen with an udder washer, milking units with automatic takeoffs, computerized milking systems, artificial insemination (AI), embryo transfer (ET), sexed semen, individual cow production records, nutritionist designed diets, computerized feed delivery systems, and "box" robots, which are automated milking systems that have a box-like appearance.
    - In 2021, at least 90 percent of U.S. milk production came from farms using individual cow production records, nutritionist-designed feed, or reproduction-related technologies (e.g., sexed semen).
    - The Fruitful Rim region contains the highest adoption rates of precision dairy technologies, although dairies across all regions of the United States use these technologies. Adopters of complex combinations of precision dairy technologies are, on average, larger than non-adopters. But the largest percentage of adopters of "box" robots are in the 50–149 head range. Partially automated technologies (like computerized feed delivery) were used in producing roughly half of U.S. milk in 2021. By contrast, only 6 percent of U.S. milk came from cows milked via "box" robots.
- The use of precision dairy technologies and robotic milking also varies significantly by farm operator and operation characteristics.
    - Relative to nonadopters, adopters are younger and more educated—with dairies that are larger, more connected via high-speed internet, and having newer barn infrastructure.
    - Adopters have lower expenditures on paid labor (e.g., hired workers on larger dairies), unpaid labor (e.g., family members on smaller dairies), and veterinary care and medicine. Similarly, adopters are more likely to milk their cows 3 or more times per day, have higher milk output per cow, and lower operator hours.
    - These differences between adopters and nonadopters are more pronounced on farms using "box" robots for milking.

Key Points (cont.)

- Precision dairy technologies and robotic milking increase dairy net returns, which are a measure of profitability that subtract the dairy enterprise's operating costs and overhead expenses from milk and cattle sales and other dairy-related income.
  - Operations using two or more classes of precision technologies (non-robotic milking, reproduction-related, or data systems) have 13 percent higher dairy net returns than nonadopting operations, on average.
  - First-of-its-kind estimates suggest that use of "box" robots for milking increases dairy net returns by 13 percent, relative to nonadopters.

Why Does This Matter?

Dairy farm numbers in the United States are decreasing but dairy farm size has been steadily increasing. As dairy farm size increases, dairy farmers streamline their management operations and increase their capital use to meet increasing consumer demand for dairy commodities. The far-reaching technological progress underlying these structural changes has implications for dairy productivity, which is linked to precision dairy farming—technologies that collect and analyze on-farm data to help operators tailor their practices to individual cows and automate routine tasks. Past academic and government research has discussed the costs and benefits of precision dairy technologies, but little work has been done to quantify their impact on U.S. farmers' net returns. This report provides an overview of conventional and precision dairy technologies, their adoption rates, and the characteristics of adopting operators and farms—and then estimates how these technologies affect dairy profitability. The analysis provides the first set of profitability estimates surrounding robotics use in U.S. dairy production using a nationally representative, multi-year sample of commodity producers across the country.

A Few More Details

The study uses data from the Agricultural Resource Management Survey (ARMS), administered by the USDA, Economic Research Service (ERS) and the USDA, National Agricultural Statistics Service (NASS). We analyze detailed data from 5 waves of ARMS—2000, 2005, 2010, 2016, and 2021—for dairy producers to determine precision technology adoption trends and their relationships to operation and operator attributes. The analysis combines these data with ERS's Commodity Cost and Returns dairy data, which provide information on dairy revenues, costs, and net returns for milk. We use the combined data to estimate an economic model of dairy net returns that controls for bias resulting from correlations between farmers' precision dairy farming decisions and unobservable factors that also influence profitability. The study also draws from the dairy science and agricultural engineering literatures to overview and describe the precision technologies of interest.

Glossary of Key Precision Dairy Terms

Artificial insemination (AI) – The practice of manually inserting semen from a selected bull into a female cow, permitting pregnancy without conventional mating, and used mainly to improve the genetic quality of the dairy herd.

Box milking robots – A milking system where a cow enters a box-like stall, is milked automatically without manual labor, and then exits.

Computerized feed delivery systems – Electronic feed bins that use cow-level data to mix rations or provide supplements to forage and grains.

Computerized milking systems – A milking system that collects cow-level data and monitors milking, typically with the ability to alter some parts of the milking process but without full automation.

Embryo transfer (ET) – Allowing producers to select dams, ET is a process that entails selecting a milking cow to serve as an embryo donor for another heifer cow that will carry the pregnancy to term.

Holding pen with an udder washer – A pen containing an automated udder washer that cleans the cows' teats prior to being milked in a parlor, which helps save labor and prevent disease.

Individual cow production records – Cow-level records of milk production characteristics, oftentimes electronic, that are used to help operators make breeding, culling, milking, and other herd management decisions.

Milking units with automatic takeoffs – A technology that guards against under- or overmilking by automatically detaching the milking apparatus from the cow's teats when milking is complete.

Nutritionist to design diets – Employment of a nutritionist to design diets that match the nutritional needs of cows, which has the potential to improve milk productivity and cow health.

Robotic carousel parlors – A high-throughput rotary parlor that automates all steps of the milking process.

Sexed semen – Semen that contains a larger proportion of male or female chromosomes, used to breed offspring of the desired sex.

Precision Dairy Farming, Robotic Milking, and Profitability in the United States

Introduction

Farmers' use of precision agriculture (PA)—modern technologies that emphasize site-specific management of agricultural production with greater precision of input applications and reliance on data-driven decision-making—has increased dramatically over the past three decades. This growth has been partly facilitated by improvements in computing resources, innovations in agricultural engineering, decreasing hardware costs, an expanding number of use cases, and greater awareness of, and familiarity with, the technologies. A more complete understanding of PA's economic impacts throughout the agricultural sector has accompanied this growth. As engineering prototypes have become commercialized technologies and controlled field trials have given way to large-scale use, evidence of the beneficial effects of PA on productivity, costs, and profitability has accumulated (Schimmelpfennig, 2016; McFadden et al., 2022b). These effects—both potential and realized—are particularly notable in the current era of consolidation and increasing digitalization of U.S. agriculture (MacDonald et al., 2018; McFadden et al., 2022b).

U.S. dairy production has experienced a striking amount of consolidation since the 1980s. In 1987, half of all U.S. dairy cows were located on operations with fewer than 80 cows, while half were on farms with greater than 80 cows. By 2017, this midpoint estimate had risen to 1,300 cows. The number of small commercial dairy farms over this period decreased by 79 percent, with declines concentrated mainly in the Northeast and Midwest (MacDonald et al., 2020; Raff & Meyer, 2022). A major driving force of dairy consolidation has been size economies—average cost of milk production falls sharply as herd size increases—partly stemming from large operations' more intensive use of labor and capital (Mosheim & Lovell, 2009; MacDonald et al., 2018). In turn, much of this is influenced by dairy farmers' use of PA technologies like computerized feed delivery systems, computerized milking systems, and other advanced tools. Development and use of these technologies, as well as other innovations in dairy production systems, have been the primary driver of total factor productivity growth in U.S. dairy farming since the early 2000s (Njuki, 2022).

Similarly automated technologies for dairy production, such as robotic milking, automated feed pushers, and automatic estrus-detection[1] monitors, in addition to other PA dairy farming equipment, have been commercially available for several years. Other technologies, especially those increasingly focused on individual cow management (e.g., temperature rumination, activity monitors), have been commercialized more recently (Borchers & Bewley, 2015). However, the extent of their use and impacts on U.S. dairy farmers' financial performance at a national scale are largely unknown (McFadden et al., 2022a). While some national scale analyses report adoption rates for select livestock technologies,

[1] Estrus, commonly termed "heat," is the recurring period of fertility and sexual receptivity in female cows.

much of the focus has been on structural issues, management practices, or general productivity issues (MacDonald et al., 2016; Njuki, 2022; Gillespie et al., 2024).

This report fills the knowledge gap in three ways. First, we overview and discuss various types of precision dairy technologies, contrasting them with conventional and/or less efficient technologies, where relevant. By reviewing the main types of PA dairy technologies (e.g., precision feeding/milking aids, breeding technologies, decision support systems, automated milking methods), this report sheds light on many of the most widely used tools and clarifies subtle technological distinctions (e.g., automated milking versus robotic milking versus computerized milking). Second, we document trends in adoption, both of individual technologies and technology combinations, emphasizing how farmers' use patterns have changed over time and across U.S. regions and farm sizes. Such trends can help identify where technologies are in highest demand, most readily available, or perhaps best suited. In addition, they can help point to the presence of potential scale effects (i.e., farm size-adoption correlations), should they exist. Lastly, we investigate the effect of these technologies on dairy profitability, an underexplored but vitally important dimension of the economics of precision agriculture. Estimates such as these can play a role in helping farmers to pinpoint opportunities for improving their returns on PA technologies. They can also inform proposals designed to boost farmers' uptake or better match operations with the kinds of technologies expected to be financially beneficial. To our knowledge, this report is the first to estimate the effects of robotics use on U.S. farm commodity profitability using large, representative samples of producers over multiple years and located across the country.

The analysis relies heavily on cross-sectional data from five waves of the U.S. Department of Agriculture's Agricultural Resource Management Survey (ARMS) (see box, Agricultural Resource Management Survey: Commodity Data) for years 2000, 2005, 2010, 2016, and 2021. This 22-year period encompasses large changes in the organization, management, and production characteristics of the U.S. dairy sector, making these years ideal for examining the role of PA technologies. To isolate the technological impacts on profitability from the many other things that changed over this time, we use statistical methods that control for a wide array of explanatory factors while removing the effects of potential confounds. The result is a set of robust estimates using a dataset that pools the five cross sections of ARMS dairy data, complementing similar findings for U.S. corn production (Schimmelpfennig, 2016).

Agricultural Resource Management Survey: Commodity Data

The data this report analyzes originate from the U.S. Department of Agriculture's Agricultural Resource Management Survey (ARMS). Conducted annually, this collaborative effort between USDA, Economic Research Service (ERS) and USDA, National Agricultural Statistics Service (NASS) serves as one of USDA's primary tools for gauging the financial conditions, production practices, and economic well-being of the agricultural sector.

ARMS is a multi-frame, stratified, and probability-weighted survey conducted in three phases. The last phase (three)—the main source of information for this report—is completed by April of the year following the survey's reference year and gathers information about farm-level finances, operator household characteristics, and demographics. Although ARMS samples farms of all types (e.g., field crop, livestock, specialty crop) across the conterminous 48 States, we use data only from dairy-specific surveys administered in 2000, 2005, 2010, 2016, and 2021. As with crop-specific surveys undertaken in the second phase of ARMS, livestock commodities like dairy are surveyed on a rotating basis every 4–10 years. Unlike dairy reporting in the Census of Agriculture, the dairy-specific ARMS only surveys farms with at least 10 milk cows.

For this report's analysis, we use data observations with non-missing information including financial outcomes like the cost of feed. The sample sizes in this report are 872 in 2000; 1,814 in 2005; 1,915 in 2010; 1,526 in 2016; and 828 in 2021. Sample farms were in the same set of 22 States in 2000 and 2005: Arizona, California, Florida, Georgia, Idaho, Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, Missouri, New Mexico, New York, Ohio, Pennsylvania, Tennessee, Texas, Vermont, Virginia, Washington, and Wisconsin. In 2010, Colorado, Kansas, Maine, and Oregon were added to the sample. Starting in 2016, dairy operations in South Dakota and Utah were added to the survey, bringing the most recent set of States surveyed to 28. Use of ARMS survey weights ensures that statistical estimates are representative of U.S. dairy production along several dimensions, including the total number of farms, economic sales classes, and physical milk production.

Although the content has changed from survey to survey, recent waves of the dairy version of ARMS Phase 3 has inquired about production and inventories, cow purchases, sales and other income, housing, milking facilities and practices, feed and pasture, and manure, among other items. Information about these characteristics form the basis of the ARMS Commodity Cost and Returns dairy data, created by USDA, ERS's Cost of Production team. These latter data include measures of revenues from milk and cattle sales and other dairy-related income; operating costs attributed to the dairy enterprise (the costs of purchased feed; homegrown harvested feed; grazed feed; veterinary and medicine; bedding and litter; marketing charges; custom services; fuel, lube, and electricity; repairs; hired labor; interest on operating capital; and the cost of organic certification for certified organic dairy farms); and allocated overhead attributed to the dairy enterprise (hired labor, opportunity cost of unpaid labor, capital recovery of machinery and equipment, opportunity cost of land, taxes and insurance, and general farm overhead). The profitability measure used in this report is net returns per hundredweight (cwt) of milk produced, equaling the gross value of milk sales and other dairy-related income less operating costs and allocated overhead expenses for the dairy enterprise (USDA, ERS, 2023).

What is Precision Dairy Farming?

Analogous to PA in crop farming, precision dairy farming is the use of technologies that allow operators to manage their milk herd at the individual cow level, rather than at the herd level. Specifically, precision dairy farming comprises a set of select technologies (e.g., sensors, data analytics, automation) that gather (and sometimes use) data on the physical, biological, and production measures of individual cows (Bewley, 2010). Dairy operators then use these data to optimize their livestock management strategy by streamlining the milking process, better managing their herd and dairy cow replacement, more efficiently using inputs, and preemptively identifying health and/or other problems with individual cows.

The Benefits of Precision Technologies in Dairy Farming

Reduction in input costs. Precision dairy technologies can reduce the input costs necessary for operation, such as feed, veterinary services, and paid and unpaid labor. Precision technologies such as computerized feed delivery can tailor diets to individual cows, thus maximizing efficiency and eliminating waste. Because dairy farming is such a labor-intensive form of agriculture, automation in the process can reduce both paid labor costs (for large farms) and the opportunity costs of unpaid operator and family labor hours (for small farms). For dairy farms with less than 500 head, automation can also impact farmer quality of life by allowing more flexibility in their day-to-day lives. Alternatively, automation in the milking process allows the operator or their family the opportunity to earn additional income off farm, because less time is necessary for the milking enterprise.

Increased revenues through improved herd management decisions and production per cow. Precision dairy technologies allow operators to make more informed decisions regarding herd management, which can increase revenues. Individual cow-level production records and automation in the milking process, for example, help to identify the appropriate milking time and length for dairy cows, which increases milking efficiency and allows for increased milking sessions each day and greater production per cow per milking session.

Improved animal health and breeding practices. Previous work suggests that precision dairy farming may be most beneficial to dairy farms by improving the health and reproduction of dairy cows (de Mol, 2000). Technologies such as artificial insemination, sexed semen, embryo transfer, and genomic selection more broadly allow dairy operators to selectively breed their animals, resulting in replacement cows that are most productive and durable or able to be sold for a greater price at market (e.g., beef-on-dairy). Similarly, precision dairy technologies supplant the need for operators to observe in person each cow for signs of health problems (e.g., lameness). Instead, cow production records, activity monitors, artificial intelligence, and other technologies can help to identify health problems and disease much sooner. This is especially important as dairy herd sizes in the U.S. continue to grow (Gargiulo et al., 2018).

Sustainability. Reducing and more efficiently using inputs, increased productivity per cow, and improved health conditions of dairy cows together improve the sustainability of dairy operations. Precision dairy technologies allow more milk production to occur using fewer cows and helps to eliminate waste in the milking process. For example, by tailoring diets to each cow, there is less feed waste and implications for manure production. And improving the health of dairy cows allows the same cows to be productive for a longer time, again resulting in greater milk production from fewer animals on the landscape.

Types of Precision Dairy Farming Technologies

Precision dairy technologies consist of varying levels of automation, data and decision support, and breeding and health benefits. Thus, available technologies naturally exist on a PA continuum, as shown in figure 1, where some primarily automate processes for individual cows (low level of PA) while others use data and automation for every component of the milking process (high level of PA). In particular, these technologies can be categorized into five overarching activities: feeding and nutrition management; milking, milk quality, and safety; health and activity monitoring and other data collection; breeding and reproduction management; and environmental management. However, in this report, we consider as precision dairy technologies those that gather or use data and allow the operator to optimize their management of the dairy herd at the individual cow level. The report does not, therefore, consider as precision dairy other technologies or infrastructure (e.g., milking facilities) used only to improve efficiency, such as the use of a milking parlor (see box, Efficiency Improvements in Dairy Farming: Precision Dairy Technology vs. Infrastructure and Other Technology, which outlines these differences).[2]

Milking Technologies Other Than Robotic Milking

This class of precision dairy technologies deals with the physical process of milking cows. In general, milking technologies help to automate and streamline the milking process, making it a less labor-intensive task. Milking technologies can also use computers and the internet to improve the productivity of each cow and promote milking conditions that help to prevent health problems. The technologies that the ARMS Phase 3, Dairy surveys track and that comprise this class are holding pen with an udder washer, milking unit with automatic takeoff, and computerized milking system.

Dairy cows' teats become dirty between milkings, as manure or other foreign matter can cake on or around the udders. More dangerous, however, are pathogens present in the cows' environment, which can impact milk quality and lead to intramammary infection, such as mastitis.[3] It is therefore necessary to wash the udders of dairy cows and disinfect the teats before milking. The first precision dairy technology in this class that the ARMS Phase 3, Dairy surveys track is a **holding pen with an udder washer**. Recent trends in milking systems have led to the use of milking parlors, where cows move to a structure outside of the barn for the sole purpose of milking. Before entering the milking parlor, cows congregate in a holding pen that is attached to the parlor, where they wait and are prepared for milking. For this technology, the holding pen contains an automated udder washer, where a system washes the udder and cleans the teats of individual cows (figure A.1, panel A). The most obvious benefit of this technology is labor savings, because without the technology, dairy operators or employees must manually wash the udders and disinfect the teats of each cow. A second benefit of automated udder washing in the holding pen is the prevention of disease, as it can help

[2] For purposes of this report, technologies that are not described in this section, including some of those in figure 1, are not considered to be precision dairy farming. The following is a nonexhaustive set of examples of conventional, rather than precision, dairy farming: older milking technologies (pail unit/bucket milkers, conventional milk meters), certain infrastructures (traditional barns and parlors) and specific barn designs (e.g., stanchions, open stalls), bedding materials (sand, dry matter, mattresses, waterbeds), some feeding technologies (automated feed pushers), certain reproduction methods (natural breeding and conventional genetic selection), basic animal health monitoring (visual inspection only), and conventional cooling technologies (e.g., misters, drenchers).

[3] Mastitis is an inflammation of the mammary gland due to physical trauma and/or infection. It is the most common, economically important disease affecting the global dairy sector, resulting in losses from decreased milk yield and/or milk quality (e.g., Hogeveen et al., 2019).

prevent mastitis. However, teat disinfection—with or without udder washing—is the most important part of the premilking cleaning process.

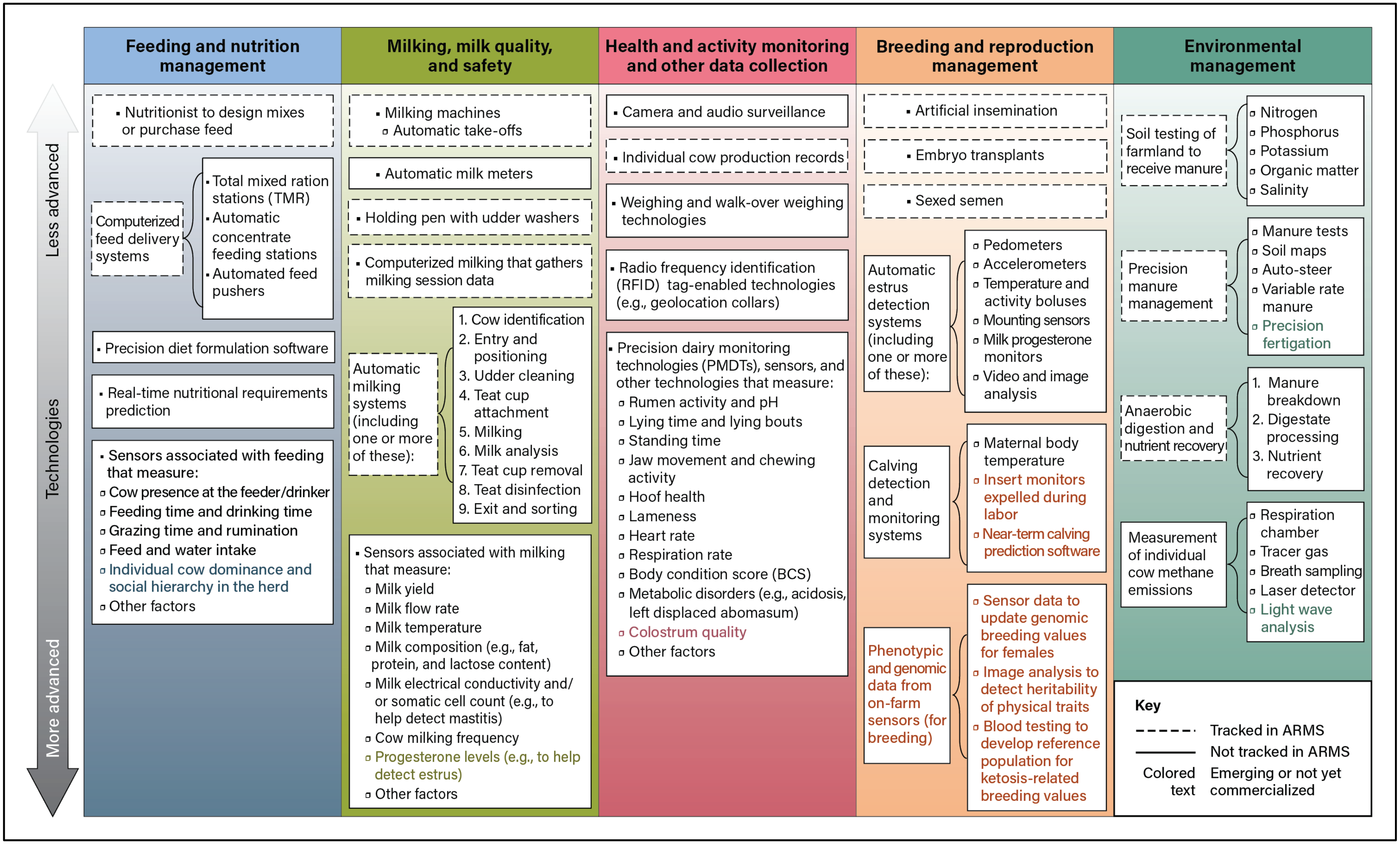
In the United States, the use of holding pens with udder washers is relatively low and has remained consistent over the past two decades; 5 percent of dairy farms used the technology in 2000 while 7 percent of dairy farms used the technology in 2021.[4] In addition to the number of U.S. dairy farms adopting holding pens with udder washers, we also examine the percentage of milk produced in the United States (hundredweight or cwt) by operations using the technology. For this and all other technologies we examine, the milk production percentage is higher than the percentage of dairy farms using the technology, reflecting the fact that large dairy operations—which produce most milk in the United States—drive most precision and other technological adoption (Palma-Molina et al., 2023; Gillespie et al., 2024). In 2000, 27 percent of all milk production occurred at U.S. dairy farms that used holding pens with an udder washer. By 2021, this percentage increased to 32 percent.

