Do precision agriculture technologies increase profitability? Evidence from a nationally representative sample of US dairy farms*

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August 16, 2026

Abstract

In this paper, we study how the adoption of precision agriculture technologies in US dairy production affects operation-level profitability. The analysis focuses on the adoption of complex technology bundles and robotic milking systems, which can improve productivity and input-use efficiency, but come with substantial upfront costs and steep learning curves. We use nationally representative data from USDA's Agricultural Resource Management Survey to extend the analysis beyond traditional small-scale case studies and ex ante budget simulations. The primary research design uses a two-stage control function approach to account for the endogenous nature of the technological adoption decision. We find that the adoption of complex technological bundles increases operation-level dairy net returns by $2/cwt of milk produced, or roughly 8.5% of the average all-milk price at the end of our sample period. The effect for robotic milking adoption is even more pronounced: almost $4/cwt, or 17% of the all-milk price. We present evidence that the effects are realized through both increased productivity (the revenue side) and decreased input costs. Our results suggest that the high capital costs of these technologies may accelerate sectoral consolidation, as large operations can better absorb the upfront costs, maintain cashflow needed for upkeep and maintenance, and capture the economic gains of continued technological adoption.

JEL Classification: Q12, Q16, Q18
Keywords: activity monitoring, automation, digital agriculture, net returns, precision dairy farming, robotic milking, smart farming

* *Acknowledgements*: We thank Brent Hueth, David Donaldson, Jeffrey Gillespie, Thomas Worth, Krishna Paudel, James MacDonald, Eric Njuki, Lizzy French, Nigel Key, Ann Stapleton, Diane Wray-Cahen, Matthew Branan, Victor Cabrera, Doug Reinemann, Marcia Endres, Jared Hutchens, Larry Tranel, and Christopher Wolf, Katie Meier, Jason French, and Grant Peissig for their valuable insights. This research was supported in part by the US Department of Agriculture, Economic Research Service. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or US government determination or policy. All remaining errors are ours.
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Introduction

Over the past three decades, US agricultural production has experienced a sizable shift towards greater use of precision agriculture (PA)—technologies characterized by automated production processes, data-driven decision-making, and operation-level management at smaller units of analysis (e.g., animal-by-animal, sub-meter zones) rather than at the whole farm level (Coble, et al., 2018; McFadden et al, 2023). This ongoing shift, commonly termed the digitalization of agriculture, has been characterized as a fundamental, perhaps irreversible, transformation of commodity production (e.g., Lowenberg-DeBoer, 2015; Basso and Antle, 2020). In principle, the adoption of PA technologies alters the economic performance of individual producers by enhancing productivity and/or improving input-use efficiency.[1] However, realizing these gains often requires paying high upfront costs and mastering steep learning curves, both of which are more difficult in periods of economic uncertainty or in highly variable production environments. The net impact of PA technology adoption on operation-level profitability therefore remains an important empirical question.

There exists some evidence on the relationship between PA technology adoption and profitability in crop production (e.g., Anselin et al., 2004; Griffin et al., 2004; Bullock et al., 2009; Schimmelpfennig, 2016). But this relationship remains understudied in livestock production, even in sectors such as dairy where the shift toward PA is especially pronounced. Precision dairy farming (PDF) technologies that automate production, such as fully robotic milking systems (RMS) and wearable sensors that track individual cows' biological and other traits, represent a rare class of precision farming tools that can fully automate the harvest of an agricultural commodity, making this sector especially intriguing (Sauer and Zilberman, 2012; Borchers and Bewley, 2015; McFadden and Raff, 2026). Although recent evidence suggests that these tools are among the primary drivers of total factor productivity growth in US dairy production, (Njuki, 2022), empirical evidence regarding their operation-level economic impacts remains minimal. This research gap stems largely from a paucity of data tracking PDF technology adoption across broad spatial and temporal scales.