Stopping the milking process at the appropriate time is important for dairy operators. Detaching the milking unit before the process is complete lowers milk yield and can lead to uncomfortable cows. And overmilking—continuing the vacuum to pump milk when the udder has stopped producing milk—decreases labor and milking efficiency. To appropriately time the milking process, operators can use **milking units with automatic takeoffs** (figure A.1, panel B). This technology gauges when the milking session is complete, ensuring that each cow is not under- or overmilked. Milking units with automatic takeoffs help to automate the milking process and save labor time because dairy workers do not need to manually detach the milking unit from each cow, thus improving milking unit and cow-level productivity. The animal health and labor-saving benefits of these units, at a comparatively low cost, help to explain the adoption rates of milking units with automatic takeoffs in the United States. In 2000, 24 percent of U.S. dairy farms used this technology; the adoption rate increased to 46 percent in 2021. And 59 percent of milk was produced at U.S. dairy farms using milking units with automatic takeoffs in 2000. By 2021, that percentage increased to 83 percent.

[4] The ARMS Phase 3, Dairy surveys only gather data on automatic udder washing in a holding pen. Udder cleaning, and teat disinfection in particular, are important components of the milking process that are not prohibitively expensive. But many operations in the United States perform these tasks either manually or outside of the holding pen, which are not measured in the ARMS Phase 3, Dairy surveys. Usage rates also may be low because of the uncleanliness of premilking washing. Wash water often collects bacteria from other parts of the cow, which can then concentrate at the teat while the water drains off.

Figure 1

Types of precision dairy technologies



Note: The diagram includes precision dairy technologies not included in the empirical analysis. In the empirical analysis, we focus on precision dairy technologies collected as part of the ARMS Phase 3, Dairy survey. Technologies in darker-shaded boxes tend to be more advanced than those in lighter-shaded boxes.

Source: USDA, Economic Research Service.

The ARMS Phase 3, Dairy surveys also collect information on the use of **computerized milking systems**, which consist of several types of automated milking technologies (figure A.1, panel C). Most important from a precision dairy perspective, these systems collect computerized data on cow health and productivity, milking performance, and other information at the individual cow level (Gillespie et al., 2014). In addition, computerized milking systems monitor important aspects of the milking process, such as duration and milk flow. Operators can then use the computerized system to alter the milking process for individual cows, if necessary. Computerized milking systems can automate some steps of the milking process and provide labor savings. Importantly, we distinguish between computerized milking systems and robotic milking systems; the former represent automated milking and data collection technologies that are connected to a computer but are not fully automated (see below for a full description of robotic milking). Computerized milking systems represent a mid-tier precision dairy farming option between traditional, labor-intensive milking and robotic milking. Coincidentally, computerized milking systems are less expensive than robotic milking systems and may be appropriate for dairy operations that do not wish to pay the large start-up costs of robotic systems. According to ARMS Phase 3, Dairy data, adoption of these systems in the U.S. increased from 6 percent of dairy farms in 2000 to 13 percent of dairy farms in 2021. The percentage of milk produced at dairy farms using computerized milking systems is higher, moving from 20 percent in 2000 to 45 percent in 2021.

Breeding Technologies

Dairy herd management has evolved to include breeding and biological technologies used to improve the genetic traits of replacement animals. In this report, we refer collectively to these technologies as breeding technologies. By selectively breeding animals, dairy operators breed replacement cows that are the most productive milkers, the most resilient to disease, and exhibit other desirable traits that command a greater price at market. Importantly, previous work has identified selective breeding and improved genetics in dairy cows, partly the result of genomic selection, as major factors in increased productivity and efficiency of U.S. dairy farms over the past several decades (DeJarnette et al., 2004; Njuki, 2022).[5] The ARMS Phase 3, Dairy surveys collect information on the usage at U.S. dairy farms of the following breeding technologies: artificial insemination (AI), embryo transfer (ET), and sexed semen. Given the sizable health and production benefits of breeding technologies at relatively low cost, their use on U.S. dairy farms—even among small farms—is abundant. In 2000, 64 percent of U.S. dairy farms used at least one form of breeding technology and 76 percent of U.S. milk was produced by these dairy farms. The farm-level adoption rate increased to 81 percent of U.S. dairy farms by 2021,

[5] Genomic selection refers to a type of genetic selection where information from single nucleotide polymorphisms (SNPs) throughout cows' genomes (i.e., the cow's complete set of DNA) is used to predict cows' genetic potential for various desirable traits (e.g., milk yield, milk composition, fertility, disease resistance). This is a data-intensive process that has involved collecting and analyzing DNA from millions of cows (Hutchins & Hueth, 2023)—a process that has revolutionized dairy cattle breeding since 2000. The rate of genetic progress has approximately doubled since its inception, with accompanying improvements in selection accuracy, reductions in breeding timelines, and—ultimately—a hardier, higher yielding stock of U.S. dairy cows (Wiggans et al., 2017). As with genetic engineering and gene editing, genomic selection is considered a precision livestock technology (McFadden et al., 2023), but it is not a focus of this report due to sparsity of data about U.S. farmers' use of genomic breeding values that can be linked to profitability, farm size, and other factors needed for analysis.

with 96 percent of milk produced by U.S. dairy farms occurring at operations using some form of breeding technology.

When breeding for replacement animals, the selection of the best-suited sires and ensuring a healthy pregnancy with minimal effort are important. From a productivity and replacement animal perspective, **artificial insemination** (figure A.1, panel D), which allows producers to select sires, is one of the most beneficial precision dairy technologies. The physical process of AI also provides benefits over traditional breeding. AI protects against venereal disease from breeding bulls, eliminates the difficult physical process of breeding, and creates situations in which dairy farms do not necessarily need to keep bulls on the farm (Gillespie et al., 2014). As a result, AI results in higher conception rates than traditional breeding (Graves et al., 1997) and a more productive and healthier herd. Collectively, AI is a relatively old precision dairy technology (Ombelet & Van Robays, 2015), but one that produces sizable benefits to dairy operators at relatively low cost.

There also exist dairy breeding technologies that allow operators to choose the most genetically superior dams for herd replacement. **Embryo transfer**, which allows producers to select dams, is a process that involves selecting a milking cow to serve as an embryo donor for another cow that will then carry the pregnancy to term (figure A.1, panel E). Like AI, this technology provides a high level of PA, because dairy operators use individual cow-level data to select donors that contain superior conformation, milk production, and disease resistance genetic traits (all of which improve the ability of the replacement to generate revenues, either through milk production or at sale). In addition to the genetic benefits for replacement animals, ET, like AI, can improve conception rates, especially for repeat breeder dairy cows (Nowicki, 2021). Reducing the number of attempts at conception can result in sizable benefits to the dairy operation's profitability. Because of the number of steps involved in ET, it is typically more expensive than AI (Ferreira et al., 2021).

AI and ET are breeding technologies (i.e., assisted reproductive technologies) that have been used on dairy farms for many years. The benefits of AI and ET are clear: they allow operators to pair sires and dams that produce calves that maximize milk production and minimize health costs. Dairy operators also benefit from breeding calves of a desired sex with technologies like sexed semen. Milking cows represent the primary component of a dairy herd, so replacing older and nonproductive milkers with newer, more productive cows is important. Without the ability to choose the sex of replacement animals, operators incur the costs of breeding for calves that cannot contribute to the milking enterprise (bull calves). In addition, adding bull calves to the herd increases its size and requires the operator to pay more in rearing and other costs that may not lead to a revenue stream. Alternatively, market prices can make it so that breeding beef-cross bull calves on dairy farms for sale is financially beneficial for operators. U.S. dairy farms have begun to use **sexed semen**, which is semen that contains a larger proportion of male (Y) or female (X) chromosomes, used to selectively breed offspring of the desired sex (figure A.1, panel F). Dairy operators frequently use sexed semen together with AI and ET to choose offspring sex and realize the genetic and health benefits of AI and ET. Sexed semen is more expensive than traditional semen (Mississippi State University Extension, 2022), though it can be cost-effective to use or economically beneficial (e.g., it can reduce the production of calves of the unwanted gender).

Data (Decision Support) Systems

Another high-PA level class of precision dairy technologies (and practices) provides data or decision support to dairy operators. This class of technologies tends to use computerized systems to provide dairy operators with individual cow-level data on items such as feed efficiency and milk production. And some data or data support systems, such as computerized feed delivery technology, both collect the data and then use the data to further automate cow-level management. In general, though, these technologies allow the operator to gather and use cow-level data to minimize input costs, reduce waste, and manage the milking enterprise more efficiently. The following technologies comprise this class and are collected in the ARMS Phase 3, Dairy surveys: the use of individual cow production records, a nutritionist to design diets, and computerized feed delivery systems.

When managing a dairy herd, it is important to identify the most productive milking cows both from a financial and breeding perspective. Thus, the collection of **individual cow production records** is a high-PA level practice that dairy operators use (figure A.1, panel G).[6] For each cow, dairy operators keep detailed (typically computerized) records of production characteristics such as the number of milkings each day, the amount of milk produced (per milking or over time), and the quality of milk produced. Dairy operators then use these data to make breeding, culling, and other herd management decisions. Alone, collecting individual cow production records is relatively inexpensive. However, if combined with other forms of precision and automated technologies, production recordkeeping and usage can become expensive. In the United States, the use of individual cow production records has remained consistent over the past two decades. The percentage of dairy farms using this practice was 61 percent in 2005 and 63 percent in 2021.[7] During that same timeframe, total U.S. milk production at dairy farms using individual cow production records increased from 82 percent to 90 percent.

Feeding and optimizing the rations of dairy cows are also key components of managing a dairy herd. Providing the appropriate diets can ensure that dairy cows have the nutrients necessary to improve milk production and quality, health and disease resistance, and reproductive performance, all of which contribute to the sustainability and profitability of the dairy operation. Properly balanced diets typically consist of a mixture of carbohydrates (e.g., grains, forages), proteins, vitamins, minerals, and feed additives (Gillespie, 2023). Also important, feed costs represent large costs on most dairy farms, so optimizing diets and eliminating waste is important from a financial perspective. To ensure proper feeding, many dairy farms (especially large dairy farms with confined animals) have moved to feeding via a total mixed ration (TMR) (USDA, Animal Plant Health and Inspection Service (APHIS), 2016a). A TMR blends the necessary components of a dairy ration into a single, homogeneous mixture. Component feeding, on the other hand, consists of feeding cows forages, grains, and concentrate supplements separately.[8] Several benefits of TMR feeding include increased milk productivity, the

[6] The use of individual cow production records, either electronic or written, paper-based records, is often part of data collection through membership in a Dairy Herd Improvement Association (DHIA). However, the wording of the ARMS Phase 3, Dairy surveys does not require membership in a DHIA for operators to state that they collect individual cow production records.

[7] The 2000 ARMS Phase 3, Dairy survey did not collect data on the farm-level use of individual cow production records.

[8] Between these two feeding styles, a partial mixed ration (PMR) contains a mixture of several dietary components (typically those present in a TMR). However, PMR feeding leaves out some key components of the feed mix, allowing for more

ability of cows to ingest a uniform and nutritionally complete diet in each bite, and improved breeding outcomes (Cabrera, 2014; Schingoethe, 2017). TMRs can be designed specifically for different groups of homogeneous animals, such as lactating cows (Cabrera & Kalantari, 2016), but it is infeasible to provide TMRs at the individual cow level.[9]

The ARMS Phase 3, Dairy surveys collect data on two technologies/management practices related to cow diets that we consider within this category of precision dairy, with both representing high-level PA practices. First is the use of a **nutritionist to design diets** (figure A.1, panel H). Nutritionists can design diets that match the nutritional needs of individual cows, improving milk productivity (especially when paired with individual cow level production records). In addition to saving on input costs, this can provide conservation benefits if the optimal diets reduce nutrient contents in manure (Gillespie et al., 2014). Over the past two decades, the use of a nutritionist to design diets has increased from 67 percent of U.S. dairy farms (2000) to 73 percent of dairy farms (2021).[10] Total U.S. milk production at dairy farms using a nutritionist to design diets has increased similarly, moving from 83 percent in 2000 to 94 percent in 2021.

Second, the ARMS Phase 3, Dairy surveys collect information on the use of **computerized feed delivery systems** (figure A.1, panel I). Like using a nutritionist to design diets, computerized feed delivery systems (i.e., electronic feed bins) use cow-level health, productivity, and other measures to optimize diets (and timing) for individual animals. These systems can monitor individual cow feed intake and provide information on feed efficiency (Bloch et al., 2021). Unlike the use of a nutritionist, who only designs the diets, computerized feed delivery systems can also mix rations or simply provide supplements to forages and grains. Computerized feed delivery systems therefore provide labor or other automation benefits that a nutritionist cannot. The use of computerized feed delivery systems has remained relatively low on U.S. dairy farms during the years that the ARMS Phase 3, Dairy surveys have gathered this information. In 2000, 8 percent of U.S. dairy farms used computerized feed delivery systems. This percentage increased 2 percentage points, to 10 percent, in 2021. However, total U.S. milk production at dairy farms using this technology has seen a larger increase. In 2000, 22 percent of U.S. milk was produced at operations using computerized feed delivery systems. By 2021, this percentage had increased to over half—52 percent—of U.S. milk production.[11]

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personalized supplements or concentrates to be fed separately. As a common PMR feeding example, dairy cows in a free flow milking system are fed a PMR and are then incentivized to visit the milking robot or automated milking system to receive their supplemental nutrients and go through the milking process.

[9] Thus, TMR feeding does not represent a precision dairy farming technology or practice.

[10] The ARMS Phase 3, Dairy questionnaires ask about the practices at each operation during that calendar year. Nearly all dairy operators consult with a nutritionist regarding diets at some point during their tenure on the farm. However, we find that 73 percent used a nutritionist to design diets during the most recent surveyed year (January 1–December 31, 2021).

[11] It is possible that dairy operators use nutritionists or computerized feed delivery systems as a part of TMR feeding. However, we do not observe this combination of practices. It is therefore possible that these data (decision support) systems range in the extent of their technological sophistication and emphasis on individual cow management.

Robotic Milking

Among the more recent and potentially transformative technological developments within precision dairy farming has been robotic milking. This set of technologies automates many or all steps underlying the milking process, from cow identification and entry to teat disinfection, exit, and sorting. Importantly, these technologies automate the preparation and harvest of milk, making them one of few precision farming tools capable of fully automating the harvest of an agricultural commodity. There are two distinct types of robotic milking technologies: box robots for use primarily in barns, which were first unveiled in the Netherlands in 1992, and robotic carousel parlors, introduced in Sweden in 2010 (Jacobs & Siegford, 2012).

Although the exact design and layout of **box robots** vary by brand and model, each has several modules that automate and, in some cases, accelerate the milking process: the milking stall, teat detection system, teat-cleaning system, robotic arm for teatcup attachment, control system, and milking machine (figure A.2, panel A). Each cow wears an electronic collar with a sensor that opens the milk stall if the cow is ready to be milked (typically on a voluntary basis) and eligible based on the cow's predetermined milking frequency. The box robot automatically cleans the teats with water and/or a disinfecting solution to (1) remove manure and other foreign matter that can contaminate milk, and (2) help stimulate the cow's milk ejection reflex. At the same time, the cow receives a nutritional supplement, typically a fraction of concentrate, primarily to incentivize the cow and make the visit more attractive. Next, the teat detection system finds the location and position of the udders through one of various methods (e.g., lasers, ultrasound), establishing a three-dimensional view needed prior to milking. The milk stall's robotic arm then attaches each of the four teatcups in succession, and sensors record milk yield and quality (e.g., temperature, hormone levels, conductivity, somatic cell count) as milking occurs at each of the cow's quarters. When finished, the teatcups detach, the teats are cleaned and an iodine solution is applied to prevent infection, the stall opens, and the cow is directed to another area based on cow-specific management plans (de Koning, 2011; Urbanz & Cardoso, 2023; Myers et al., 2017).

Soon after the development of automatic teatcup attachment in the 1980s, box robots were commercialized in the early 1990s and global adoption increased quickly. Over 35,000 units were available on farms worldwide as of 2017, but the vast majority of those were on European operations (Salfer et al., 2017). The dairy farms that adopt box robots tend to be smaller and thus better suited to the scale that the industry considers optimal: roughly 50–75 cows per unit on farms with up to 300 cows (Marques et al., 2023). Nonetheless, there are several thousand box robots in North America on dairy farms of various sizes.[12] The ARMS Phase 3, Dairy data from 2021 indicate that 3 percent of U.S. dairy farms used box robots.[13]

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[12] The adoption of box robots, even for farms larger than 350 head, has recently increased. This trend is likely to continue because of labor issues present at these operations (Mills et al., 2021; Wolf & Karszes, 2023).

[13] The ARMS Phase 3, Dairy questionnaires gather data on the use of robotic milking in the barn (one or two box robots) and robotic milking in a parlor (the collection of several box robots in a single location outside of the barn). This report follows the guidance of previous work and aggregates the usage of robotic milking into a single measure that represents box robots in the barn and in the "parlor" (Marques et al., 2023).

By contrast, **fully robotic carousel parlors** (i.e., automated rotary milking) have been developed and commercialized to help meet the needs of large-scale dairy farms with potentially thousands of cows (figure A.2, panel B).[14] These systems automate all steps of the milking process, and milking (generally nonvoluntary) is performed on a high-throughput rotating carousel. On a fully robotic carousel, there are multiple robotic arms that prepare the teat (to clean and stimulate milk release), attach the teatcups, and initiate milking (including the discarding of foremilk). The milking process begins after the cow walks through the entry gate and into an empty stall on the slowly rotating platform and it ends just before the cow leaves the stall and steps down through the exit gate. Newer models feature stalls with individual robots, which allows for simultaneous milking of all cows at rates of several hundred cows per hour. Compared to box robots, fully robotic carousel usage is much lower in the United States, both in terms of the number of operations using them and as a percentage of milk produced.[15]

Given the increasing adoption of robotic milking, recent studies examine the underlying economics of these systems (Bach & Cabrera, 2017; Prendergast et al., 2024; Salfer et al., 2017; Sauer & Zilberman, 2012; Steeneveld et al., 2012; Tse et al., 2018; Zulovich et al., 2018). The potential for improvements in animal health and welfare and production efficiency are major benefits from roboticization of the milking process, but the main benefits are reductions in labor. For instance, between four and six operators are commonly required for nonrobotic carousel parlors in the United States, whereas robotic carousels tend to employ only one operator. Labor savings from box robots may not be as substantial as those for robotic carousels, though aggregate effects could be comparable depending on herd size, layout of the milking facility, and management considerations (e.g., milking frequency). However, these benefits come with substantial costs. Box robots that can milk 50–70 cows each cost $150,000–$200,000 per robot during our sample period, with annual maintenance expenses of $20,000–$25,000 (Urbanz & Cardoso, 2023). Using the upper end of these price ranges, the costs are between roughly $2,900 and $4,000 per cow for capital costs and $357–$500 per cow for annual maintenance. Robotic carousels that cost roughly $69,000 per stall (Zulovich et al., 2018) suggests that a 30-stall system, which can accommodate about 1,200 cows (Nitzan et al., 2006), costs $2 million, or almost $1,700 per cow.

Other Precision Dairy Technologies

A wide range of other precision technologies with various purposes, functionalities, technical sophistication, and availability levels (from precommercialization to broadly diffused) exist in the dairy sector, but the ARMS Phase 3, Dairy data do not contain information on their use. Some of the technologies have been used for several decades (e.g., automatic milk meters, automatic concentrate

[14] Currently, on large U.S. dairy farms (e.g., more than 350 head), virtually all milking is performed by hired, immigrant labor. For these operations, the decision to employ fully robotic carousels depends largely on the cost of hired labor, which itself depends on immigration policy, wages in Central America, and wages in alternative U.S. employment (Zahniser et al., 2018).

[15] For example, one currently prominent supplier of robotic carousels completed its first installation in North America in 2015 (Feedstuffs, 2014). Author discussions with academic and industry experts revealed that there were likely fewer than 10 dairy farms in the United States in 2024 using fully robotic carousel milking technologies, consistent with estimates from the 2016 and 2021 ARMS 3, Dairy data. This report therefore omits this statistically negligible usage of fully robotic carousel milking when discussing overall robotic milking adoption in the United States.

feeding stations), while others are currently emerging (e.g., precision fertigation, predicting individual cows' methane emissions based on lightwave analyses from milk samples). As with the technologies described above, these other technologies fit within the continuum shown in figure 1.

A major line of demarcation across the five groupings (figure 1) relates to the use and proliferation of sensors that collect and analyze data at the individual cow level (Hogeveen & Ouweltjes, 2003; Stone, 2020; Stygar et al., 2021). Some sensors, like those measuring individual cow activity and milk quality, have been widely used for well over a decade (Borchers & Bewley, 2015). A more recent focus has involved application of machine learning to large datasets from automated sensors for prediction of calving, genetic heritability of physical traits, and cow behavior, among others (Borchers et al., 2017; Nye et al., 2020; Pedrosa et al., 2024).

Efficiency Improvements in Dairy Farming: Precision Dairy Technology Versus Infrastructure and Other Technology

Efficiency improvements on dairy operations can occur in many ways. One avenue is the substitution of capital for labor, typically using automated equipment like that described above. Other common examples include the use of higher-quality inputs (e.g., breeds that produce more milk per dollar of total input expense), waste-reducing technologies (e.g., improved milk collection equipment), fuel-saving inputs (e.g., feed pushers), or even reconfigurations of preexisting input combinations. This last example—increasingly facilitated by sensor data and farm management information systems—is notable as it does not necessarily require the farmer to adopt costly and sometimes proprietary technologies. Rather, data analyses help pinpoint opportunities to streamline operations given current technology and resource levels. Regardless of the exact application, all of these permit farmers to either produce more milk using the same quantity of inputs or the same quantity of milk with fewer inputs.

Precision agriculture (PA) and digitalization are gradually underpinning more and more of the efficiency increases experienced on U.S. dairy farms (Njuki, 2022). However, farmers' transitions from barn milking to parlor milking—independent of PA use—can also generate significant productivity gains. Relative to barns, parlors tend to (1) allow for simultaneous milking of multiple cows, (2) have controlled entry and exit gates for streamlined traffic, (3) incorporate simplified cleaning and sanitation processes, (4) better lend themselves to scalability (i.e., adding more parlor stalls is generally more feasible than expanding or modifying a barn), and (5) allow for greater cow comfort. Improvements in labor efficiency are among parlors' greatest benefits, owing largely to their particular design and configuration features (e.g., exit/entry control, cow positioning and stall angles, worker placement).

Besides carousel parlors, the Agricultural Resource Management Survey (ARMS) Phase 3, Dairy questionnaires inquire about farmers' use of several other parlor types:

- **Herringbone parlors** (figure A.3, panel C) feature an elevated platform where the cows face away from the milking pit at a 35°–45° angle. Cows exit together as a group on one side of the parlor.
- **Parallel (side-by-side) parlors** (figure A.3, panel D) have an elevated platform where the cows stand side by side facing away from the milking pit at a 90° angle, with cows exiting together as a group on one side of the parlor. Due to less total space, milking units are applied from the back of the cow, so

it is not possible to use certain types of automatic takeoffs, though the distance walked by the operators during milking is shorter.

- **Side opening (tandem) parlors** (figure A.3, panel E) have stalls that may angle away from the milking pit like a herringbone, with the advantage that cows are released individually instead of waiting for the entire side to finish milking (as with herringbone and parallel designs).
- **Swing parlors** (figure A.3, panel F) tend to have a configuration that is a hybrid of herringbone and parallel parlors (i.e., parabone: the stall width is like a parallel parlor, but the cows are at a greater angle (65°) than in the herringbone). The milking units are in the center of the milking pit, permitting only one side of the parlor to be milked at a time.
- **Polygon parlors** (figure A.3, panel G) have a polygonal shape with three or more sides and tend to have multiple entries and exits, thus combining some benefits of the herringbone and side-opening parlor. Relative to a herringbone parlor, there can be fewer cows per side, which improves cow flow, and the operator (in the center of the polygon) is never isolated at an extreme end of the parlor (USDA, APHIS, 2016b; Reinemann, 2019; Bickert et al., 1974).

Trends in Conventional Milking Systems—Precursors to Precision Dairy Farming

In the 20th century, U.S. dairy farms underwent profound changes in technological development, management practices, breeding and genetics, and organizational structure that transformed virtually all aspects of the sector. Mechanization of the industry ushered in milking machines, milk tanks, herringbone parlors, cubicle cow houses, and new foddering systems (Gallardo & Sauer, 2018)—to say nothing of computerization that began in the 1980s (see appendix section, Milking Systems Overview and Conventional Milking Technologies). Although current conventional milking systems are not typically classified as modern precision dairy farming, they nonetheless embed certain levels of automation and productivity-improving technology—an understanding of which can help contextualize the rise and current status of precision dairy farming.

As late as the 1930s and early 1940s, farmers milked roughly 90 percent of all U.S. dairy cows by hand. However, this declined to roughly 50 percent by 1950 as the milking machine (figure A.4, panels A and B) began to diffuse widely and quickly (Olmstead & Rhode, 2008). In the late 1950s and 1960s, use of milking machines began to change from bucket-and-carry (milking machine) methods (figure A.4, panel C) to dump stations and then to pipelines that transported milk to on-farm tanks (figure A.4, panel D) (McCroskey et al., 1966; Weimar & Blayney, 1994).[16] However, 66 percent of milking facilities on U.S. dairy farms still involved pail milkers in stanchion barns in 1971 (Nott et al., 1981). Rising labor costs in the mid-1970s and substantial economies of size reinforced increasing automation (Matulich,

[16] Dairy farm operators use milking machines to harvest milk, for sanitation, and for milk cooling and storage. Appendix figure A.4 (panels A and B) provides images of a milking machine and describes in detail each of these components of the milking process.

1978; Gallardo & Sauer, 2018). By the early 1990s, barns with pipelines represented 48 percent of milking capacity on U.S. dairy farms, with 10 percent of capacity coming from mechanical pail/bucket milkers (Short, 2000).

Despite increasing technical progress in the 2000s, (e.g., advances in computer processing power, digital information storage, internet speeds), some U.S. dairy farms still use pail unit and bucket milkers, although the percentage is very low. These systems are labor intensive so they tend to be used (1) on small-scale farms that may not be able to finance a barn pipeline or parlor, (2) on operations that prefer traditional farming methods for religious or other reasons (e.g., Amish dairy farms), or (3) as backup systems (Tauer, 1998). According to ARMS Phase 3, Dairy data, less than 2 percent of milk in the United States was produced using pail and bucket milkers in 2021, likely as part of operations that use additional milking styles.

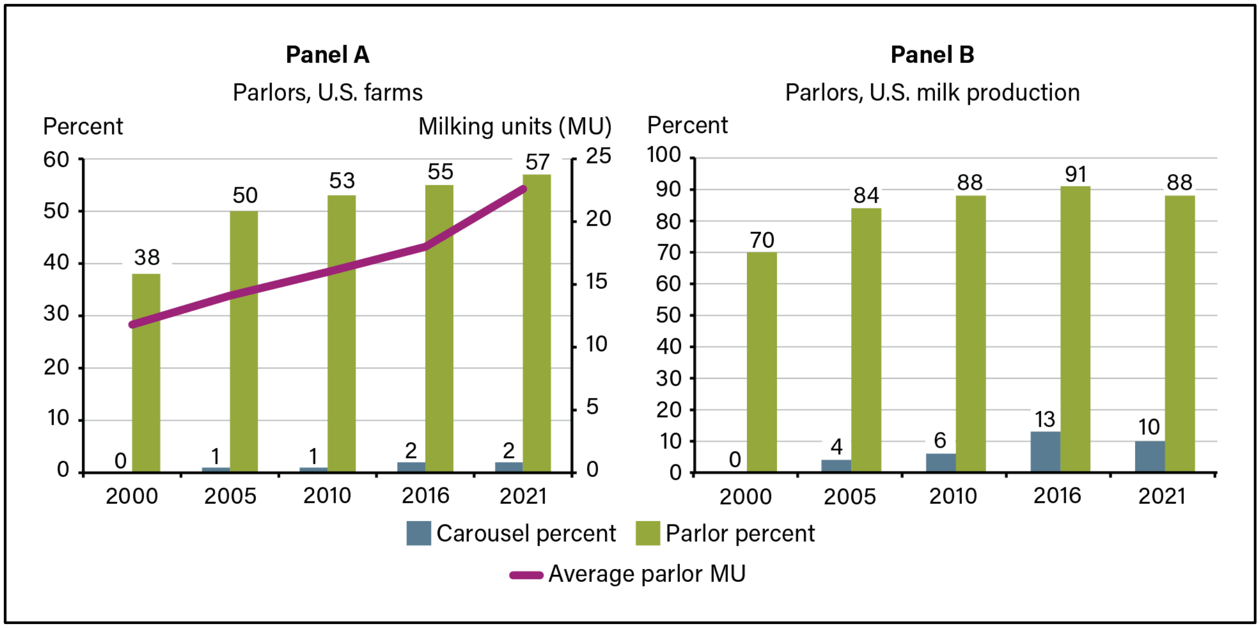
Dedicated milking parlors—infrastructure solely devoted to milking outside of the barns—were a major labor-saving technological advancement and obviated the inefficient process of workers with mechanical milkers walking from cow to cow in barn housing. Although now common, dairy farms adopted milking parlors slowly in the United States prior to the 1950s (Hogeveen & Ouweltjes, 2003).[17] The herringbone parlor (figure A.3, panel C) (see box, Efficiency Improvements in Dairy Farming: Precision Dairy Technology Versus Infrastructure and Other Technology)—another major advancement over slower and more cumbersome methods involving walk-through or side-opening parlors (figure A.3, panel E)—came to the United States in 1957 (Grant, 1998; Weimar & Blayney, 1994). Adoption of all parlor types took off in the 1950s and 1960s (McCroskey et al., 1966), and by 1971, 17 percent of U.S. milking facilities used parlors, with about two-fifths of them having a herringbone design (Nott et al., 1981). In the early 1990s, herringbone parlors accounted for 30 percent of U.S. milking capacity and adoption has since increased (Khanal et al., 2010; Gillespie et al., 2014). Similarly, rotary parlors with a carousel design (figure A.3, panel H) were invented in the 1930s and reemerged in the 1970s, though adoption was low during this period due to equipment reliability issues and limited labor-saving benefits. Carousel parlor size and mechanical integrity increased in the 1990s, but they still accounted for only 1 percent of milk production in 1993 (Short, 2000).

Since 2000, the use of carousel parlors, and parlors in general, as well as the number of milking units within parlors (figure A.4, panel B) has been increasing (figure 2, panel A). Parlor usage overall increased from 38 percent of U.S. dairy farms in 2000 to 57 percent in 2021. Average parlor size, as measured by the number of milking units, nearly doubled from 11.8 per parlor in 2000 to 22.6 in 2021. Throughout the two decades, carousel parlor usage as a percentage of all U.S. milk parlors remained steady at 1 percent. Though such estimates may seem low, they represent large shares of U.S. milk production. As of 2021, 88 percent of U.S. milk came from parlors (as distinct from barns), and 10 percent of parlor milk came from cows milked in a carousel (figure 2, panel B).[18]

[17] There exist several types of dairy cow barn and parlor styles. Appendix figure A.3 provides images of the different types.

[18] We provide two notes about the apparent decrease in the percentage of U.S. dairy operations using carousel parlors from 2016 to 2021. First, although the percentage in 2021 is qualitatively lower than in 2016, we are unable to reject the null hypothesis that the difference is equal to zero. Second, there is a marked increase between the 2 years in the percentage of

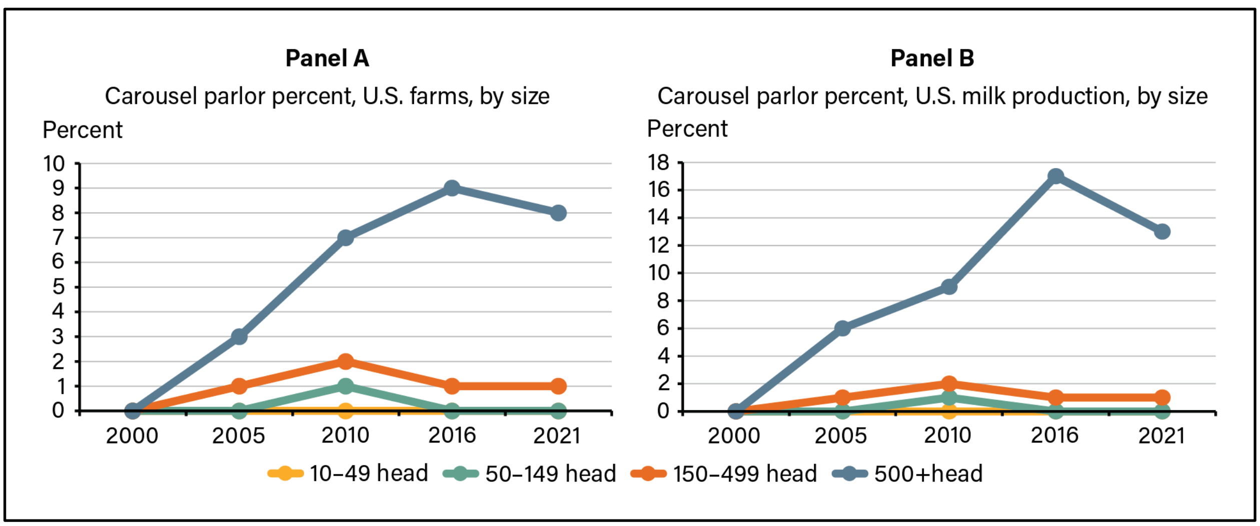
Figure 2
Trends in milking parlor usage



Note: Figure shows the percentage of U.S. dairy farms (panel A) and milk production (panel B) using traditional and carousel parlors. Panel A also includes the average parlor size, in milking units, for each operation. This value represents milking units within all types of parlors, including traditional (e.g., herringbone) and carousel parlors.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2000, 2005, 2010, 2016, 2021 Agricultural Resource Management Survey (ARMS) dairy version.

Figure 3
Trends in carousel parlor usage, by farm size



Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2000, 2005, 2010, 2016, 2021 Agricultural Resource Management Survey (ARMS) dairy version.

Use of parlors of any type, including carousels, and the share of milk produced in these structures, increases as dairy farm size increases. In 2021, 8 percent of U.S. dairy farms with 500 or more cows used carousels, representing 13 percent of milk production in that group (figure 3, panels A and B).

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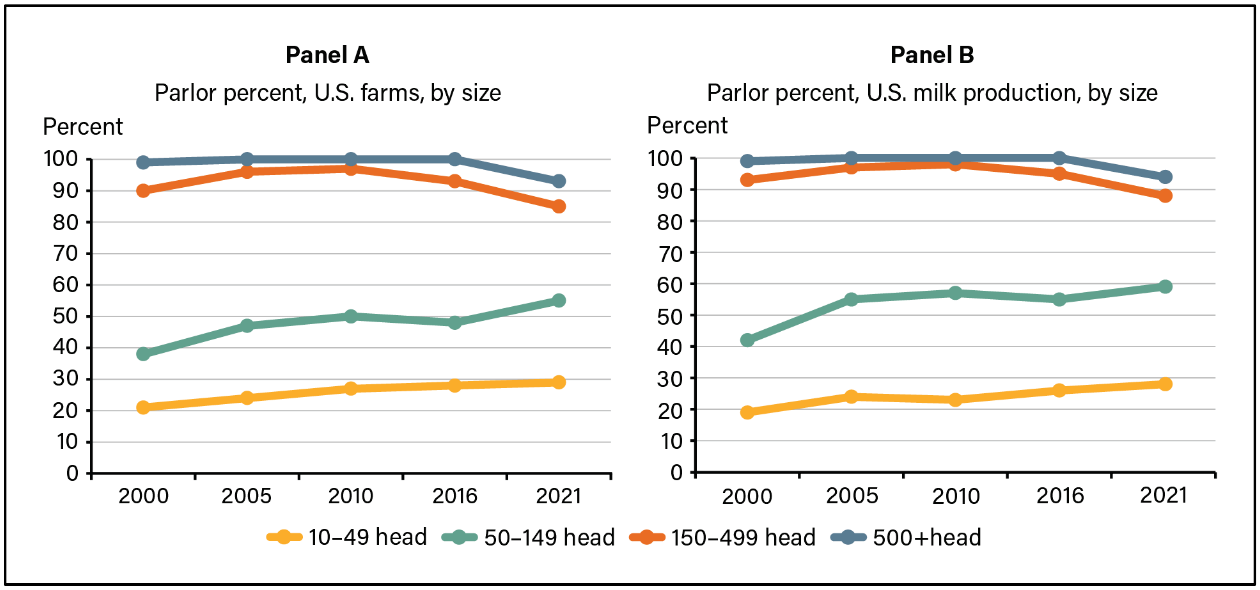
operations that have "other" parlor styles (2 percent of operations in 2016 to 7 percent in 2021). It is possible that carousel parlor adopters during this time period selected "other" because of uncertainties in the questionnaire language.

These estimates are larger than those for the next-largest size class, 150–499 head. Only 1 percent of dairy farms in this size class used carousels, and milk produced from this technology accounted for 2 percent of group output. Given the large upfront costs of carousel parlors and the financial benefits of higher throughput, (i.e., usage; Kuhberger et al., 2009), they are generally viable for large dairy farms with hundreds of milking cows (MacDonald et al., 2018; Prendergast et al., 2024). In the 500 or more head size class, nearly all dairy farms used parlors (ranging from 99 percent in 2000 to 93 percent in 2021) and nearly all milk produced on these farms came from milking in parlors (figure 4, panels A and B). In contrast, only 21 percent of dairy farms among the smallest farms (between 10 and 49 head) used parlors in 2000, which comprised 19 percent of this group's milk supply, but both shares have been rising since this time. The proportion of dairy farms using carousels appears to have plateaued for the two largest size classes in the early- to mid-2010s.[19]

Figure 4
Trends in milking parlor usage, by farm size



Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2000, 2005, 2010, 2016, 2021 Agricultural Resource Management Survey (ARMS) dairy version.

Precision Dairy Adoption in the United States

The use of precision dairy technologies in the United States has increased significantly over the past two decades. In fact, many types of precision dairy technologies, especially those with low upfront costs, have become nearly ubiquitous in U.S. dairy production, particularly for dairy farms of a certain size and in specific regions. In this section, we provide an in-depth look at precision dairy adoption, specifically highlighting combinations of technologies and practices that USDA, Economic Research Service (ERS) and USDA, National Agricultural Statistics Service (NASS) collect information on as part of the ARMS Phase 3, Dairy program. We also highlight other technologies that have been understudied (e.g., robotic milking).

[19] The percentage of U.S. dairy farms using carousel parlors and the percentage of milk production coming from these farms has increased since 2021 (the last year of our sample period), as most new parlor construction since 2021 has been large carousels, altering the plateauing trend of the past decade.

Trends in Combinations of Precision Dairy Technologies

Previous research on PA adoption in U.S. crop production suggests that combinations of technologies are common, especially when they provide productivity- and cost-related benefits or when suppliers bundle technologies together (Lambert et al., 2015; Schimmelpfennig, 2016; McFadden et al., 2023). Like previous reports, we do not provide analysis of why certain combinations of technologies are more common than others (McFadden, 2023), but we note that consolidation in the U.S. dairy industry and the corresponding economies of size are linked with greater technological adoption, especially for more complex combinations of technologies (MacDonald et al., 2020).

The use of breeding technologies on U.S. dairy farms is nearly ubiquitous, as the costs of adoption are comparatively low and the breeding and replacement benefits are high. As a result, the top four combinations of precision dairy technologies in 2021 contained the use of breeding technologies (table 1). Of the top 16 combinations of precision dairy technologies that U.S. dairy farms used (those adopted by more than 1 percent of farms), 12 contained breeding technologies in its suite. Also frequently paired together is the use of breeding technologies with individual cow records. This combination is intuitive, because cow production and other records are valuable when selectively breeding replacement cows. Several common combinations of technologies also included the use of a nutritionist to design diets. The precision technology combinations that we witness result from two key factors. First is the bundling of technologies that necessarily work together (e.g., breeding technologies and individual cow records). Second, and perhaps more important, is size economies, as large dairy farms can adopt more complex bundles of technologies than small dairy farms. We examine these factors in-depth in a subsequent section.