The purpose of this paper is to causally identify the effect of PDF technology adoption on the aggregate economic performance of US dairy operations. We examine two distinct types of PDF technologies: 1) a complex bundle of primarily non-automated technologies (i.e., a combination of more than one non-robotic milking, breeding, or data technologies) and 2) RMS. Our outcome of interest is dairy net returns, which is the gross value of milk production (and other dairy enterprise revenue) less the sum of operating expenses and allocated overhead costs.[2] Importantly, we answer our research question using an operation-level, nationally representative dataset of US dairy producers that includes information on PDF technology adoption, costs, revenues, and other operation-level characteristics. This allows us to provide wide-scale, generalizable results that, to our knowledge, do not exist in any other analyses of US dairy farming. Our results are also among

[1] As one example, variable rate technologies allow operators to apply fertilizer to individual field locations depending on the specific nutrient needs of that spot (rather than homogeneously applying the same amount to entire fields), which can reduce input use (Lee et al., 2025; Gajbhiye et al., 2026).

[2] Briefly, net returns include allocated overhead expenses, which include items like labor expenses and the opportunity cost of land, while operating profit only includes operating expenses. We discuss these measures in detail in a later section.

the first large-sample, multi-year estimates of the returns to robotic agricultural production in the US.

A sizable literature examines the economic outcomes associated with PA technology adoption. Previous studies show a positive relationship between PA adoption and profitability in crop production (e.g., Griffin et al., 2004; Dhoubhadel, 2021; Wang et al., 2023). With the notable exceptions of Schimmelpfennig (2016) and companion research that makes use of USDA microdata (e.g., Schimmelpfennig, 2018), the literature uses small-scale case studies and ex ante budget simulations—limiting the external validity of the conclusions about profitability. Arguably more important, the findings from field crops do not necessarily translate to livestock production, where the (more tightly-controlled) biological production cycle and commodity harvest are continuous rather than seasonal, and come with certain production shocks that operators manage in distinct ways (e.g., droughts, disease outbreaks).

For dairy production in particular, prior work on this relationship has similarly focused on the use of data from small-scale surveys or ex ante budget simulations (Bewley, 2010; Borchers and Bewley, 2015; Mayo et al., 2019). This is also true for studies examining the profitability of PDF technologies in other countries (e.g., Bijl et al., 2007). Existing national-scale analyses in the US do not focus on economic outcomes, instead prioritizing trends in structural transitions (MacDonald et al., 2020), aggregate productivity (Njuki, 2022), or general management practices (Gillespie et al., 2024). McFadden and Raff (2026), however, examine economic characteristics and PDF technology adoption, but they focus primarily on dairy industry characterization, technological classifications, adoption trends, and descriptive relationships—largely for the benefit of a policy-making audience.

To empirically answer our research question, we construct a repeated cross-sectional dataset integrating five waves of USDA's Agricultural Resource Management Survey (ARMS) Phase 3, Dairy version (2000, 2005, 2010, 2016, 2021). These data are nationally representative of more than 90% of US dairy production in each survey year and provide granular information on operation-level PDF technology adoption, production practices, cost structures, and revenue streams. They also provide information on farmer characteristics (e.g., demographics, human capital) that the literature has found critical in modeling technological choice. Leveraging these large-scale spatial and temporal data allows us to account for the considerable cross-sectional heterogeneity in dairy production practices across time and space. Ultimately, this comprehensive approach allows us to arrive at externally valid estimates, a significant advancement over the localized scope of existing small-scale case studies.

We first use the ARMS data to characterize the observable characteristics associated with PDF technology adoption. Then, we evaluate the effects of PDF technology adoption on net returns using OLS regression, propensity score matching (PSM), and a two-stage control function (CF) approach. The CF is our primary estimation strategy because it explicitly addresses the endogenous nature of the PDF technology adoption choice. Within our CF framework, we use the concurrent state-level adoption rate (which we calculate as a leave-one-out mean) as an exogenous instrument for operation-level adoption. We motivate this instrument with regional technological diffusion and the presence of localized support infrastructures, such as equipment dealer networks and social learning through producer peer networks. We empirically confirm the relevance of the instrument,

as operation-level adoption is highly correlated with state-level diffusion. The instrument is also excludable. Aggregate state-level adoption represents a market-level trend that does not directly influence an operation's net returns, except through its influence on the operator's technological adoption choice.