Table 1
Most common combinations of individual precision dairy technologies, 2021

Technology or practice combination	Percent of U.S. dairy farms
Breeding technologies + individual cow records + milking unit with automatic takeoff + nutritionist	18
Breeding technologies + individual cow records + nutritionist	15
Breeding technologies + nutritionist	10
Breeding technologies only	7
None	7
Breeding technologies + computerized milking + individual cow records + milking unit with automatic takeoff + nutritionist	5
Breeding technologies + milking unit with automatic takeoff + nutritionist	5
Breeding technologies + individual cow records	4
All technologies excluding holding pen with udder washer and robotic milking	4
Individual cow records only	4
Nutritionist only	3
Individual cow records + nutritionist	2

Technology or practice combination	Percent of U.S. dairy farms
Breeding technologies + computerized feed delivery + individual cow records + milking unit with automatic takeoff + nutritionist	2
All technologies excluding robotic milking	2
Breeding technologies + individual cow records + milking unit with automatic takeoff	2
Milking unit with automatic takeoff + nutritionist	1

Note: The breeding technologies category indicates use of artificial insemination, embryo transfer, or sexed semen. Only combinations used on at least 1 percent of U.S. dairy farms in 2021 are included in the table, thus the percentages do not sum to 100.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2021 Agricultural Resource Management Survey (ARMS) dairy version.

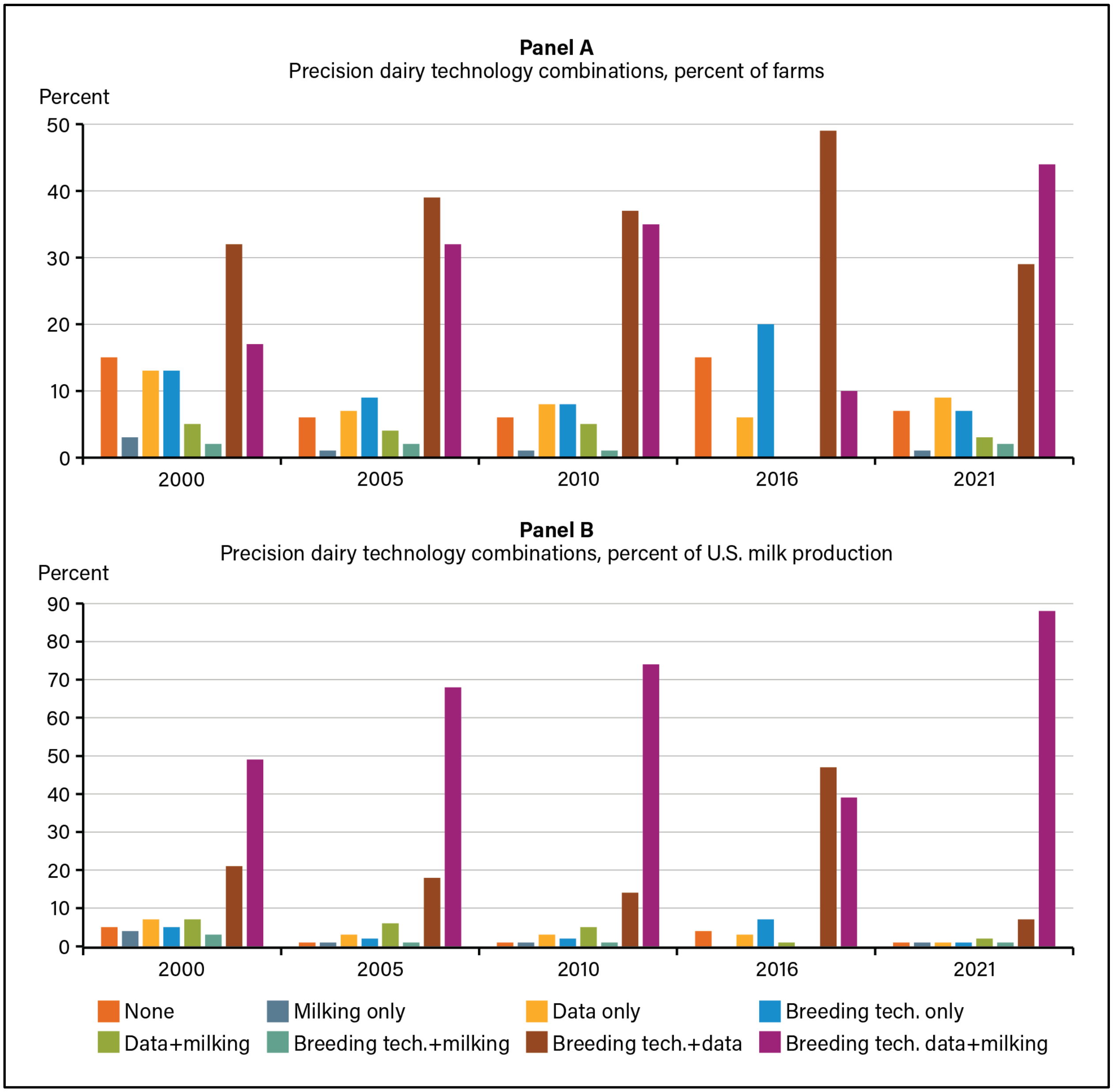
For the remainder of this report, when examining combinations of precision dairy technologies (excluding robotic milking) we group each technology depending on its purpose in the dairy enterprise, as defined in a previous section: (1) milking technologies, (2) breeding technologies, or (3) data/decision support tools. Adoption ranges from the lowest—none in any of the three categories—to the highest, which are U.S. dairy farms that use at least one type of technology in each of the three categories. Over the past two decades, U.S. dairy farms have moved toward greater technological sophistication, as 45 percent of farms used milking technologies, breeding technologies, and data support systems in 2021—up from 17 percent in 2000 (figure 5, panel A). The percentage of farms using no technology has also decreased, from 15 percent of dairy farms in 2000 to 6 percent in 2021.

Like with individual precision dairy technologies, the percentage of U.S. milk production that comes from operations using bundles of technology is higher than the percentage of farms (figure 5, panel B). This suggests that larger operations, which produce more milk, adopt precision dairy technologies at higher rates than smaller operations. By 2021, most milk produced in the United States (88 percent), came from operations using at least one type (each) of milking, breeding, and decision support technology. The overall percentage is a sizable increase from 2000, where 49 percent of U.S. milk production came from dairy farms using at least one type of each dairy technology category. The increase in milk production from dairy farms using all technology types from 2000 to 2021 came largely from the production increase at farms adopting milking technologies, though also from breeding and decision support technologies. In 2000, 21 percent of U.S. milk production came from farms using only breeding and decision support technologies; this percentage fell to 8 percent by 2021 as the number of farms also using milking technologies increased.

Much prior work documents the differences in farm-level management of dairy farms based on the operation's herd size (MacDonald et al., 2020; Gillespie et al., 2024). Large operations experience economies of size, which we show contributes to a greater percentage of U.S. milk production coming from a smaller percentage of farms adopting precision dairy technologies. Other work suggests that large farms and consolidation in U.S. crop production increase the demand for bundled technologies aimed at easing operators' management burden of the farm (MacDonald et al., 2020; McFadden et al., 2023). We therefore examine the adoption rates of dairy technology combinations on U.S. farms by herd size, using four size classes, between the years 2000 and 2021 (table 2). The percentage of U.S.

dairy farms that adopted more complex combinations of technologies increases with herd size. And for all herd sizes, there are noticeable increases in technological adoption over time.

Figure 5
Trends in adoption of combinations of precision dairy technologies



Tech = technology.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2000, 2005, 2010, 2016, 2021 Agricultural Resource Management Survey (ARMS) dairy version.

For operations with 10–49 cows, nearly a quarter did not use any type of precision dairy technology in 2000. By 2021, only 14 percent of the farms in this rapidly disappearing size class had adopted no technologies. For this smallest category of dairy farm, 51 percent of operations had zero or one type of technology in 2021. The 50–149 head size class adopted more complex technological combinations during this period. Although containing relatively small farms, only 11 percent of operations in this class used no precision dairy technologies in 2000. This percentage dropped to 6 percent by 2021. The percentage of farms in this class using all three technology types increased from 2000 to 2021, moving from 18 percent of operations to 40 percent of operations. For all sizes in 2021, 98 percent of U.S. dairy farms had more than one type of technology. The percentage of farms with no precision dairy technologies decreased sharply after crossing the 150 head threshold, and the complexity of technological combinations sizably shifted, for all years. For operations with between 150 and 499 dairy cows, 56 percent of farms used all three precision dairy technology types in 2000. By 2021, 77 percent of operations with between 150 and 499 dairy cows had adopted all categories of precision dairy technologies. Operations with 500 or more dairy cows had adoption rates for the "all technologies" category of 79 percent in 2000, which increased to 91 percent by 2021.

Table 2
Precision dairy technology combinations by herd size, percent of U.S. farms

Technology category	Herd size (head)			
	10–49	50–149	150–499	500 or more
Panel A. 2000				
None	24	11	4	0
Milking only	1	4	7	3
Data only	18	13	4	2
Breeding only	24	8	2	0
Data + milking	2	5	13	5
Breeding + milking	0	2	4	6
Breeding + data	31	39	11	5
All three technology types	2	18	56	79
Panel B. 2021				
None	14	6	2	1
Milking only	0	2	3	0
Data only	19	6	2	1
Breeding only	19	4	1	0
Data + milking	0	3	9	3
Breeding + milking	3	2	1	1
Breeding + data	35	40	7	4
All three technology types	12	39	77	91

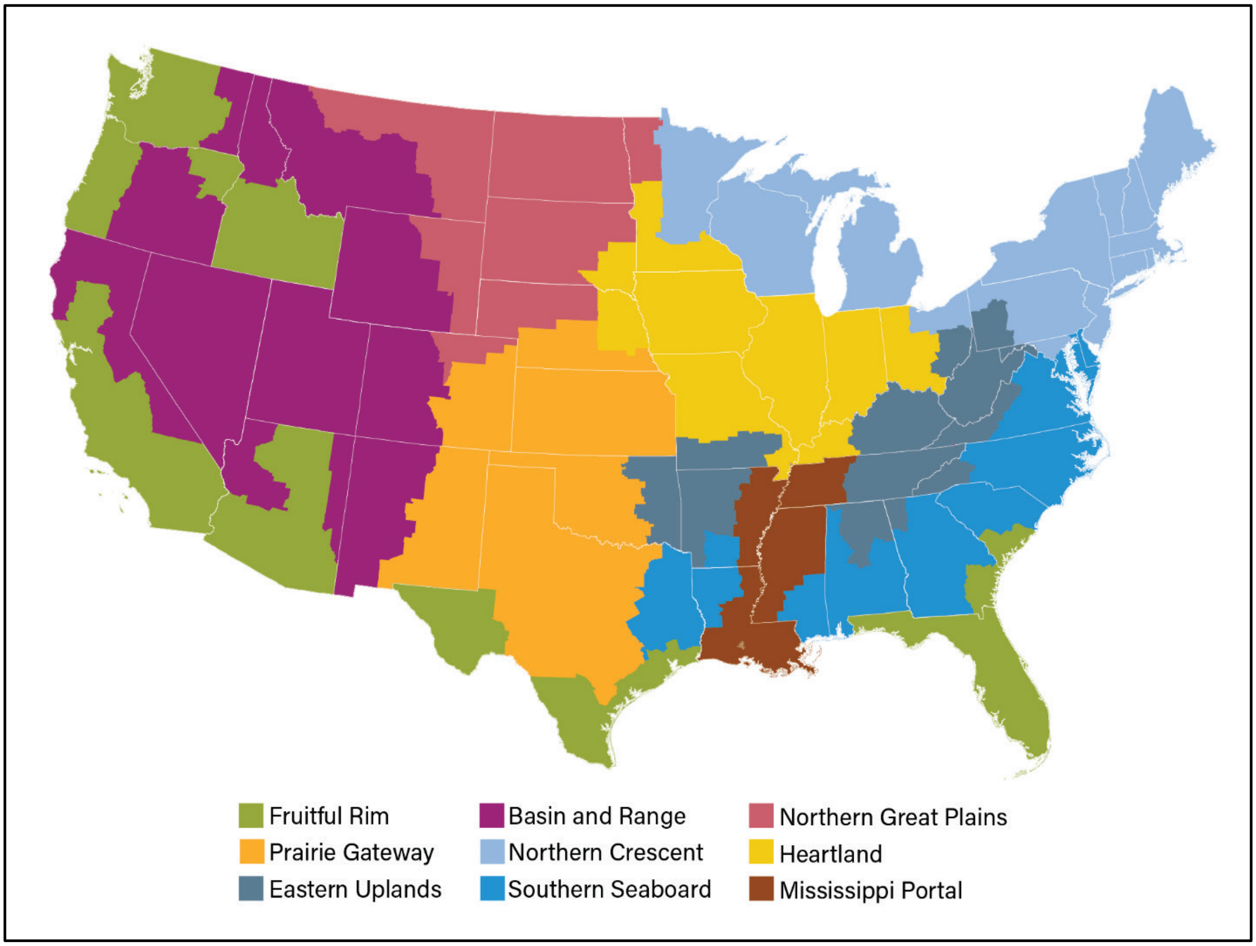
Note: Percentages represent the number of U.S. dairy farms adopting the combination of technologies in each year. Milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2000 and 2021 Agricultural Resource Management Survey (ARMS) dairy version.

The size, type, and management of dairy operations vary considerably throughout the country, with large, consolidated farms typically found in the Western United States and small operations typically in the Northeast, where there is also much organic production (Gillespie et al., 2024). In this report, we use USDA, ERS Farm Resource Regions to help illustrate regional adoption differences, which highlight agricultural production specializations by geographic area. USDA, ERS (2000) describes the Farm

Resource Regions in detail and figure 6 depicts the regions on a map. Here, our analysis omits four USDA, ERS Farm Resource Regions due to disclosure concerns because of minimal dairy production in those regions (Northern Great Plains, Prairie Gateway, Basin and Range, and Mississippi Portal). [20]

Figure 6
USDA, Economic Research Service Farm Resource Regions



Note: Note: Alaska and Hawaii are not included in the USDA, Economic Research Service Farm Resource Regions.

Source: USDA, Economic Research Service (2000).

The Eastern Uplands region has low adoption of complex precision dairy technology combinations (table 3). In 2000, 23 percent of farms in this region had no technological adoption, with 51 percent of dairy farms in the Eastern Uplands region having zero or only one type of technology. Only 9 percent of dairy farms in this region had adopted all technologies in 2000. Other Farm Resource Regions with low precision dairy technology adoption are the Heartland and Northern Crescent regions. Comparatively, the dairy farms of the Fruitful Rim have high percentages of complex technological

[20] However, observations in our final analysis sample are located in all nine of the regions. USDA, ERS (2000) describes the creation of the regions in depth. Briefly, USDA creates Farm Resource Regions using farm characteristics, USDA's old farm production regions, USDA's land resource regions, and USDA, NASS crop reporting districts. These regions are delineated by county, rather than State, which improves on previous geographical regions for agricultural production. As one example, the Northern Crescent region contains many dairy farms during our sample period. This region is the most populous region and contains 15 percent of the nation's farms and 9 percent of the nation's cropland. The primary commodities of the Northern Crescent region are dairy and grains.

adoption. In 2000, 29 percent of dairy farms in the Fruitful Rim had zero or one technology type, while 53 percent of farms were in the “all technologies” category.

In general, operations in all regions increased the complexity of their technological bundles over time. Large technological advances took place in the Heartland, Eastern Uplands, and Fruitful Rim regions. In the Heartland, 10 percent of dairy farms had adopted all technology categories in 2000, but by 2021 this percentage had increased to 43 percent. The Eastern Uplands also experienced an adoption rate increase for all technology categories from 2000 to 2021, moving from 9 percent of farms adopting all to 42 percent of farms adopting all. Operations in the Fruitful Rim had the largest percentage of adoption rates of all technology categories in 2021: 85 percent of operations had adopted all technology categories, a 33 percentage point increase over the sample period. We attribute regional trends in the adoption of different technological bundles to various factors, including differences in the distribution of dairy farm sizes across Farm Resource Regions (USDA, ERS, 2000; MacDonald et al., 2020).

Table 3

Precision dairy technology combinations, percent of U.S. farms, by the five USDA, Economic Research Service Farm Resource Regions with the most dairy production

Technology category	USDA, ERS Farm Resource Region				
	Heartland	Northern Crescent	Eastern Uplands	Southern Seaboard	Fruitful Rim
Panel A. 2000					
None	18	13	23	14	14
Milking only	1	1	10	13	11
Data only	14	17	5	10	2
Breeding only	16	13	13	7	2
Data + milking	6	3	8	9	9
Breeding + milking	1	1	3	6	4
Breeding + data	34	36	30	7	6
All three technology types	10	17	9	35	53
Panel B. 2021					
None	7	7	19	5	0
Milking only	1	1	0	9	3
Data only	11	5	10	5	0
Breeding only	9	8	7	0	0
Data + milking	2	1	14	21	4
Breeding + milking	2	2	0	3	3
Breeding + data	26	37	10	8	6
All three technology types	43	40	42	58	85

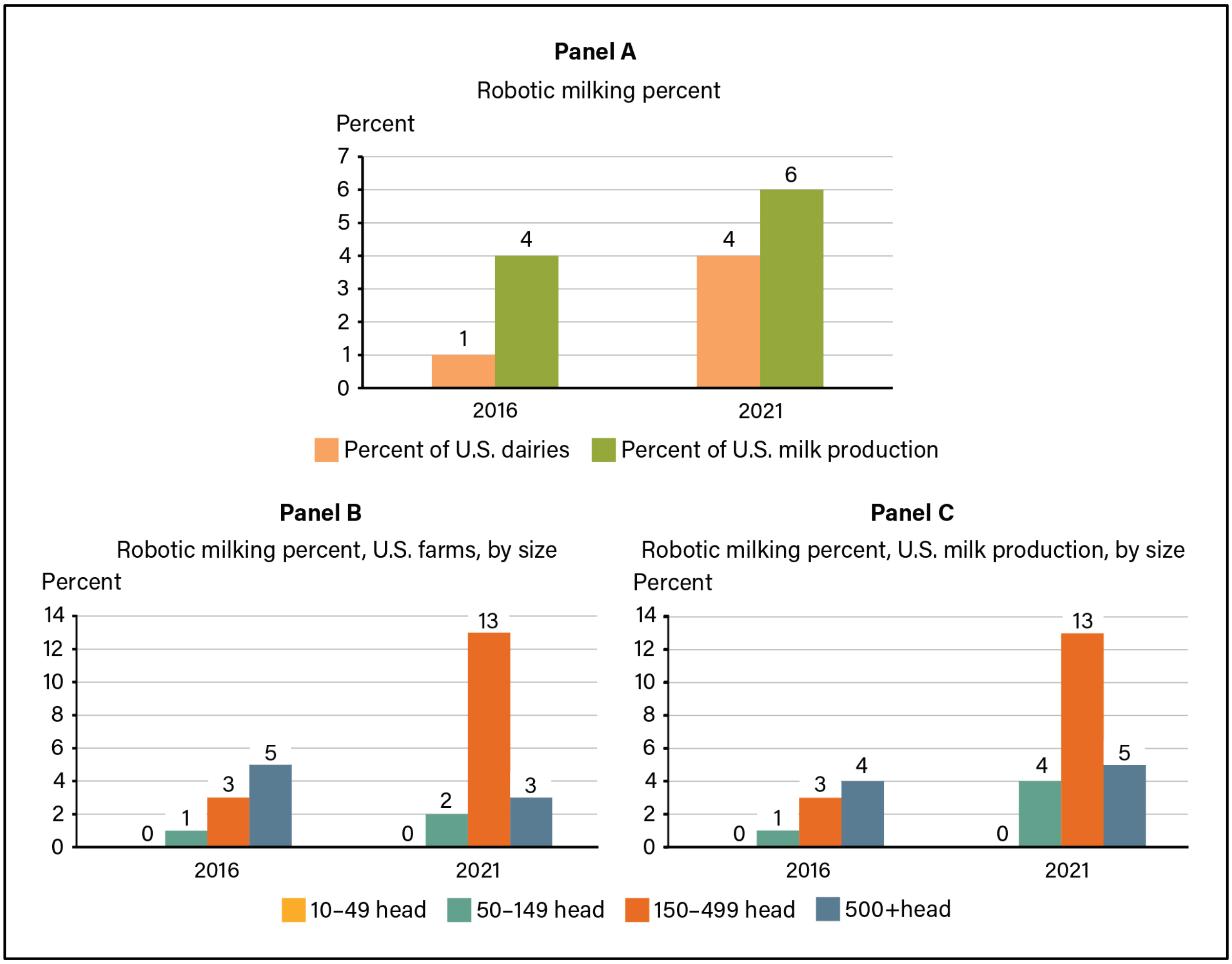
Note: Percentages represent the number of U.S. dairy farms adopting the combination of technology in each year. Milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. Table omits four USDA, Economic Research Service Farm Resource Regions due to disclosure concerns resulting from dairy production (Northern Great Plains, Prairie Gateway, Basin and Range, and Mississippi Portal).

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2000 and 2021 Agricultural Resource Management Survey (ARMS) dairy version.

Trends in Robotic Milking

The adoption rate of robotic milking in the United States is considerably lower than the adoption rates of other precision dairy technologies. In recent years, however, the use of robotic milking systems has begun to increase. The ARMS Phase 3, Dairy surveys began tracking the use of robots in 2016. In that year, 1 percent of U.S. dairy farms used robotic milking technologies (figure 7, panel A). By 2021, the adoption rate increased to 4 percent of U.S. dairy farms. The percentage of U.S. milk that was produced at operations using robotic milking is higher; 4 percent in 2016 and 6 percent in 2021.

Figure 7
Trends in robotic milking adoption



Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, 2016 and 2021 Agricultural Resource Management Survey (ARMS) dairy version.

In 2016, robotic milking adoption rates increased linearly as farm size increased, as with other technologies (figure 7, panel B). Zero percent of farms with between 10 and 49 head used robots to milk their herd. For farms with more than 500 dairy cows, 5 percent of U.S. operations used robotic milking technologies. From 2016 to 2021, there was no change in robotic milking usage among farms with 10–49 head, as virtually none of those farms used the technology. However, farms with 150–499 head experienced an increase in robotic milking adoption during this timeframe. In 2021, 13 percent of dairy farms with 150–499 head used robotic milking, a 10 percentage point increase from 2016.

Growth in usage for this size class is consistent with other evidence suggesting that box robots are suited for operations in this size class due to technology parameters, barn designs, and labor wage rates (Rodenburg, 2017). Farms with over 500 head saw a slight decrease in robotic milking usage between 2016 and 2021, moving to 3 percent of U.S. operations.[21] Changes in the percentage of milk produced using box robots follow similar trends (figure 7, panel C). Three percent of milk from farms with 150–499 head was produced using robotic milking in 2016, but this share increased to 13 percent in 2021. We expect the adoption percentages to increase in the future, especially for dairy farms with many hundreds of cows.

Robotic milking adoption also differs geographically. Dairy farms in the Fruitful Rim have the highest adoption of robotic milking; 8 percent of operations used the technology in 2016. Of the five highest dairy producing regions highlighted above, robotic milking adoption in 2016 was lowest in the Northern Crescent and Eastern Uplands, with 1 percent of farms in each region using robots. The overall growth in robotic milking shown in figure 7 is driven by increases in adoption in the Heartland and Northern Crescent regions, where 3 percent and 4 percent of farms, respectively, used the technology in 2021.

Who Adopts Precision Dairy Technologies?

The decision to adopt PA technologies or participate in other management practices at dairy farms depends on several factors, such as operation type or size, operator personal characteristics/demographics (e.g., education level, age), geography, and the expected impacts on costs and/or revenues (Campi et al., 2024; Daberkow & McBride, 2003; Pierpaoli et al., 2013; USGAO, 2024). We examine the differences in means of various characteristics of dairy farms and their operators to help identify the types of operations that have adopted precision dairy technologies over the past two decades.[22] The characteristics that we examine consist of three broad categories: (1) operation type, size, and infrastructure, (2) operator characteristics and demographics, and (3) financials.[23]

Adopters of "more-than-one-technology-type" (i.e., use of technologies from at least two of the three main categories: milking, breeding, data) and robotic milking operate on more farmland acres and with larger herds than nonadopters of the technologies (table 4). Differences in means across the groups are both economically and statistically significant, with adopters having average herd sizes nearly three times larger for more-than-one-technology-type and nearly two times larger for robotic milking than nonadopters. Farm infrastructure also differs between technology adopters and nonadopters. Fifty-two percent of U.S. dairy farms with more complex technology combinations use a parlor, while 41 percent of nonadopters use a parlor. These percentages contrast with robotic milking, where adopters use a parlor less often than nonadopters, although the difference is not statistically

[21] The jackknife standard errors for the robotic milking summaries are high, suggesting the estimates are imprecise. We are therefore unable to statistically differentiate changes between years and regions from zero.

[22] Note that the underlying sample sizes are different between the two technology types. While all 5 years of the ARMS dairy surveys asked about nonrobotic milking, breeding, and data/decision support technologies, only the surveys in 2016 and 2021 asked about robotic milking.

[23] Here, we examine basic financial backgrounds of each operation, such as the operator's net worth. In the subsequent section, we examine costs, revenues, and profitability.

significant. These differences in adoption highlight how the technologies work. Milking, breeding, and data support technologies can work together with parlors to make the milking enterprise more efficient. ARMS Phase 3, Dairy data, however, suggest that robotic milking in the United States consists almost exclusively of box robots rather than robotic milking in the parlor. Therefore, robotic milking adopters typically have the boxes in the barn or clustered together in a barn to serve as a parlor. Barns at dairy farms adopting technologies are newer, on average, than barns at nonadopting farms.

Table 4

Operator characteristic summaries by precision dairy technology adoption

Operator characteristic	>1 technology type		Robotic milking	
	Adopters	Nonadopters	Adopters	Nonadopters
Farmland acres operated	379***	218	793**	469
Herd size	226***	77	501***	258
Parlor usage	0.52***	0.41	0.51	0.56
Newest barn age	15***	22	9.4***	17
Organic	0.07***	0.15	0.06***	0.16
Operator age	51*	52	54	54
Beginning farmer	0.10	0.11	0.041	0.10
Operator has at least high school degree	0.80***	0.68	0.99***	0.71
Household size	3.8***	4.4	2.6***	4.1
Retired operator	0.017	0.022	0.058	0.026
High speed internet access	0.85***	0.74	0.87**	0.74
Net worth (million dollars)	2.7***	1.4	5.7***	3.4
Government payments received (dollars)	26,088***	10,510	82,844***	26,244
Any debt use	0.78***	0.64	0.72	0.69
Any contract use	0.44***	0.34	0.27	0.34

Note: The "> 1 technology type" indicates the farm is using technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (support). Nonadopter under the “>1 technology type” column refers to farms that adopt one or none of the technology types, while nonadopter under the “robotic milking” column refers to farms that did not adopt robotic milking. Non-robotic milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. The ***, **, and * indicate that mean values for adopters are statistically different than mean values for nonadopters at the 1 percent, 5 percent, and 10 percent levels, respectively. Difference of means tests were conducted using a delete-a-group jackknife variance estimator with replicate weights provided by USDA, National Agricultural Statistics Service in the ARMS survey data. “Operator has at least high school degree” indicates the farm operator had a high school degree plus some college or a college degree. All dollar values are normalized to real 2021 dollars using the Consumer Price Index (CPI).

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS) dairy version, years 2000, 2005, 2010, 2016, and 2021.

Demographics and operator characteristics also play a role in distinguishing adopters from nonadopters (table 4).[24] Organic certified dairy farms are less likely to adopt multiple technologies or

[24] We acknowledge that the size of the operation is important when considering differences in these factors among technological adopters and nonadopters. Given the focus of this report is on the relationships between costs, revenues, and other farm-level financial factors, we save a more thorough examination of the factors by operation size for those financial factors below. We present the summaries of operator characteristics in table 4 only as background for the interested reader, rather than a full-scale analysis.

use robotic milking than non-organic dairy farms. Only 7 percent of U.S. dairy farms that adopt more than one technology combination are certified organic, compared to 15 percent of nonadopters; these percentages are 6 percent and 16 percent, respectively, for robotic milking. The percentages are unsurprising, because organic dairy operations are typically smaller than conventional operations and require pasture-based forages. For the more-than-one-type of precision dairy technology category, on average adopters are younger, more likely to have a high school degree plus some college experience or a college degree, and operate the farm with a smaller household. The summaries for operator characteristics are similar for robotic milking. Robotic milking adopters are more likely to have at least a high school degree and operate the farm with a smaller household.[25] Also important in this category, adopters and nonadopters of precision dairy technologies differ significantly in their access to high-speed internet. For adopters of more than one technology, 85 percent had access to high-speed internet, compared to 74 percent of nonadopters. For robotic milking, 87 percent had access to high-speed internet, while 74 percent of nonadopters had similar access. McFadden et al. (2023) found a similar bundling of PA adoption for row crops and high-speed internet access, as a connection to the internet is important for many types of PA technologies to function properly.

The final group of characteristics we examine are financials. The financial situation underlying dairy operations can be important in deciding to adopt precision technologies because of the technologies' large upfront costs. Indeed, the average net worth of operators that adopt more than one type of technology is significantly higher than the average net worth of nonadopters. The difference is larger for robotic milking, where adopters have an average net worth of $5.7 million compared to $3.4 million for nonadopters. Adopters of precision dairy technologies also receive more government payments than nonadopters.[26] Operations that adopted more than one technology type received, on average, $26,088 in government payments, compared to $10,510 in payments for nonadopters. For the robotic milking sample, adopters received, on average, $82,844 in government payments; nonadopters received $26,244 in government payments on average.[27] Lastly, adopters of more than one technology type are more likely than nonadopters to finance their operations with debt and produce milk under either a production or marketing contract. Collectively, these summaries suggest that larger farms tend to adopt precision dairy technologies more than smaller farms.

Precision Dairy Technologies and Farm Profitability

Precision dairy technologies, especially those that are technologically intensive such as robotic milking systems, come with high start-up costs and often have high operation and maintenance costs.

[25] That adopters of robotic milking have smaller households is consistent with the notion that less unpaid family labor available from the farm household encourages the adoption of labor-saving technology (Gallardo & Sauer, 2018).

[26] Government payments include all transfers and grants from government agencies to the operation, including commodity payments, conservation program payments, and other price protection program payments (e.g., Dairy Margin Coverage program).

[27] The much higher values for robotic milking are the result of the sample period and Coronavirus (COVID-19) pandemic payments. For the more-than-one-technology-type sample, the analysis spans 2000, 2005, 2010, 2016, and 2021. For robotic milking, the sample is only 2016 and 2021. The sizable government payments to dairy farmers after the COVID-19 pandemic make up a large percentage of the observations in the robotic milking sample, thus substantially increasing mean values.

Even less technologically intensive precision practices, such as AI or ET, come with additional costs (Ribeiro et al., 2012).[28] However, precision dairy technologies can benefit operators by reducing input costs, increasing productivity and revenues, improving animal health and breeding, and/or reducing waste (see box, The Benefits of Precision Dairy Farming).

Indeed, prior work found a positive relationship between PA adoption for crop production and profitability (Griffin et al., 2004; Schimmelpfennig, 2016; Wang et al., 2023). Related to our work, Schimmelpfennig (2016) used ARMS Phase 2, Corn data to analyze the impacts of PA technologies, such as variable rate technologies (VRT), on farm-level profits. That study found small positive effects of adoption on farm profits. However, there exists little empirical evidence of such a relationship outside of crop production, specifically, for the use of PA in livestock production. In dairy production, even fewer studies hypothesize or model the impacts that precision technologies have on profitability (Bewley, 2010; Mayo et al., 2019; Wang et al., 2023).

This report uses ARMS data to provide empirical evidence on the relationship between precision dairy technology adoption and farm profits in several ways. First, we statistically test for differences in average operating and allocated overhead costs, time use, productivity, and profitability between adopters and nonadopters of precision dairy technology. Second, we expand upon this analysis and estimate the effects of precision dairy technology adoption on dairy enterprise-level profitability, making use of the repeated cross-sectional nature of the ARMS data. Finally, we control for the bias inherent in naïve estimation methods when the main variable of interest—technology adoption—is a choice of the operator by applying an endogenous treatment effects model (Imbens & Wooldridge, 2009).

Correlations Between Precision Dairy Technology Adoption and Expenditures, Time Use, and Productivity

An analysis of how precision dairy technology adoption correlates with outcomes of crucial interest to farmers, like revenues and costs, provides two complementary sets of insights. First, it provides additional insight into the types of operations that adopt precision dairy technology, because expenditures and output may lead to farmers adopting the technologies to change those outcomes. Second, and more important from a profitability perspective, this analysis can suggest possible mechanisms by which precision dairy technology adoption impacts profitability. For example, if expenditures differ between adopters and nonadopters, it is possible that the decision to adopt led to such differences. Or if precision dairy technology improves productivity of the herd, this likely impacts profitability. In this subsection, we do not differentiate between these possible explanations (i.e., we do not attempt to establish a causal link between precision dairy technology adoption and expenditures or output). Because we examine the variables of interest over time, the timing of technology adoption is important. If, for example, adoption is earlier in the sample period, then such adoption likely leads to changes in expenditures/revenues. Alternatively, if adoption is later in the sample period, it is likely then that operators endogenously choose to adopt the technology because of their expenditures or revenues. In the following subsections, we use the repeated cross-sectional

[28] These costs, however, are often offset by the additional gains. For example, AI costs more than traditional breeding practices, but these higher costs are offset by the foregone costs of not needing bulls in the herd.

nature of the data to address these concerns and estimate the causal impacts of precision dairy technologies and robotic milking on dairy farms' net returns later in this report.

In addition to cost and output relationships, farmer quality of life and the amount of time put into the dairy enterprise can be impacted by technologies that more fully automate the milking process—especially through robotic milking. For example, Tse et al. (2023) found that farmer quality of life improves after transitioning the operation to an automated milking system. As a proxy for quality of life, we look at operator hours spent on the dairy enterprise. If precision dairy technology adoption decreases operator labor hours, that time could be spent on leisure or more enjoyable work tasks, thus improving quality of life. We note that this exercise applies to dairy operations with less than 500 head, as operator hours are less important for operations with more than 500 head given their reliance on paid labor.

Technological adoption, expenditures, and other key factors describing the dairy enterprise vary considerably by the herd size of the operation (MacDonald et al., 2020; Gillespie et al., 2024). For example, large dairy farms are more likely to be in the more-than-one-technology-type group (table 4), and these large dairy farms also expend considerably more on paid labor (rather than unpaid labor) compared to small dairy farms. Thus, any comparison of means of expenditures or key variables that impact profitability between technology adopters and nonadopters necessarily conflates the impacts of operation size with those of technology adoption. In this subsection, we therefore examine differences of means of these variables within the size classes examined above, which effectively controls for dairy herd size.

For dairy farms with fewer than 150 head, expenditures per cwt of milk production on paid labor are much lower than unpaid labor costs (i.e., the opportunity cost of time) (table 5). Paid labor is often difficult to find and afford for these operations, and the necessary and routine timing of milking requires much operator and household member effort that is mostly unpaid (MacDonald et al., 2007). The adoption of precision dairy technology and robotic milking correlates with lower unpaid labor costs for small dairy farms—10–49 head and 50–149 head—but there are no differences between the groups for paid labor (table 5, panels A and B).[29] Unpaid labor costs for nonadopters of more than one technology type average $27.44/cwt for 10–49 head dairy farms and $12.59/cwt for 50–149 head dairy farms.[30] For adopters, this cost is economically and statistically smaller, at $16.09/cwt and $8.64/cwt, respectively. For dairy farms between 50 and 149 head, robotic milking nonadopters expend, on average, $9.22/cwt. But for adopters, the value is significantly lower, at $5.30/cwt.

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[29] For dairy farms in these size categories, nearly all labor consists of unpaid, oftentimes family, labor (MacDonald et al, 2020). The lack of statistical differences between adopters and nonadopters of precision technologies are therefore unsurprising.

[30] Unpaid labor costs, as calculated by USDA, ERS, are the opportunity costs of providing unsalaried labor. This type of labor includes unpaid work performed by the farm operator, farm business partners, and family members. ARMS directly inquires about unpaid labor hours, which USDA, ERS values using an estimate of the (off-farm) wages paid to farm operators working off farm (USDA, ERS, 2023).

Table 5
Operator expenditure summaries by farm size and precision dairy technology adoption

Outcome	>1 technology type		Robotic milking	
	Adopters	Nonadopters	Adopters	Nonadopters
Panel A. 10–49 head [average size]	[37 cows]	[31 cows]	[(D)]	[34 cows]
Paid labor	0.70	0.46	(D)	0.64
Unpaid labor	16.09***	27.44	(D)	19.29
Feed	17.45	14.90	(D)	14.39
Capital recovery	10.42	10.58	(D)	9.74
Veterinary and medicine	1.18***	0.81	(D)	0.83
Panel B. 50–149 head [average size]	[84 cows]	[78 cows]	[117 cows]	[82 cows]
Paid labor	1.31	1.10	1.32	1.01
Unpaid labor	8.64***	12.59	5.30**	9.22
Feed	13.27	13.75	8.55***	13.85
Capital recovery	7.12***	8.47	4.97***	6.81
Veterinary and medicine	1.14***	0.81	0.88	0.88
Panel C. 150–499 head [average size]	[257 cows]	[241 cows]	[264 cows]	[259 cows]
Paid labor	2.23	2.08	1.17***	2.10
Unpaid labor	2.82**	4.01	1.71*	2.53
Feed	12.21	12.86	11.73	12.31
Capital recovery	6.85	5.02	6.69	5.48
Veterinary and medicine	1.10***	0.69	0.90	0.88
Panel D. More than 500 head [average size]	[1,417 cows]	[1,199 cows]	[1,628 cows]	[1,642 cows]
Paid labor	2.42	2.17	2.36	2.48
Unpaid labor	0.58*	0.72	0.86	0.47
Feed	11.73	11.84	11.31	11.79
Capital recovery	3.35	3.55	3.84	3.99
Veterinary and medicine	0.94	0.76	0.55**	0.83

Note: All costs are measured in dollars/cwt. The "> 1 technology type" indicates the farm is using technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (support). Nonadopter under the “>1 technology type” column refers to farms that adopt one or none of the technology types, while nonadopter under the “robotic milking” column refers to farms that did not adopt robotic milking. Non-robotic milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. Within each size category, the average size for adopters and nonadopters is reported in brackets. The ***, **, and * indicate that mean values for adopters are statistically different than mean values for nonadopters at the 1 percent, 5 percent, and 10 percent levels, respectively. Difference of means tests were conducted using a delete-a-group jackknife variance estimator with replicate weights provided by USDA, National Agricultural Statistics Service in the ARMS survey data. All dollar values are normalized to real 2021 dollars using the Consumer Price Index (CPI). (D) = disclosure issue (i.e., insufficient number of observations).

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS) dairy version, years 2000, 2005, 2010, 2016, and 2021.

As herd size increases, the primary labor costs flip; large operations—150–499 head and more than 500 head—expend more on paid labor (primarily immigrants) than on unpaid labor (table 5, panels C and D). However, these operations have lower unpaid labor costs per cwt of milk sold than operations in the two smallest size categories. For dairy farms in the more-than-one-technology group, unpaid labor costs average \$2.82/cwt (150–499 head) and \$0.58/cwt (more than 500 head). For nonadopters, these costs are \$4.01/cwt and \$0.72/cwt, respectively. Average unpaid labor costs for 150–499 head dairy farms that adopt robotic milking (\$1.71/cwt) are statistically lower than those of nonadopters (\$2.53/cwt). There are no significant differences in unpaid labor costs between adopters and nonadopters of robotic milking for dairy farms with more than 500 head.

Compared to paid and unpaid labor, costs of veterinary services and medicine make up a small portion of dairy operations' finances. However, for nearly all herd size categories, there are significant differences between adopters and nonadopters of precision dairy technology and robotic milking for this category of expenditure (table 5). The use of breeding technologies can benefit from the use of a veterinarian. The use of breeding and other technologies that monitor the health and optimize nutrition for dairy cows, such as robotic milkers, can also decrease costs on medicine and caring for sick animals. Mean costs of veterinary services and medicine for adopters of more than one technology type are \$1.18/cwt (10–49 head), \$1.14/cwt (50–149 head), \$1.10/cwt (150–499 head), and \$0.94/cwt (more than 500 head). For nonadopters, mean costs are lower, at \$0.81/cwt, \$0.81/cwt, \$0.69/cwt, and \$0.76/cwt, respectively (although the last difference is not statistically significant). For robotic milking, the only significant difference between adopters and nonadopters is for dairy farms with more than 500 head. Adopters of robotic milking in this size class spend, on average, \$0.55/cwt on veterinary services and medicine and nonadopters spend \$0.83/cwt, perhaps suggesting robots deliver health benefits that result in less veterinary and medicine costs.

For the remaining dairy operation costs that we examine—feed and capital recovery—there are few significant differences of means between adopters and nonadopters of the two technology groups within each size class. For dairy farms of all sizes, feed represents a primary cost that impacts profitability (Connor, 2015). In the samples of farms used in the statistical analysis, total feed costs (including homegrown and grazed feed) range between \$8.55/cwt and \$17.45/cwt (table 5). Average feed costs are significantly different between adopters and nonadopters of robotic milking in the 50–149 head class: \$8.55/cwt for adopters and \$13.85/cwt for nonadopters. This difference suggests that box robots can optimize feed and rations to better serve the dietary needs of dairy cows, at least for operations within this size class.