Descriptive results indicate that adopters of PDF technology bundles and RMS are younger, more educated, and more likely to have access to high-speed internet than nonadopters. Furthermore, adopters exhibit higher milk production and generally lower input costs than nonadopters, suggesting that the economic benefits of PDF technology adoption are realized through both enhanced revenue generation and cost-minimization. The primary CF estimates reveal that adoption of the technology combination measure and of RMS significantly increases dairy net returns. Specifically, adoption of the technology combination increases operation-level net returns by $2/cwt of milk produced, or roughly 8.5% of the average all-milk price in the final year of the sample period. The effect for RMS adoption is even more pronounced: almost $4/cwt, or 17% of the average all-milk price. These values represent meaningful gains in an agricultural sector where net returns are consistently negative.

This study contributes to the literature in three ways. First, and most important, we provide the first national-scale, representative, and causal estimates of the adoption of PDF technologies on profitability within the US dairy sector. In doing so, we address a critical gap in the PA literature that has relied largely on case studies, ex ante simulations, and descriptive correlations. Our estimates are also among the first to rigorously quantify the effects of robotic agricultural production. Second, we leverage a unique and granular dataset to examine specific PDF technology bundles and RMS that are largely unexplored in prior work. Finally, we provide several sets of analyses that characterize PDF technology adopters, thus providing a profile of the types of operations that adopt PDF technology bundles and RMS.

Our findings are important for individual producers, policymakers, and the broader dairy industry. Most PDF technologies entail high fixed investment costs, ongoing maintenance costs, and steep learning curves, making it crucial for operators to understand the economic implications associated with adoption. Further, the US dairy sector has experienced profound sectoral consolidation in recent decades (MacDonald et al., 2020; Raff and Meyer, 2022). A major driving force of this structural shift is size economies, which dairy farmers' use of PDF technologies influences (Mosheim and Lovell, 2009; MacDonald et al., 2018). Our analysis, therefore, sheds light on whether these innovations could enhance the economic viability of small operations or, alternatively, reinforce the competitive advantages of large-scale, capital-intensive operations—potentially accelerating further consolidation in dairy production.

The remainder of this study proceeds as follows. The following section provides the necessary industry background and develops a conceptual framework for the PDF technology adoption decision. Then, we describe the data, including variable construction and descriptive statistics. The next section presents baseline empirical results using OLS and PSM. We then provide details on our primary identification strategy and provides causal estimates via the CF approach. The penultimate section offers a discussion of the results and their policy implications. Finally, we conclude.

Background and technological adoption decision

In this section, we provide background information about PDF and its potential benefits. Then, we present a simple conceptual framework that models the operator's decision to adopt PDF technologies.

Precision dairy farming and its potential benefits

In its broadest sense, PDF is the use of technologies that allow operators to manage the milking herd at the individual cow level, rather than at the aggregated herd level. This paradigm shift mirrors precision crop farming, where analogous tools facilitate the heterogeneous management of sub-field units (e.g., grids, management zones) as opposed to homogeneous treatment of entire plots or fields.[3] PDF uses sensors and automation tools to aggregate—and sometimes autonomously act upon—high-frequency data on the physical, biological, and production metrics of individual animals (Bewley, 2010). Examples of such technologies include RMS, precision diet formulation software, computerized feed delivery, and an array of wearable sensors such as activity trackers and estrus detectors.[4] (Appendix Figure A1 contains a schematic detailing the commercially available PDF technologies.) Operators then use these data to optimize production practices by, for example, managing replacement cows, more efficiently using inputs, and preemptively identifying health and/or other problems with individual cows.

The economic rationale for PDF technology adoption rests on the realization that the economic benefits outweigh the associated costs. Here, we focus on three categories of potential economic benefits of PDF technology adoption. We consider these benefits as "potential" because, to date, large-scale empirical evidence confirming their realization remains sparse. Instead, prior work relies on small-scale case studies or ex ante budget simulations, which do not fully capture the heterogeneity of dairy production throughout the US.

First, the adoption of PDF technologies can increase gross revenues, primarily by improving herd management strategies and increasing milk yield per cow. For instance, individual cow level data on feed intake and conversion efficiency enable producers to transition from uniform feeding regimes to precision nutrition, where nutritionists or the operator tailor diets to the requirements of each animal. This optimization allows for superior biological performance, resulting in greater weight gain and increased milk productivity. Similarly, automation in the milking process (e.g., RMS) can expand the production frontier by decreasing total milking time for the herd and increasing the frequency of daily milking sessions. Indeed, McFadden and Raff (2026) show that RMS adopters are more likely than nonadopters to milk their herd at least three times per day.