Capital costs are also important to farm finances and impact dairy operations' profitability. We capture dairy enterprise-level machinery and equipment costs through capital recovery costs, which represent the annualized value of machinery and equipment costs (including the annualized cost of using buildings and investments in animals), rather than the large upfront costs typically made to acquire capital. Precision dairy technologies and robotic milking necessarily require capital recovery costs, but this cost category also comprises other common, non-PA technology on dairy farms, such as milking machines. The only significant difference in capital recovery costs between technological adopters and nonadopters is in the 50–149 head size class. Here, operations that adopt more than one technology type face average yearly equipment and machinery costs of \$7.12/cwt, while these costs for nonadopters are, on average, $8.47/cwt. For robotic milking the average capital recovery costs are even lower: $4.97/cwt for adopters $6.81/cwt for nonadopters.[31]

Table 6
Operator time and productivity summaries by farm size and precision dairy technology adoption

Outcome	>1 technology type		Robotic milking	
	Adopters	Nonadopters	Adopters	Nonadopters
Panel A. 10–49 head [average size]	[37 cows]	[31 cows]	[(D)]	[34 cows]
Operator hours/cwt	0.75	1.2	(D)	0.088
Milking at least three times per day	0.017***	0.000010	(D)	0.014
Milk production (cwt/cow)	162***	134	(D)	153
Panel B. 50–149 head [average size]	[84 cows]	[78 cows]	[117 cows]	[82 cows]
Operator hours/cwt	0.33**	0.45	0.19***	0.35
Milking at least three times per day	0.038***	0.0080	0.71***	0.022
Milk production (cwt/cow)	181***	146	214**	182
Panel C. 150–499 head [average size]	[257 cows]	[241 cows]	[264 cows]	[259 cows]
Operator hours/cwt	0.094***	0.14	0.088**	0.063
Milking at least three times per day	0.24***	0.079	0.69***	0.25
Milk production (cwt/cow)	200***	157	231	212
Panel D. More than 500 head	[1,417 cows]	[1,199 cows]	[1,628 cows]	[1,642 cows]
Operator hours/cwt	0.018*	0.023	0.016	0.016
Milking at least three times per day	0.55***	0.34	0.36*	0.61
Milk production (cwt/cow)	221***	193	218	237

Note: The "> 1 technology type" indicates the farm is using technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (support). Nonadopter under the ">1 technology type" column refers to farms that adopt one or none of the technology types, while nonadopter under the "robotic milking" column refers to farms that did not adopt robotic milking. Non-robotic milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. Within each size category, the average size for adopters and nonadopters is reported in brackets. The ***, **, and * indicate that mean values for adopters are statistically different than mean values for nonadopters at the 1 percent, 5 percent, and 10 percent levels, respectively. Difference of means tests were conducted using a delete-a-group jackknife variance estimator with replicate weights provided by USDA, National Agricultural Statistics Service in the ARMS survey data. All dollar values are normalized to real 2021 dollars using the Consumer Price Index (CPI). (D) = disclosure issue (i.e., insufficient number of observations).

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS) dairy version, years 2000, 2005, 2010, 2016, and 2021.

Differences between adopters and nonadopters in time use and productivity attributes are also important for assessing the profitability effects from precision technology use. Operators who adopt more than one type of technology on average put significantly less time into the dairy enterprise (per cwt of milk produced) than nonadopting operators, for all size classes (table 6). Similar differences exist for robotic milking, excepting operators of dairy farms with more than 500 head. The largest

[31] Schimmelpfennig (2016) found that capital recovery costs are higher for adopters of PA technologies for corn producers than nonadopters, likely because of the high costs of the PA technologies themselves. We find the opposite for dairy production. The difference in the sign of this correlation between crop and dairy production likely represents the extensive machinery and equipment expenses necessary for operating a dairy enterprise, regardless of precision technology adoption.

differences exist for operators of dairy farms with between 50 and 149 head: 0.35 hours/cwt for nonadopters of box robots compared to 0.19 hours/cwt for adopters. The lower mean operator hours at dairy farms with robotic milking suggests that the automation from robots allows for more flexibility in the operators' lives.

Many of the expenditure-reducing benefits of precision dairy technology adoption (e.g., optimizing input usage, health and performance improvements) can also increase revenues through increases in milk production and dairy cow productivity. For all size classes, adopters of more than one technology type milk their herd three or more times per day at a higher rate than nonadopters (table 6).[32] For dairy farms with more than 500 head, 55 percent of operations that adopt more than one technology type milk their herd three or more times per day, compared to 34 percent of nonadopting farms. The differences are mostly similar for robotic milking. All adopters with less than 500 head have a milking frequency of three or more times per day at a higher rate than nonadopters. However, for dairy farms with more than 500 head, 36 percent of robotic milking adopters have a milking frequency of three or more times per day, compared to 61 percent of nonadopters. The differences here likely represent the efficiency gains of carousel parlors common for very large dairy farms.

We also examine productivity per cow, which we measure as cwt of milk produced per cow per year at each operation. For the 5 years of survey data from ARMS Phase 3, Dairy, the average milk production per cow per year for all operations is roughly 169 cwt/year.[33] For precision dairy technology adopters and nonadopters, however, the average values are significantly different for each size category (table 6). For adopters of more than one technology type, the average milk production per cow is 162 cwt/year (10–49 head), 181 cwt/year (50–149 head), 200 cwt/year (150–499 head), and 221 cwt/year (more than 500 head). For nonadopters, average production ranges from 134 cwt/year to 193 cwt/year, with only the 50–149 head size class average not statistically different than the average production of adopters. Robotic milking adoption is less correlated with productivity, with only the 50–149 head size class experiencing significant differences between adopters (214 cwt/year) and nonadopters (182 cwt/year).

Net Returns on Milk

The USDA, ERS Commodity Cost and Returns methodology produces two profitability measures per unit of commodity sold: (1) operating profit and (2) net returns. Operating profit is the gross value of the commodity's production less operating expenses for the commodity. Net returns are the gross value of the commodity's production less operating expenses and allocated overhead expenses for the commodity. Importantly, operating costs do not include items such as hired labor and land expenses, nor do they include the opportunity cost of capital and unpaid labor. Because unpaid labor is a large

[32] The ARMS Phase 3, Dairy questionnaire asks "… was the cow herd milked three or more times per day?" Traditionally, this refers to the average milkings per day for each cow, which in a traditional parlor setting would be the same for each cow. Robotic milking, however, allows cows to be milked as few or as many times as they would like. Therefore, this question uses the average for each cow for adopters of robotic milking.

[33] For the robotic milking sub-sample, however, this value is 184 cwt/year. The robotic milking sample includes only 2016 and 2021 data, which corresponds to a period of increasing yields as compared to the full sample which includes 2000, 2005, and 2010 data.

expense category for many small dairy farms, and because paid labor and the opportunity costs of capital can be substantial for large dairy operations, it is inappropriate to use operating profit in our analysis. Since net returns account for labor and other major dairy costs, their use is critical for accurately assessing the profitability situation of milk production.

Annual net returns per hundredweight of milk sold are the gross value of production (i.e., the dollar value of milk sold, dairy cattle sold, and other income) less operating costs and allocated overhead expenses attributed to the dairy enterprise. Other income includes revenue from renting or leasing dairy stock to other operations, renting space to other dairy operations, co–op patronage dividends associated with the dairy, assessment rebates, refunds, and other dairy-related resources, and the fertilizer value of manure production. Operating expenses are the cost of feed, veterinarian care and medicine outlays, bedding and litter, marketing, and third-party organic certification (if applicable), as well as the cost of custom services, repairs, interest on capital, and fuel, lube, and electricity attributed to the dairy enterprise.

Allocated overhead expenses include hired labor costs, the opportunity cost of unpaid labor, capital recovery of machinery and equipment, the opportunity cost of land, taxes and insurance, and general farm overhead.[34] Consistent with recommendations by a former Agricultural and Applied Economics Association (AAEA) Commodity Costs and Returns task force, the opportunity cost of unpaid labor is based roughly on off-farm wages paid to farm operators working off-farm. The opportunity cost of land is based on cash rental rates for land used to produce dairy (USDA, ERS, 2023).

On average, the gross value of milk production in the analysis sample is less than total costs, resulting in negative net returns for nearly all size categories and technology adoption groups (table 7).[35] As operation size increases, net returns increase across the board, regardless of technology adoption status. For adopters of more than one non-robotic-milking precision dairy technology, there are significant mean differences in net returns for the 50−149 head and 150−499 head size categories. Adopters had higher (less negative) net returns than nonadopters in each category: -$12.82/cwt versus -$18.73/cwt for 50−149 head, -$4.60/cwt versus -$7.31/cwt for 150−499 head. For robotic milking, mean net returns are only significantly different for the 50-149 head size category (-$3.89/cwt for adopters versus -$13.57/cwt for nonadopters).

Collectively, these summaries provide suggestive evidence that adoption of precision dairy farming could improve operators' profitability. The type of correlational evidence in table 7, while useful, points only to a statistical association, rather than providing a rigorous assessment of the technologies' profitability impacts. For those, careful regression analysis is needed to control for other necessary factors (i.e., demographics, farm structure aspects, infrastructure, and other equipment)

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[34] Since allocated overhead expenses are a measure of economic costs—not accounting costs—they will not align with measures of dairy expenses from other sources that focus exclusively on accounting costs. Similarly, measures of dairy profitability from other sources based solely on cash expenses will not align with USDA, ERS's net returns for milk.

[35] Because net returns include allocated overhead expenses, which involve various opportunity costs (e.g., labor, land), they are typically negative for milk. Over the 24 years since 2000, there have been only 3 years with positive annual net returns for milk nationally. However, operating profits, which do not include allocated overhead expenses, have been positive for all years since 2000.

and the fact that farmers' technology choices could result in bias if selection-type effects considered in the next section are not removed.

Table 7
Net returns by farm size and precision dairy technology adoption

Profitability measure	>1 technology type		Robotic milking	
	Adopters	Nonadopters	Adopters	Nonadopters
Panel A. 10–49 head [average size]	[37 cows]	[31 cows]	[(D)]	[34 cows]
Net returns ($/cwt)	-26.70	-34.71	(D)	-25.46
Panel B. 50–149 head [average size]	[84 cows]	[78 cows]	[117 cows]	[82 cows]
Net returns ($/cwt)	-12.82**	-18.73	-3.89***	-13.57
Panel C. 150–499 head [average size]	[257 cows]	[241 cows]	[264 cows]	[259 cows]
Net returns ($/cwt)	-4.60*	-7.31	-5.03	-5.41
Panel D. More than 500 head [average size]	[1,417 cows]	[1,199 cows]	[1,628 cows]	[1,642 cows]
Net returns ($/cwt)	-0.37	1.86	2.74	-1.30

Note: The "> 1 technology type" indicates the farm is using technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (support). Nonadopter under the ">1 technology type" column refers to farms that adopt one or none of the technology types, while nonadopter under the "robotic milking" column refers to farms that did not adopt robotic milking. Non-robotic milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. Within each size category, the average size for adopters and nonadopters is reported in brackets. The ***, **, and * indicate that mean values for adopters are statistically different than mean values for nonadopters at the 1 percent, 5 percent, and 10 percent levels, respectively. Difference of means tests were conducted using a delete-a-group jackknife variance estimator with replicate weights provided by USDA, National Agricultural Statistics Service in the ARMS survey data. All dollar values are normalized to real 2021 dollars using the Consumer Price Index (CPI). (D) = disclosure issue (i.e., insufficient number of observations).

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS) dairy version, years 2000, 2005, 2010, 2016, and 2021.

Benchmark Analysis

The previous subsections present evidence that dairy enterprise finances—including net returns—and other operator characteristics correlate with precision dairy technology adoption. However, omitted variables such as time, geography, or operator characteristics likely bias that analysis. For example, operations that are already more profitable may self-select into the group of technology adopters, thus biasing the correlations presented above (i.e., the correlations do not distinguish between situations where the technologies cause higher net returns vs. operators of already profitable farms choose to adopt them). To account for this bias, we rely on the repeated cross-sectional nature of the ARMS data to estimate a regression model that accounts for numerous factors important for explaining farmers' profitability. Specifically, this analysis minimizes bias and increases the precision of our estimates by controlling for time, geography, finances (e.g., costs), and operator-level characteristics (e.g., herd size) that correlate with precision dairy technology adoption and plausibly impact net returns (see the last three sections of the appendix for details of the regression model).

Table 8 presents estimation results for the cross-sectional regression analysis. Like above, we use two different analysis samples depending on the technology that we study: (1) the full sample of ARMS Phase 3, Dairy data (2000, 2005, 2010, 2016, and 2021) that contain information on non-robotic milking, breeding, and data support technologies and (2) a subsample of ARMS Phase 3, Dairy data (2016 and 2021) that contains information on robotic milking adoption.

The adoption of more-than-one-type of precision dairy technology, compared to the counterfactual of zero or one type of technology adoption, is associated with an increase in net returns of $1.22/cwt. This value is 5 percent of the national milk price (in real 2021 dollars) in our sample of $23.65/cwt (table 8).[36] The second column of table 8 presents analogous results, but for a treatment of robotic milking technology adoption. Compared to the counterfactual of no robotic milking, net returns for adopters of robotic milking are, on average, $1.00/cwt higher than those for nonadopters, which is 4 percent of the national milk price.[37] The coefficient for robotic milking is imprecisely estimated and statistically significant only at the 20 percent level (p=0.176).

Table 8

Effects of precision dairy technology adoption on net returns, benchmark results

Variable	(1) Net returns	(2) Net returns
Panel A. Regression coefficients		
>1 technology type	0.141***	
	(0.0481)	
Robotic milking		0.144
		(0.106)
Panel B. Implied marginal effects ($/cwt)		
>1 technology type	$1.22	
Robotic milking		$1.00
Panel C. Percent of national milk price		
>1 technology type	5%	
Robotic milking		4%
State indicators	Yes	Yes
Year indicators	Yes	Yes
Operator characteristics controls	Yes	Yes
Expenditure controls	Yes	Yes
Dependent variable mean	-3.260	-2.576
Observations	6,830	2,253

Note: The "> 1 technology type" indicates the farm is using technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (support). Non-robotic milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are

[36] Prior to estimation, we arcsinh-transform the net returns dependent variable because it behaves similarly to a logarithm transformation while permitting zero and negative values to be retained. For this and all other analyses, we follow Bellemare and Wichman (2020) in calculating the marginal effect (in levels) as $\sinh\left(\boldsymbol{X_{it}}'\widehat{\boldsymbol{\beta_2}} + \widehat{\beta_1} + \hat{\varepsilon}\right) - \sinh\left(\boldsymbol{X_{it}}'\widehat{\boldsymbol{\beta_2}} + \hat{\varepsilon}\right)$, where $\sinh(\cdot)$ is the hyperbolic sine function, $\boldsymbol{X_{it}}'\widehat{\boldsymbol{\beta_2}}$ are the predicted values from the regression, $\widehat{\beta_1}$ is the coefficient on the technology combination or robotic milking variable (depending on column 1 or 2), and $\hat{\varepsilon}$ are the residuals. See the appendix for more details about the regression models.

[37] We discuss results for the control variables with the complete results of the endogenous treatment effects model in the last section of the appendix.

individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. Three asterisks (***) indicate coefficients are statistically different from zero at the 1 percent level. Standard errors were estimated using the delete-a-group jackknife method with replicated weights provided by USDA, National Agricultural Statistics Service in the ARMS survey data. Column 1 shows results from the estimation on a repeated cross-section of data from all 5 survey-years of the ARMS Phase 3, Dairy version. Column 2 shows results from the estimation of a repeated cross-section of data from ARMS Phase 3, Dairy for 2016 and 2021. Outcome is arcsinh-transformed net returns at the farm-year level ($/cwt). All dollar values are normalized to real 2021 dollars using the Consumer Price Index (CPI). The national milk price in our sample in real 2021 dollars was $23.65/cwt. The operator characteristics controls include herd size, among other variables. Regressions use weights designed to ensure the results are representative of the quantity of U.S. milk production.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS) dairy version, years 2000, 2005, 2010, 2016, and 2021.

Analysis Accounting for Farmers' Non-random Precision Technology Choices

Even after controlling for factors that are correlated with technology adoption and plausibly affect net returns, our estimates up-to-this-point are possibly biased. This is because there exist other unobservable characteristics that lead to precision technology adoption (i.e., self-selection into treatment). For example, farmers' attitudes about technology or ideas about how to best operate a dairy farm can affect adoption, but they cannot be included in the model because data on these variables do not exist. The fact that these and other omitted variables cannot be included effectively results in biased estimates. It is also possible that operations with higher net returns or a large herd are better able to afford technology, an example of so-called simultaneity bias. Because of this latter possible bias, the results so far do not indicate whether adoption leads to greater profitability or if greater profitability leads to adoption.

To mitigate the possible effects of these biases, we estimate an endogenous treatment effects model (Imbens & Wooldridge, 2009), which can more strongly identify the causal effect of interest.[38] The endogenous treatment effects model accounts for farmers selecting into receiving treatment (i.e., adopting precision agriculture technologies) rather than being randomly assigned to treatment, as typically occurs in controlled field trials in agronomic experiments. The model consists of two equations, the technology adoption equation and the net returns equation, which are estimated in two different stages. In the first stage, technology adoption is estimated as a function of observable factors known to influence farmers' technology use. In our case, these factors include operator characteristics and demographics, as described above, and expenditures. In the second stage, net returns are estimated as a function of factors like those in the first stage, and a variable that represents PA technology adoption.[39] If this model's assumptions are met, then the results can be considered causal (i.e., the estimated effects are as if they came from a controlled trial where farmers were randomly assigned to be adopters or nonadopters of the PA technologies). See the appendix section Endogenous Treatment Effects Model: Methodology for more information.

For adopters of both more than one technology and robotic milking, it is evident that the effects found in the previous benchmark analysis were biased in a way that made the effects smaller (table 9). Adoption of more than one technology type leads to an increase in net returns of $3.18/cwt (13

[38] Our analysis resembles that of Schimmelpfennig (2016), who used a similar model. The endogenous treatment effects model is appropriate when treatment is self-selected, and there are data on both adopters and nonadopters of the precision technologies. The appendix section Endogenous Treatment Effects Model: Methodology describes our estimation in greater detail.

[39] This technology adoption variable consists of the predicted values from the first stage equation.

percent of the national milk price),) which is over twice as large as the percentage produced in the benchmark analysis (table 8).[40] However, the downward bias in the benchmark analysis for robotic milking is more substantial. The heterogeneous treatment effects model estimates the coefficient on robotic milking adoption more precisely, as it is statistically significant at the 5 percent level. The adjusted estimate suggests that adoption of robotic milking leads to an increase in net returns of \$3.15/cwt (13 percent of the national milk price), compared to the counterfactual of nonadoption.

Table 9
Effects of precision dairy technology adoption on net returns, accounting for farmers' non-random technology choices

Variable	(1) Net returns	(2) Net returns
Panel A. Unadjusted regression coefficients		
>1 technology type	0.343***	
	(0.0778)	
Robotic milking		0.427**
		(0.177)
Panel B. Implied marginal effects (\$/cwt)		
>1 technology type	\$3.18	
Robotic milking		\$3.15
Panel C. Percent of national milk price		
>1 technology type	13%	
Robotic milking		13%
Observations	6,830	2,253

Note: The "> 1 technology type" indicates the farm is using technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (support). Non-robotic milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. Three asterisks (***) indicate coefficients are statistically significant from zero at the 1 percent level and two asterisks (**) indicate coefficients are statistically different from zero at the 5 percent level. Standard errors were estimated using the delete-a-group jackknife method with replicate weights provided by USDA, National Agricultural Statistics Service in the ARMS survey data. Column 1 results are estimated using a repeated cross-section of data from all five survey-years of the ARMS Phase 3, Dairy version. Column 2 results are estimated using a repeated cross-section of data from ARMS Phase 3, Dairy for 2016 and 2021. The national milk price in our sample in real 2021 dollars was \$23.65/cwt. Regressions use weights designed to ensure the results are representative of the quantity of U.S. milk production.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS) dairy version, years 2000, 2005, 2010, 2016, and 2021.

Few studies to date have rigorously examined the profitability impacts of robotic milking, and even fewer have used data from U.S. dairy farms. Bijl et al. (2007) analyzed a sample of 62 Dutch farms with an average of 105 cows per farm. They found that automated milking adopters' margins (revenues minus feed, livestock, and land use costs) were not significantly different than nonadopters' margins, though adopters' margins per full-time employee were higher. In related work using a sample of 400 Dutch farms (average farm size of between 110 and 113 head), Steeneveld et al. (2012) found no

[40] The percentage change in net returns does not equal the values found in panel A or B of the table. To arrive at the correct percentage change estimates shown in panel C, we must adjust for correlations between the two equations brought on by the fact that both equations contain many of the same explanatory factors. After this adjustment, we also must adjust the coefficient using the methodology described in footnote 35 (Bellemare & Wichman, 2020).

difference between automated milking adopters' net outputs (revenues minus materials costs) and those of nonadopters. More recent analysis by Salfer et al. (2017) employing partial budget simulations of U.S. dairy farming showed that automated milking on 120- and 240-cow farms is more profitable than on nonadopting farms of the same size with parlors.[41] Profits were measured as the net present value, in annual terms, of milk revenues minus feed, labor, maintenance, debt payments, and income tax. They found that to be more profitable than nonadopting parlor dairy farms, adopters need to reduce milking labor to 45 minutes per robot and have slightly higher milk yields per cow each day, assuming the robots last 10 years and there is no additional facility construction (e.g., new barns). We are among the first to produce causal estimates of the effects of precision dairy technology adoption on net returns using large, representative samples of U.S. producers over time.