Second, PDF technology adoption can reduce variable input costs. The largest expenses for dairy operations in the US are feed, labor, and capital recovery costs (USDA-ERS, 2023). PDF technologies improve resource allocative efficiency by minimizing input waste, especially in the feed

[3] As one example, variable rate technologies (VRT) allow farmers to apply different fertilizer (N, P, K) amounts across a single field, dependent on the specific requirements of each location or zone (McFadden et al., 2022; Gajbhiye et al., 2026).

[4] In the subsequent empirical analysis, we focus on a select set of technologies for which adoption data are available in the ARMS Phase 3, Dairy surveys. We describe these technologies in depth in the appendix.

space. By transitioning away from uniform feeding, producers can reduce the over-nutrition that occurs when individual cows consume diets that exceed their biological requirements for milk production. Further, PDF facilitates capital-labor substitution; automated systems, such as RMS, reduce the demand for both hired and unpaid family labor. For smaller operations in particular (i.e., those with fewer than 300 head), automation may also lower the opportunity cost of time. This allows operators or their family members the ability to earn additional off-farm income, because less time is necessary for the milking enterprise.[5]

The adoption of PDF technologies necessarily increases capital recovery costs because of the large upfront costs and oftentimes high operation and maintenance costs. But the costs of conventional dairy capital, such as milking units or parlors, are also high. Consequently, we remain agnostic as to the effect of PDF adoption on capital recovery costs.

Finally, PDF technology adoption can enhance economic returns by improving animal health and reproductive efficiency. de mol (2000) shows that PDF may be most economically beneficial by improving the health and reproduction of dairy cows. Technologies such as automatic estrus detection and artificial insemination (AI), and genomic selection more broadly, allow operators to implement sophisticated breeding strategies that result in replacement heifers that are most productive and durable. Additionally, the recent beef-on-dairy trend allows operators to use these technologies to produce high-value crossbred calves for the beef market.

PDF technologies also mitigate the monitoring costs—primarily time—necessary in dairy production by allowing operators the freedom to not observe in-person each cow for signs of health problems. Instead, PDF technologies, especially wearable sensors or individual cow production records, can help to identify health problems much sooner. This is especially important as herd sizes in the US continue to grow (Gargiulo et al., 2018).[6]

The operator's adoption decision

The structure of US dairy production has changed considerably in the past several decades, characterized primarily by rapid consolidation and increased herd size (MacDonald et al., 2016, 2020). But inertia persists regarding the adoption of new production practices, particularly among older operators or when adoption requires considerable upfront capital outlays or steep learning costs (Wolf, 2003).[7] Consequently, the decision to invest in PDF technologies is fundamentally an economic one. We model this choice within a profit-maximization framework, incorporating the potential economic benefits to adoption described above. Briefly, we assume that the operator will adopt PDF technologies if the decision maximizes profit (net returns), i.e., marginal revenue gains (including those off-farm) and marginal reductions in variable input costs exceed the technologies'

[5] More broadly, operators can invest labor time freed up by automation in multiple ways, including reallocation among on-farm work, off-farm work, and leisure. For simplification, we forego attempting to value all sources of time savings, although we note that our measure of net returns includes the opportunity cost of unpaid labor.

[6] While not a direct component of the enterprise's private net returns, PDF adoption may also generate positive environmental benefits Improved feed efficiency and animal productivity can reduce the aggregate nutrient load and greenhouse gas emissions per cwt of milk produced. Although these sustainability outcomes are important in PA, they remain outside the scope of this paper.