We reiterate the distinction between operating profits and net returns. Our estimates are statistically significant and economically meaningful, in part, because net returns incorporate not only paid labor costs, but unpaid labor costs. Operating profit, which is the gross value of the commodity's production less commodity operating costs, omits both labor expenses. The inclusion of unpaid labor costs is imperative in our analysis, because dairy production is a labor-intensive task where much paid labor (on large dairy farms) and unpaid labor (on small dairy farms) is necessary.

Linkages with USDA Programs and Policy

The relationship between precision dairy technology use and participation in risk management programs like USDA's Dairy Margin Coverage (DMC) program remain unstudied. The DMC Program provides enrolled dairy producers a payment on covered milk production when the margin (the difference between the all-milk price and the average feed price) falls below a dollar amount pre-specified by the producer. Premiums paid for coverage above the catastrophic coverage level are partly based on the dairy farm's production history, which in turn is linked to its past productivity (USDA, FSA, 2024). The extent to which the use of precision technologies boosts dairy profitability could, in theory, influence producers' decisions to enroll in the program and subsequent coverage choices. However, it is unclear how enrolled dairy operations that expect major productivity increases through precision technologies would adjust their DMC participation—if at all.

There are clearer connections between the use of precision technologies and the demand for conservation programs like the Conservation Stewardship Program (CSP) and the Environmental Quality Incentives Program (EQIP). As of the 2018 Farm Bill, at least 50 percent of EQIP financial assistance funds each year must be targeted to conservation practices related to livestock production (including dairy). Many of these EQIP practices and related CSP enhancements can be carried out, in part, using precision technologies. For example, silage crop management practices could involve soil testing to determine nutrient needs, variable rate manure applications, and precision pesticide

[41] Partial budget simulation is a standard methodology for assessing the effects of new technologies, programs, policies, and other market-influencing factors—especially when observational data from commercial farms are scarce or nonexistent (Lowenberg-DeBoer et al., 2020). This methodology is useful for constructing initial impact estimates, but the accuracy of these estimates can decline substantially if observed market behavior deviates considerably from key assumptions and scenarios embedded in the simulation.

applications (USDA, NRCS, 2024). Dairy producers could also use variable rate seeding as part of conservation practices related to cover cropping and conservation crop rotations. More generally, automated equipment steering can be used for various silage-related field operations as part of implementing many EQIP practices and CSP enhancements.

The USDA, Agricultural Research Service (ARS) has a long history of conducting basic and applied research on precision agriculture and in recent years has documented research breakthroughs in automation and reducing labor requirements. Between 2020 and 2022, some of these accomplishments included development of the first automated peanut sampling system, an efficient apple harvesting robot, and an autonomous robot for high-throughput phenotyping (USDA, ARS, 2021a; USDA, ARS, 2022a; USDA, ARS, 2023a). These kinds of innovations are expected in the future. The USDA, ARS Action Plans for upcoming years mentions that certain research areas will focus on advanced automation systems, technologies for precision management and diversification of forage-livestock systems, autonomous weeding robots and precision herbicide applications, and development of data-driven agroecosystem management (USDA, ARS, 2019; USDA, ARS, 2021b; USDA, ARS, 2022b; USDA, ARS, 2023b).

Underlying the precision dairy farming dimensions of USDA policies and programs are data collection efforts like ARMS that provide detailed information to improve decision making. Another such effort is the USDA, Animal and Plant Health Inspection Service's (APHIS) National Animal Health Monitoring System (NAHMS), which undertakes national studies on the health and health management of domestic livestock, equine, aquaculture, and poultry populations. These studies are designed to assist with information needs from specific commodity sectors and in recent decades the NAHMS unit has been surveying U.S. dairy operations on a recurring basis, with 2014 being the most recent dairy survey year. Top management issues, diseases and disorders, and producer incentives within the dairy sector are addressed in the survey. Unlike with ARMS, a substantial component of the NAHMS dairy program involves estimation of cow and cow health parameters using on-farm biological samples and other data, in addition to estimation of antibiotics use and antimicrobial resistance patterns of certain foodborne pathogens (USDA, APHIS, 2016a). In principle, it would be possible to expand our understanding of precision dairy farming from future NAHMS data collection given the structure of the dairy questionnaire development process.[42]

Conclusion

Dairy operations in the United States have become increasingly technologically sophisticated in recent decades, resulting from greater development and use of precision agriculture in the dairy sector. Although technologies like computerized milking, automatic milking detachments, and artificial insemination—to name only a few—have been used for years, especially among large dairies, adoption has become more widespread and given way to more advanced tools and production techniques.

[42] The 2014 NAHMS General Dairy Management Questionnaire inquired about a wide variety of dairy management practices, including parlor type and use of some precision dairy farming technologies (e.g., cow-level records, nutritionist-designed diets). Because the scope and aims of the NAHMS dairy data differ substantially from ARMS, we do not present NAHMS estimates in this report. For more information see USDA, APHIS (2016a, 2016b).

Modern dairy farming now incorporates technologies with a wide array of sensors designed to monitor and adjust feed and nutrition; milk production and quality; animal health, activity, and reproduction; and environmental factors. The availability of large amounts of highly detailed sensor data, together with advances in processing power, statistical methods, and agricultural engineering, have spurred innovations like fully robotic milking systems. As such, precision dairy farming in the United States represents a transformative paradigm shift in production methods—with management emphasizing individual cows rather than herds and automating routine tasks like feeding and milking—towards the goal of increased efficiency.

This report focuses on adoption trends, adopter characteristics, and profitability impacts of four broad classes of precision dairy technologies:

- Non-robotic milking (holding pens with an udder washer, milking units with automatic takeoffs, computerized milking),
- Breeding technologies (artificial insemination, embryo transfer, sexed semen),
- Data (decision support) systems (individual cow production records, nutritionists to design diets, computerized feed delivery systems), and
- Robotic milking.

Automated milking performed by box robots, a costly and recently developed technology, was used to produce 4 percent of U.S. milk in 2016 and 6 percent in 2021. Overall, 13 percent of dairy farms with 150–499 head used robotic milking in 2021, consistent with evidence suggesting that this size class stands to benefit from this technology, although dairies with more than 500 are expected to increase adoption in future years (MacDonald et al., 2020). Further, many dairy farms use more than one of these technologies: 45 percent of dairy farms used at least one technology from all three of the non-robotic milking, breeding, and data systems technology categories in 2021, though only 2 percent of farms used the nine precision dairy technologies analyzed in this study, excluding robotic milking.

Depending on operation size, average paid and unpaid labor costs are lower for adopters than nonadopters, while average veterinary and medicine costs are higher for adopters of bundled technologies. Adopters of precision dairy technologies also milk more often per day and produce more milk per cow than nonadopters, on average. These output benefits and cost savings are similar for robotic milking adopters in the 50–149 head range. For most herd size classes, dairy farms using one or more precision technologies, excluding robotic milking, have higher net returns on milk than nonadopters, though both have negative net returns, on average. This same pattern is true for robotic milking adopters, although the difference is most meaningful for those with between 50 and 149 head.

To our knowledge, this report is the first study to estimate the effects of precision and robotic technologies on farm profitability in U.S. agriculture using large, representative samples of commodity producers across multiple years. The use of more than one non-robotic milking, breeding, or data systems technologies increases net returns on milk by $3.18/cwt (13 percent of the 2021 national milk price). A similar profitability effect for robotic milking prevails—dairy farms using box robots have $3.15/cwt (13 percent of the 2021 national milk price) higher net returns than nonadopters, on average. Importantly, we hold herd size constant in these estimations, so the results apply to operations of all sizes. We note however, that economies of size are present in dairy production (MacDonald et al., 2020). Large dairy farms adopt more complex combinations of precision technologies than small farms, but box-style robotic milking is likely best suited for farms in the 50−149 head size category.

Large dairy farmers might use profit from their operations to invest in precision technologies that could generate further output gains and cost savings. This pattern could contribute to—and likely has contributed to—some dairy industry consolidation (MacDonald et al., 2020). However, technological change, price fluctuations in agricultural output and input markets, operational efficiency and firm survival, and related factors can influence the magnitude and extent of size advantages. Our profitability estimates, taken together with current demographic conditions (e.g., aging operators beginning to retire) and relatively high labor costs, suggest there are incentives that will likely spur greater adoption of precision dairy farming, and thus greater U.S. dairy output, in the future. Broader use of automation technologies like robotic milking could have large impacts on dairy productivity, cow health, labor demand, operators' quality of life, and industry structure in the long run.

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Appendix

Here, we first provide an overview of milking technologies and images of the precision and robotic dairy technologies, common dairy barn and parlor designs, and conventional milking technologies described in the text. Then, we describe in greater detail the empirical analysis of the main text, where we provide the regression equation, discuss the components of the cross-sectional regression model, and discuss the endogenous treatment effects model, which includes a complete tabulation of its first and second stages.

Milking Systems Overview and Conventional Milking Technologies

On modern dairy farms, cows are reared and milked according to the herd's biological requirements, which involve feed and nutrition, housing, insemination and birthing, and monitoring of animal health and behavior. Although dairy cows may be milked by hand, the milking process is typically performed either mechanically (e.g., with a milking machine) or robotically (e.g., with digital technologies that automate most or all steps of the milking process).[43] A milking system is a collection of technologies that characterize the method and facility (e.g., barn or parlor) of the milking process, as well as on-farm transportation and storage of milk output (Wagner et al., 2001). Below are several (but not all) of the primary technologies underlying conventional milking systems without dedicated milking parlors or milking robots.

Milking machines. Modern dairy farms use milk harvesting, cooling, and storage technologies for more hours per year than any other equipment (figure A.4, panel A). Although milking machines can vary substantially across operations, they all contain: (1) a vacuum system, (2) a pulsation system, (3) one or more milking units to withdraw milk from the cows' udders, and (4) an arrangement for transporting milk away from the unit. Within the milking machine, air is continuously removed by a vacuum pump, which creates a partial vacuum and the force to withdraw milk from the udder. Milk enters the unit through cups attached to the cow's teats (teatcups) and exits through tubes that ultimately connect to a pail or bucket (as in the case of pail unit/bucket milkers) or to the milk cooling and holding tank. The pulsation system regulates the vacuum and pressure levels by creating air in short, regular bursts that mimic the natural sucking motion of a calf during nursing (Reinemann, 2019).

Stanchion and tie stall barns. In the stall (stanchion) barn, each cow is tied in a stall for resting, feeding, and watering (figure A.3, panel A). The typical barn plan has two rows of stalls. In older buildings, farmers store hay and straw in an overhead loft, but modern layouts typically use adjacent buildings. Cows are usually milked by hand or with a milking machine while tied up in the stall barn (USDA, NASS, 2021). The operator moves to each cow and milks them individually—a highly labor-intensive practice.

[43] The milking process is comprised of several steps: (1) check foremilk and udder for mastitis, (2) apply premilking sanitizer to teats, (3) remove any debris from and dry the teats, (4) attach milking unit after stimulation, (5) adjust unit as necessary, (6) shut off vacuum and remove unit, and (7) apply postmilking germicide to teats (USDA, APHIS, 2016b; Reinemann, 2019).

Flat barns. In a flat barn, the milking area and the operator's area are typically at the same level of elevation, in contrast to parlors where cows stand on elevated platforms (figure A.3, panel B). Flat barns are like stanchion and tie-stall barns, although the milking equipment is often permanently mounted, and the cows move to the equipment. Because they can be inexpensively fitted into existing stanchion or tie-stall barns, flat barns may be a good choice for farmers considering transitioning to labor-efficient parlors with elevated platforms (USDA, APHIS, 2016b; Reinemann, 2019).

Around the barn pipeline systems. In pipeline systems, a series of pipes transports milk from the milking facility to the cooling and storage area (e.g., bulk tank) (figure A.4, panel D). Around-the-barn pipeline systems increase the speed of on-farm milk transportation, obviate the need for operators to empty pails or buckets of milk into portable dump stations or bulk storage, and improve milk sanitary conditions relative to manual transportation (Reinemann, 2019). These systems can be used on stanchion and tie-stall barns and flat barns, as well as parlors.

Images of Precision and Robotic Milking Technologies, Common Barns and Parlors, and Conventional Milking Technologies

Figure A.1
Non-robotic precision dairy technologies

Panel A
Teat cleaning step of udder washing

Panel B
Milking unit with automatic takeoffs

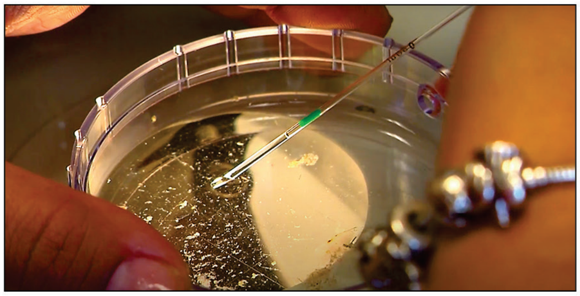
Panel C
Computerized milking system

Panel D
Artificial insemination

Non-robotic precision dairy technologies

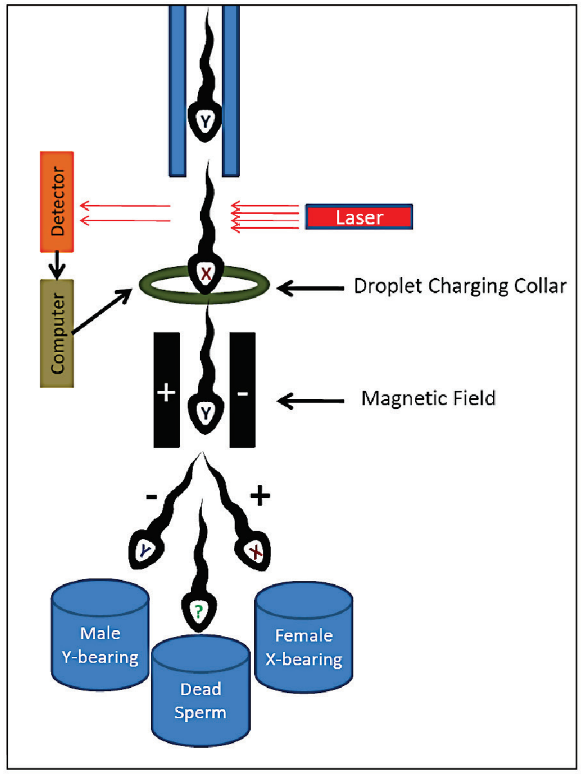
Panel E

Embryo transfer



Panel F

Sexed semen



Panel G

Individual cow production record

INDIVIDUAL COW RECORD

Cow's Name _____ Registration or eartag number _____ Date of birth _____ Breed _____

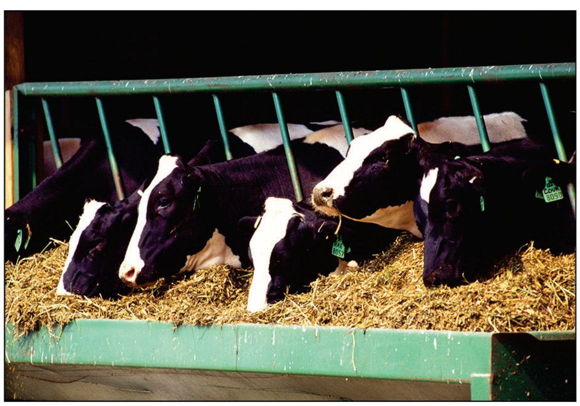
Dam's registration or eartag number _____ Sire's registration number _____

Date for starting this record _____ Date cow freshened _____ Sex of calf _____

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Current month or test period	Daily Milk Weights 1st milking	2nd milking	Total	Days in Milk	Total lbs. milk for this period	% Fat Test	Pounds butterfat for this period	Value of milk for this period	Cost of feed	Income over feed cost	Days cow dry for this period	Instructions
Totals												

Panel H

Nutritionist-designed diets



Panel I

Computerized feed delivery system

Note: Panel F illustrates how sperm are sorted into male, female, and waste. Before sorting, the sperm cells are stained with a dye and then passed through a flow apparatus as drops of liquid containing a single sperm cell per droplet. Because of the difference in amount of DNA, the X-bearing sperm shine brighter than the Y-bearing sperm when exposed to light. This allows a laser and detector to determine the gender of the sperm cell based on the amount of light it emits. A positive or negative charge is then applied to the droplet containing the single sperm cell. Positively charged drops are deflected one way, negatively charged drops are deflected the other, and uncharged droplets pass straight through. The uncharged drops may contain multiple sperm, damaged material, or cells that were not aligned in the proper direction (Mississippi State University Extension, 2022).

Source: All figures are reproduced with permission. Panel A: USDA official photostream on Flickr; Panel B: AgrAbility PA; Panel C: USDA official photostream on Flickr; Panel D: Adrian Sanchez Gonzalez, Montana State University; Panel E: Marianna Jahnke, Iowa State University; Panel F: Mississippi State University Extension Service; Panel G: Purdue University 4-H youth development; Panel H: USDA official photostream on Flickr; and Panel I: Marcia Endres, University of Minnesota.

Figure A.2
Robotic milking technologies

Panel A
Box robot

Panel B
Robotic carousel parlor

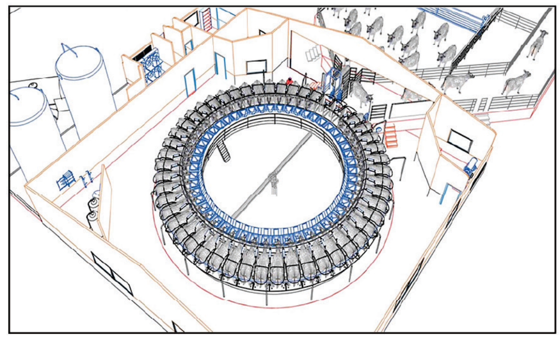
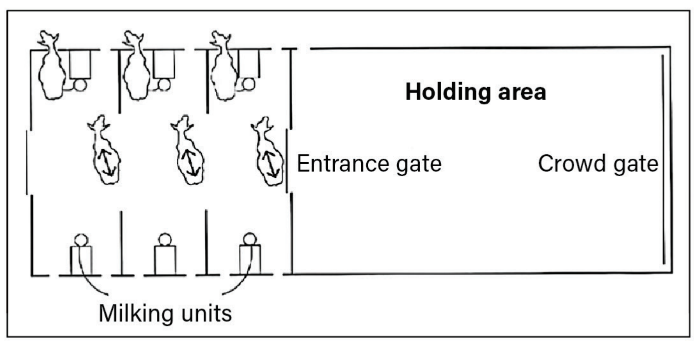


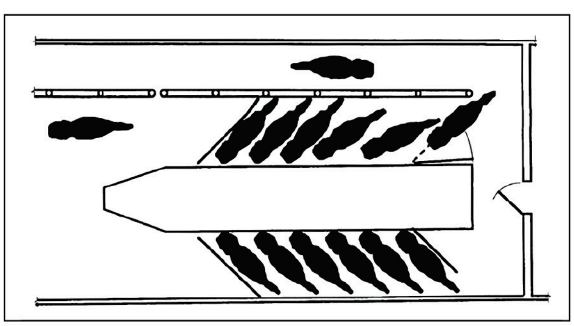
Figure A.3
Common dairy barns and parlors