[7] We abstract from dynamic considerations and model the adoption decision in a static profit-maximizing framework, recognizing that these adjustment frictions may contribute to delayed adoption in practice.

marginal costs.[8]

Consider a dairy operation producing some amount of milk Q in period t. The standard inputs to production are conventional capital, e.g., barns, milking machines, (K_t), paid and unpaid labor (L_t), feed (F_t), and herd health and genetic makeup (H_t). Additionally, the operator can adopt PDF technologies ($T_t(\psi_t)$), where $\psi_t \geq 0$ is a continuous measure that represents the level of adoption.[9] The production function for this operation is therefore:

$$Q_t = f(K_t, L_t, F_t, H_t) \times T_t(\psi_t). \tag{1}$$

The operation faces opportunity and actual costs for labor (w_L), the price of feed (p_F), capital recovery (r_K), and veterinary and healthcare costs (v_H). In addition, PDF technology adopters must pay for the technology, which includes the cost of the capital itself and operation and maintenance ($\Gamma_t(\psi_t)$) The cost function is therefore:

$$C_t(\psi_t) = w_L L_t(\psi_t) + p_F F_t(\psi_t) + r_K K_t(\psi_t) + v_H H_t(\psi_t) + \Gamma_t(\psi_t). \tag{2}$$

We assume that the operation's economic benefits of PDF technologies (described above) increase monotonically with the level of technological adoption, $\psi_t > 0$. Specifically, as ψ_t increases, the marginal costs of labor, feed, and veterinary/healthcare decrease ($\frac{\partial C}{\partial \psi_t} < 0$). Conversely, the effect of PDF technology adoption on capital recovery costs remains theoretically ambiguous, depending on the scale of the investment relative to the efficiency gains.

In addition to these cost-minimizing effects, PDF technology adoption can bolster gross revenues by shifting the production frontier upward and diversifying revenue streams. Revenue gains are realized through increased milk yields, optimized breeding outcomes, and increased off-farm income. We denote the revenue function, $R_t(\psi)$:

$$R_t(\psi_t) = P_{m,t} Q_t(\psi_t) + w_O \Delta L_O(\psi_t), \tag{3}$$

where $P_{m,t}$ is the price of milk in time period t, w_O is the off-farm wage rate, and $\Delta L_O(\psi_t)$ is the change in off-farm labor hours.

The dairy operator therefore chooses the level of PDF technology adoption, ψ_t, to maximize total profit ($R_t(\psi_t) - C_t(\psi_t)$). Which yields the first order conditions:

$$P_{m,t} \frac{\partial Q}{\partial \psi_t} + w_O \frac{\partial L_O}{\partial \psi_t} = \frac{\partial C}{\partial \psi_t}. \tag{4}$$

[8] Qualitative evidence from producer interviews suggests that bottom-line profitability is the primary driver of PDF adoption decisions, supporting our focus on net returns.

[9] We consider a continuous measure to account for the various levels of PDF technology adoption possible. For example, a dairy operation can adopt many types of technologies (e.g., milking automation, wearable sensors) or they can adopt technology for some subset of the herd. This framework easily applies to the adopt or do-not-adopt indicator situation as well.

Verbally, the dairy operator will increase their adoption of PDF technology until the marginal revenues from that technology (due to, e.g., increased milk yield, off-farm income) equal the marginal costs of the technology, which include both capital outlays and the ongoing operation and maintenance costs. Subsequent sections examine empirically this adoption decision and its effect on operation-level dairy net returns.

Data

This section details the data that we use for our empirical analysis. First, we describe the source of data: USDA's ARMS Phase 3, Dairy version. Second, we discuss the construction of our outcome and primary regression measures. We then describe the creation of our analysis samples. Finally, we present statistical summaries and examine the differences-in-means of some key operational measures.

Data source

Our sole data source is USDA's ARMS. The ARMS is a collaborative effort between USDA's Economic Research Service (ERS) and USDA's National Agricultural Statistics Service (NASS). The ARMS is one of USDA's primary tools for assessing the financial health and other structural characteristics of the US agricultural sector (see, e.g., ERS's Commodity Costs and Returns series). ARMS uses a multi-frame, stratified, and probability-weighted methodology across three distinct phases.

For this paper, we use data from ARMS Phase 3, which ERS and NASS complete annually by April of the following calendar year (e.g., 2021 ARMS Phase 3 data collection completed in April of 2022). Phase 3 gathers granular information about farm-level finances, operator and household characteristics, and demographics. ARMS collects data from many types of agricultural commodity producers, but we focus specifically on the dairy-specific surveys that ERS and NASS administered in 2000, 2005, 2010, 2016, and 2021. This multi-year spanning is consistent with USDA's rotating survey schedule for Phase 3. USDA typically surveys specific livestock and crop commodities on a rotating basis every four to 10 years.

For our analysis, we use observations with non-missing information for our measures of interest (PDF technology adoption and economic measures like feed prices). Table 1 details survey waves (years) and the corresponding sample sizes within the commodity costs and returns dataset. In addition, Table 1 includes the states represented in each ARMS Phase 3, Dairy version. These states are the top-producing dairy states in the country. When applied, ARMS survey weights ensure that any statistical estimates are nationally representative of more than 90% of US dairy production across multiple dimensions, including farm count, economic sales class, and physical milk production. The most recent version of the ARMS Phase 3, Dairy data contain operations with at least 10 milking cows in 28 states.

Over the past several decades, the content of the ARMS Phase 3, Dairy version has changed considerably, mirroring the industry's structural and technological transformation over that time. Regardless, ARMS Phase 3, Dairy surveys maintain a consistent core, repeatedly asking respondents

Table 1. ARMS Phase 3, Dairy background

Year	States	Observations
2000	AZ, CA, FL, GA, ID, IL, IN, IA, KY, MI, MN, MO, NM, NY, OH, PA, TN, TX, VT, VA, WA, WI	872
2005	AZ, CA, FL, GA, ID, IL, IN, IA, KY, MI, MN, MO, NM, NY, OH, PA, TN, TX, VT, VA, WA, WI	1,814
2010	AZ, CA, CO, FL, GA, ID, IL, IN, IA, KS, KY, ME, MI, MN, MO, NM, NY, OH, OR, PA, TN, TX, VT, VA, WA, WI	1,915
2016	AZ, CA, CO, FL, GA, ID, IL, IN, IA, KS, KY, ME, MI, MN, MO, NM, NY, OH, OR, PA, SD, TN, TX, UT, VT, VA, WA, WI	1,526
2021	AZ, CA, CO, FL, GA, ID, IL, IN, IA, KS, KY, ME, MI, MN, MO, NM, NY, OH, OR, PA, SD, TN, TX, UT, VT, VA, WA, WI	828

Notes: ARMS Phase 3, Dairy waves, sampled states, and number of observations in each year. The sum of these observations does not make up our sample size, due to missing observations for some PDF technology questions.

about production, inventories, cow purchases and sales, and milking infrastructure. These data points form the basis of the ARMS Commodity Costs and Returns accounts, which categorize the dairy enterprise's financial performance into three components: gross value of production, operating costs attributed to the dairy enterprise, and allocated overhead attributed to the dairy enterprise. We use these characteristics to construct an appropriate measure of operation-level profitability, which we describe below.

Variables of interest

Here, we describe the construction of our regression measures. We first describe the profitability outcome: net returns per hundredweight (cwt) of milk produced. This measure is a standardized metric that allows for comparisons across diverse operation sizes. We then define our key regressors and categorize them based on their functional economic contributions: digitalization and data management, breeding and animal health, and automation. Finally, we discuss the control factors.

Outcome: Dairy net returns. Our objective is to identify the impacts of PDF technology adoption on operation-level profitability. We therefore must identify a metric that accounts for the revenue and cost structures of US dairy operations, as described above. Following the recommendations of the AAEA National Task Force on Commodity Costs and Returns (USDA-ERS, 2023), we use ERS's standardized measures of dairy profitability.

The first measure, operating profit, is the gross value of dairy production less total operating expenses. The gross value of dairy production is the total market value of milk and dairy cattle sold, plus supplemental income streams such as revenue from renting/leasing dairy stock, 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. And operating expenses reflect the variable costs of the dairy enterprise, including those for feed, veterinary care and medicine, bedding and litter, marketing, third-party organic certification, custom services, repairs, interest on capital, and fuel, lube, and electricity attributed to the dairy enterprise.

However, operating profit omits important financial components of dairy enterprises, most notably hired labor, land expenses, and the opportunity costs of capital and unpaid labor. The omission of unpaid labor is particularly problematic for small dairy operations, while paid labor and the opportunity costs of capital are substantial for large dairy operations. Consequently, using operating profit as our outcome would paint an incomplete picture of the economic trade-offs of PDF technology adoption.