Panel A
Tie stall barn

Panel B
Flat barn



Panel C
Herringbone parlor



Panel D
Parallel (side-by-side) parlor

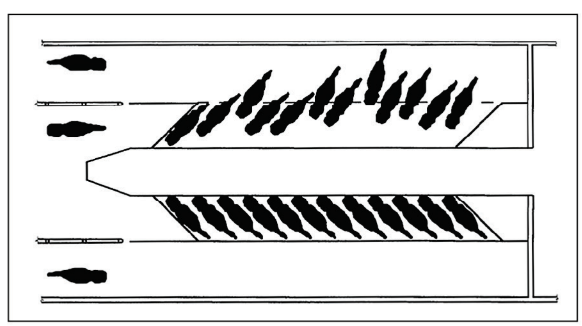
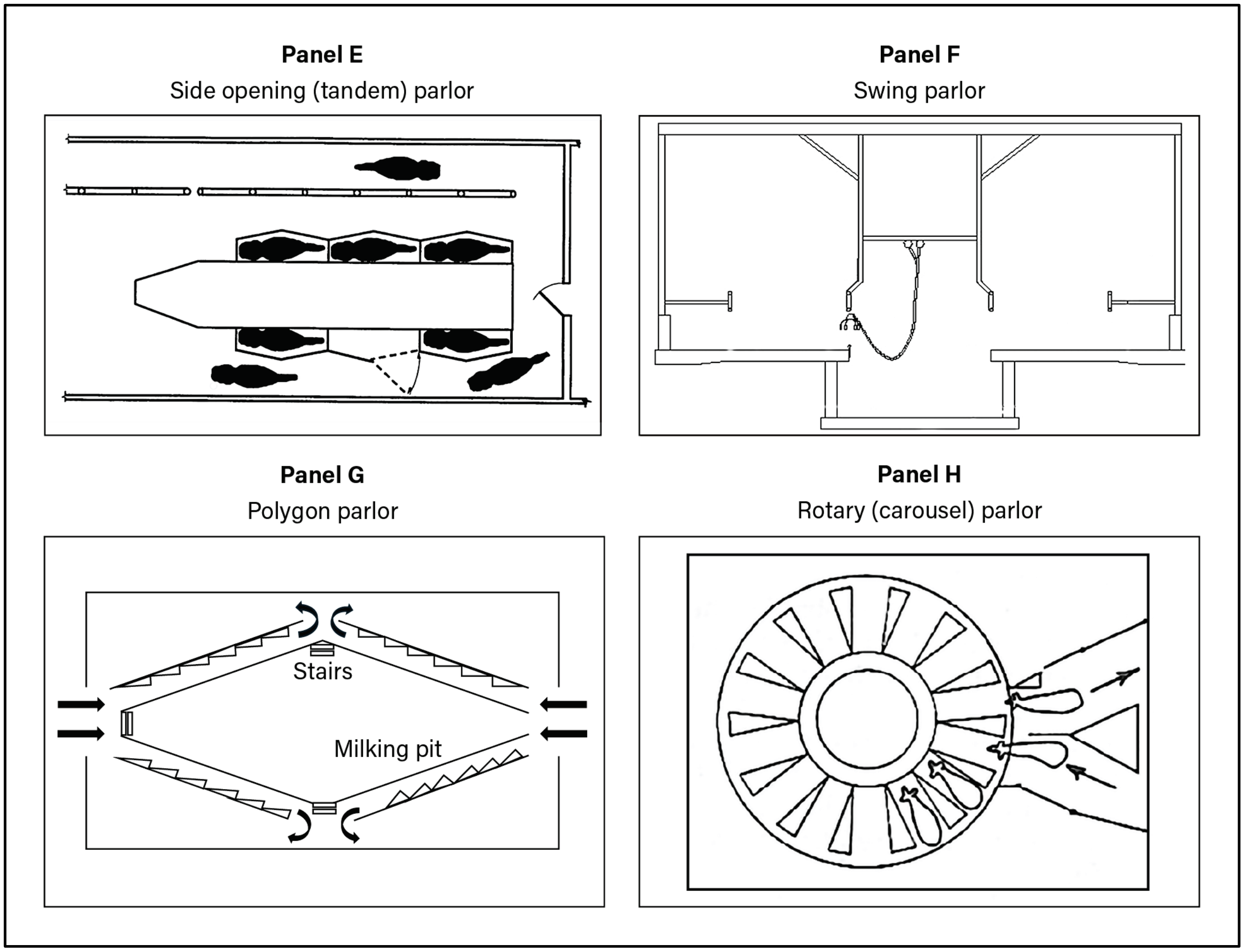


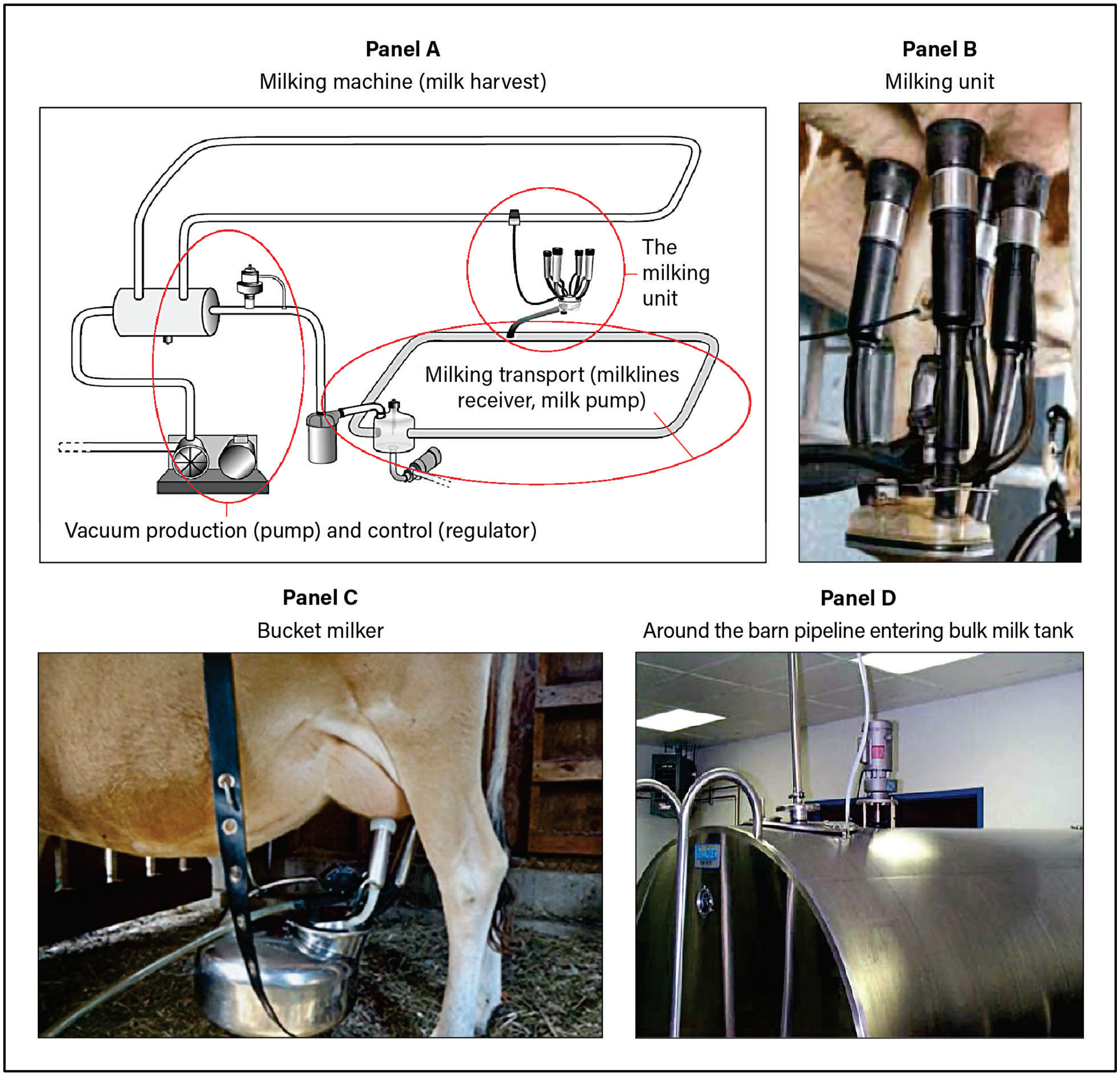
Figure A.3 (cont.)
Common dairy barns and parlors



Note: Panels B–E and G–H are top-down views of dairy parlors.

Source: All figures are reproduced with permission. Panel A: Masoud Hashemi, University of Massachusetts-Amherst Extension Crops, Dairy, Livestock and Equine Program; Panels B–F and H: Douglas Reinemann, University of Wisconsin. Panel G: Authors' illustration based on Bickert and Armstrong (1976).

Figure A.4
Conventional or standard milking technologies



Note: A milking machine consists of three basic functional groups: (1) milk harvest (which includes milking units and pulsation, vacuum production and control system, and milk transport system), (2) machine cleaning and sanitation (which includes wash vats, manifolds, and delivery lines, as well as controls and chemical dispensers), and (3) milk cooling and storage (which includes plate coolers, chillers, bulk tanks, etc.). Panel A emphasizes the milk harvest component of the milk machine. Although panel D only depicts the milk pipeline entering the bulk milk tank (from above), the pipeline in this milking system extends around the barn, collecting milk from cows that are connected to the milk transport system.

Source: All figures are reproduced with permission. Panels A–D: Douglas Reinemann, University of Wisconsin.

Cross-Sectional Regression Estimating Equation for Benchmark Analysis

Our interests lie in estimating the effects of precision dairy technology and robotic milking adoption on dairy enterprise-level profitability, which we measure using net returns. We therefore estimate the following regression specification:

$$f(Y_{ist}) = \beta_0 + \boldsymbol{TECH}_{it}{}'\boldsymbol{\beta_1} + \boldsymbol{X}_{it}{}'\boldsymbol{\beta_2} + \gamma_s + \lambda_t + \varepsilon_{ist}, \quad \text{(A1)}$$

where Y_{ist} is the net returns ($/cwt) for dairy operation i in State s in year t. We use an inverse hyperbolic sine transformation of the outcome variable which is appropriate given the heterogeneity in our unit of analysis, especially in terms of size. $\boldsymbol{TECH_{it}}$ represents a vector of our primary regressors. We examine two primary regressors in our cross-sectional regression analysis: (1) adoption of "more-than-one-type" of precision dairy technology and (2) adoption of robotic milking. Vector $\boldsymbol{\beta_1}$ contains the coefficients of interest, which we report in table 8. Identification of $\boldsymbol{\beta_1}$ comes from changes in dairy enterprise-level net returns coincident with variation in precision dairy technology adoption across operations and over time. Because of the labor-saving and herd management-improving benefits of precision dairy technology adoption, we hypothesize $\boldsymbol{\beta_1}$ to be positive.

We denote the set of control factors at the operation-year level as $\boldsymbol{X_{it}}$. Importantly, the components of $\boldsymbol{X_{it}}$ control for factors that are correlated with precision dairy technology adoption and likely impact dairy net returns (Schimmelpfennig, 2016; McFadden et al., 2023). We therefore include these controls to reduce bias and to improve the precision of our estimates of $\boldsymbol{\beta_1}$. The control factors in $\boldsymbol{X_{it}}$ fall into three broad categories. First is financials, which include operation-level costs and other measures (overhead and operating costs, government payments received, net worth). We hypothesize a negative relationship between allocated overhead and operating costs and dairy net returns, because additional expenditure necessarily takes away from net returns. Like Schimmelpfennig (2016), we include these expenses as a control factor to isolate the mechanism through which precision technologies affect net returns. By holding operating and allocated overhead costs constant in the regression framework, any impact on net returns from the more-than-one-technology-type and robotic milking treatments will be through productivity or revenue side increases. Likewise, if milk revenue correlates with government payments, potentially through price or demand effects, such payments could have an impact on dairy net returns.[44] For net worth, we hypothesize a positive relationship with net returns for the opposite reason. The second group of controls that we include in $\boldsymbol{X_{it}}$ is operation type, size, and infrastructure (herd size, acres operated, organic,[45] and parlor usage).[46] We hypothesize these controls to be positively associated with dairy net returns given the economies of size present in dairy production, organic milk premiums, and increased efficiency from parlors. Finally, $\boldsymbol{X_{it}}$ contains operator characteristics and demographics controls (operator age, operator high school degree plus some college, high speed internet access). We hypothesize that younger, more

[44] Government payments and DMC participation costs are not used by USDA, ERS's Cost of Production team to calculate net returns for milk from the ARMS Commodity Cost and Returns dairy data. However, a large literature exists on the capitalization of agricultural subsidies into farmland rental values (Ciaian et al., 2021). In our data, net returns are partly a function of pastureland cost, which itself partly relies on pastureland rental rates. Thus, even though we control for operating and allocated overhead costs, it may be useful to control for government payments as they could have an unmodeled, indirect effect on pastureland costs (independent of any potential impact on milk revenues).

[45] Organic is only a control factor in the robotic milking analysis, because it was not collected in early versions of the ARMS Phase 3, Dairy survey.

[46] Although herd size and operated acres are (weakly) positively correlated, and we would expect herd size to have more explanatory power in modeling dairy net returns, we use both in the regressions as they capture different aspects of dairy returns. After accounting for herd size, acres operated could impact dairy net returns through other enterprise income (e.g., renting space to other dairy operations) and various costs not fully reflected in herd size (e.g., the opportunity cost of land, excess capacity in structures).

educated operators with access to high-speed internet are more likely to have higher net returns than older, less educated operators without access to high-speed internet.

Equation (A1) also contains two sets of dummy variables that control for additional unobserved variation that may bias our estimation. First, γ_s is a series of state dummies that control for state-level characteristics that impact net returns, such as state-level policies or the general structure of a state's dairy industry. Next, λ_t are year dummies that control for time effects experienced by all dairy operations in our sample, such as changes in national dairy markets and Federal dairy policies. Finally, ε_{ist} is the exogenous error term.

Endogenous Treatment Effects Model: Methodology

There exists a large economics literature that examines the impacts of programs and policies on various outcomes of interest. Since much of this literature estimates exogenous policy changes using panel data, a dummy variable estimation strategy is appropriate. In our case, however, we wish to estimate the impacts of an endogenous choice variable on dairy enterprise-level net returns. A naive regression of our outcome on the choice dummy variable may produce biased estimates. Several methods exist to estimate a causal effect of interest with endogenous treatment variables (e.g., sample selection models, instrumental variables). For our analysis, we use the methods of previous USDA, ERS work (Schimmelpfennig, 2016) and estimate an endogenous treatment effects model, which is a form of a sample selection model (Imbens & Wooldridge, 2009). The endogenous treatment effects model works in our setting because it allows for the correlation between factors that affect both the treatment and the outcome. In other words, this model allows us to estimate two equations simultaneously, where the right-hand side of each equation contains some of the same variables (i.e., variables that simultaneously impact both the decision to adopt technology and dairy net returns).

The endogenous treatment effects model has two simultaneously estimated equations. First, the technology adoption equation is estimated using a logit model:

$$TECH_{it} = \beta_0 + \boldsymbol{Z_{it}}'\boldsymbol{\beta_1} + \varepsilon_{it}, \tag{A2}$$

where $TECH_{it}$ represents the endogenous treatment dummy, which is the adoption of more than one technology type or robotic milking at dairy farm i in year t. $\boldsymbol{Z_{it}}$ represents a vector of factors that influence the adoption of treatment at the farm level. In our analysis, we restrict $\boldsymbol{Z_{it}}$ to include only variables that statistically influence the adoption of technology, which can be found in appendix table A.1 below. All other notation is like that of equation (A.1).

Second, the predicted values of the technology adoption equation enter the net returns equation, which we estimate linearly as:

$$f(Y_{ist}) = \beta_0 + \widehat{\boldsymbol{TECH}}\boldsymbol{_{it}}'\boldsymbol{\beta_1} + \boldsymbol{X_{it}}'\boldsymbol{\beta_2} + \gamma_s + \lambda_t + \varepsilon_{ist}, \tag{A3}$$

where $\widehat{\boldsymbol{TECH}}\boldsymbol{_{it}}$ are the predicted values from the technology adoption equation. Outside of the fitted values predicted using equation (A2), the rest of the notation for equation (A3) is identical to that of equation (A.1), including all components of the control vector $\boldsymbol{X_{it}}$.

In addition to the estimating equations, there are two important items to note regarding the endogenous treatment effects model. First, we wish to quantify the correlation of the error terms between the two equations; we denote this correlation coefficient as ρ. Estimation of an endogenous treatment effects model produces $\hat{\rho}$ and a Wald test of the independence of the two equations, where the null hypothesis is no correlation in the error terms between the equations. If we fail to reject the null hypothesis of the Wald test, then there is no correlation between the two equations, and we can estimate them separately. Appendix table A.1 contains the ρ correlation coefficients and results of the Wald test for each analysis sample. The null hypothesis is rejected.

Second, we must account for the correlation in the error terms between the two equations. To do so, we adjust the treatment coefficients estimated using the endogenous treatment effects model. The adjustment is as follows: the sum of the coefficient estimated from the model (β) and the product of the cross-equation correlation coefficient (ρ) and the variance of the error terms from the model distribution (σ^2). That is, $\mathit{Adjusted}\,\beta = \hat{\beta} + (\hat{\rho} \times \hat{\sigma}^2)$.

Endogenous Treatment Effects Model: Full Results

Panel A of appendix table A.1 presents operator characteristics associated with the adoption of more than one precision technology type and robotic milking. Older operators are less likely to adopt complex combinations of precision dairy technologies, but more educated operators are more likely to adopt more than one type of technology. Operating a larger herd and access to high-speed internet are also correlated with greater adoption of more complex technological bundles.

The financials of dairy operations also matter for the adoption of precision dairy technology. For more-than-one-type of technology adoption, higher net worth is associated with greater adoption (appendix table A.1). Unpaid labor costs are negatively correlated with adoption, but higher veterinary and medicine costs are positively associated with adoption. For the robotic milking adoption equation, net worth and several operating and overhead costs are negatively correlated with adoption (paid labor, unpaid labor, feed). The type of dairy operation also proves important in the robotic milking adoption decision, as farmland acres operated and use of a parlor impact the decision in opposite ways.

Next, panel B of appendix table A.1 presents the results for the second, net returns equation. The results for the control variables are generally consistent with the hypothesized direction of the effect, lending support to the internal validity of our estimation model. We wish to highlight that outside of the technology treatment variables, the inclusion of additional regressors serve only as controls to improve the precision of our estimates. The coefficients of our control factors therefore only represent correlations.

The use of a parlor and net worth are positively associated with net returns in both sets of analyses (appendix table A.1). Operator age is positively associated with net returns in the robotic milking equation, while education is negatively associated with net returns in the equation for the more than one technology type. As expected, the expenditures controls are negatively associated with total net returns. Higher allocated overhead and operating expenses necessarily decrease net returns, suggesting that the net returns impacts of precision dairy technology and robotic milking adoption discussed in the main text are through improved revenues/productivity of adopters.

Table A.1

Effects of precision dairy technology adoption on net returns, endogenous treatment effects full model results

Variable	(1) >1 technology type	(2) Robotic milking
Panel A. Precision dairy technology adoption		
Herd size (000s)	0.130***	
	(0.0475)	
Farmland acres operated (000s)		0.546***
		(0.134)
Operator age	-0.0121***	
	(0.00264)	
Operator has at least high school degree	0.460***	
	(0.0928)	
High speed internet access	0.226**	
	(0.0891)	
Net worth (000,000 dollars)	0.0175***	-0.0158**
	(0.00593)	(0.00647)
Parlor usage		-1.318***
		(0.298)
Cost of paid labor (dollars/cwt)		-0.566***
		(0.192)
Cost of unpaid labor (dollars/cwt)	-0.544***	-0.345**
	(0.0391)	(0.163)
Cost of veterinary and medical services (dollars/cwt)	0.910***	
	(0.0827)	
Cost of feed (dollars/cwt)		-0.713***
		(0.204)
Panel B. Net returns		
>1 technology type (predicted values)	0.343***	
	(0.0778)	
Robotic milking (predicted values)		0.427**
		(0.177)
Herd size (000s)	-0.00536***	-0.0468***
	(0.00931)	(0.0126)
Farmland acres operated (000s)	-0.00520	-0.0389**
	(0.0108)	(0.0174)
Operator age	-0.000438	0.00380**
	(0.00123)	(0.00185)
Operator has at least high school degree	-0.0293***	0.0971
	(0.0496)	(0.0924)
High speed internet access	-0.0819*	0.0115
	(0.0462)	(0.0700)
Government payments received (000 dollars)	0.000344***	0. 000469***

	(0.000130)	(0.000149)
Organic		3.0505***
		(0.128)
Net worth (000,000 dollars)	0.00702***	-0.00965***
	(0.00126)	(0.00166)
Parlor usage	0.264***	0.265***
	(0.0495)	(0.0837)
Allocated overhead expenses (dollars/cwt)	-2.07***	-2.1616***
	(0.0327)	(0.534)
Operating expenses (dollars/cwt)	-2.66***	-2.8787***
	(0.0425)	(0.0611)
State dummies	Yes	Yes
Year dummies	Yes	Yes
Correlation of error terms between equations (ρ)	-0.146	-0.273
Wald test of independent equations (ρ = 0) p-value	0.001	0.053
Observations	6,830	2,253

Note: The "> 1 technology type" indicates the farm is using technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (support). Non-robotic milking technologies are holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems; breeding technologies are artificial insemination (AI), embryo transplants (ET), and sexed semen; data technologies are individual cow production records, nutritionist-designed diets, and computerized feed delivery systems. The ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively. Standard errors were estimated using the delete-a-group jackknife method with replicate weights provided by USDA, National Agricultural Statistics Service in the ARMS survey data. Column 1 results are estimated using a repeated cross-section of data from all 5 survey-years of the ARMS Phase 3, Dairy version. Column 2 results are estimated using a repeated cross-section of data from ARMS Phase 3, Dairy for 2016 and 2021. “Operator has at least high school degree” indicates the farm operator had a high school degree plus some college or a college degree. All dollar values are normalized to real 2021 dollars using the Consumer Price Index (CPI). Regressions use weights designed to ensure the results are representative of the quantity of U.S. milk production.

Source: USDA, Economic Research Service and USDA, National Agricultural Statistics Service, Agricultural Resource Management Survey (ARMS) dairy version, years 2000, 2005, 2010, 2016, and 2021.

Finally, we consider the correlation of the error terms between the two sets of simultaneously estimated equations. Both sets of equations have correlation coefficients (ρ) that are negative, suggesting that unobservable factors that increase net returns are inversely related to unobservable factors that increase technological adoption. For the precision dairy technology sample, ρ is economically meaningful at -0.146. We reject the Wald test’s null hypothesis of independent equations (no statistical correlation between the two equations) (p=0.001). For the robotic milking sample, ρ is also economically meaningful, -0.273, and we reject the null hypothesis of the Wald test (p=0.053). The results suggest that the error terms of each set of equations are strongly correlated, meaning that it is necessary to estimate the equations jointly. The efficiency gains of the endogenous treatment effects model are inherent in the differential estimates between the cross-sectional regression model and the endogenous treatment effects model for both sets of equations.