ERS therefore produces a second profitability measure: dairy net returns. This measure equals the gross value of dairy production less the sum of operating expenses and allocated overhead expenses for dairy production. Allocated overhead incorporates the previously omitted financial considerations plus some others: hired labor, the opportunity cost of unpaid labor, capital recovery of machinery and equipment, the opportunity cost of land, taxes, insurance, and general farm overhead.[10]

Given these important considerations, we focus exclusively on operation-level net returns as our outcome of interest. We argue that using net returns is critical for a complete assessment of dairy profitability, especially in the context of PDF technology adoption, given the importance of the relationship between PDF technology adoption and capital recovery and paid and unpaid labor costs.

Primary regressor: Technology combination. The ARMS Phase 3, Dairy surveys contain several sets of questions relating to PDF technology adoption. Importantly, the questions for non-robotic milking technologies have remained consistent during the five waves of ARMS surveys that we use, so we have many observations to leverage in our empirical analysis. We describe here the specific technology adoption questions that we use from the ARMS Phase 3, Dairy surveys. In addition, we categorize these technologies into three distinct functional classes: 1) non-robotic milking, 2) breeding, or 3) data (decision support).

We discuss each technology class and highlight the varying degrees of benefits in digitalization (i.e., data collection and knowledge creation), breeding/health, and automation that each technology provides. We hypothesize that the economic returns to these classes vary depending on whether the technology primarily automates physical tasks or provides sophisticated diagnostic information. Here, we only briefly discuss the specific technologies or management practices, while providing a complete description of each in the appendix.

The first class of technologies that we examine are non-robotic milking technologies, which facilitates the physical extraction of milk. These technologies are primarily labor-augmenting, designed to streamline the milking process and reduce variable input costs such as paid and unpaid labor. The ARMS Phase 3, Dairy surveys collect adoption data for the use of holding pens with an udder washer, milking units with automatic takeoff, and computerized milking systems. Table 2 (panel A) shows a range of benefits from the technologies in this class. Computerized milking systems provide the highest benefits, as these systems help to automate the milking process, and gather and use data to increase cow-level productivity.

[10] ERS estimates the opportunity cost of unpaid labor using the off-farm wages paid to farm operators working off-farm. And ERS calculates the opportunity cost of land using cash rental rates for land used to produce dairy (USDA-ERS, 2023).

Table 2. ARMS Phase 3, Dairy PDF technologies and levels of digitalization, breeding/health benefits, and automation

Technology	Digitalization	Breeding/ health	Automation	Overall
Panel A. Milking technologies (non-robotic milking)				
Holding pen with an udder washer	Low	Low	Medium	Low
Milking units with automatic takeoff	Low	High	High	Medium
Computerized milking systems	High	Medium	High	High
Panel B. Breeding technologies				
Artificial insemination	Medium	High	Medium	Medium
Embryo transfer	Medium	High	Medium	Medium
Sexed semen	Medium	High	Low	Medium
Panel C. Data (decision support) systems				
Individual cow production records	High	High	Low	Medium
Nutritionist to design feeds	Medium	High	Low	Medium
Computerized feed delivery systems	High	High	High	High
Panel D. Robotic milking				
Box robots	High	High	High	Very high

Notes: The columns for digitalization, breeding/health, and automation represent the level (low, medium, or high) of that category that each individual PDF technology or management practice provides. Digitalization is the integration of digital technologies into dairy production to gather real-time data, thus providing knowledge and decision support. Breeding/health are the benefits (e.g., heat detection, weight gain) of each that the technologies or management practices provide. Automation is the use of the technology or management practice to perform tasks while decreasing the need for human labor. The overall column aggregates each row to a total level of PDF technology, with high representing technologies or management practices that collect individual cow-level data and provide breeding/health and automation benefits. Each panel contains the classes of technologies or management practices that the ARMS Phase 3, Dairy survey collected in the ARMS waves of 2000, 2005, 2010, 2016, and 2021.

Next, a class of PDF technologies consist of breeding and reproductive management, which dairy operations use to optimize the genetic traits of replacement animals. Dairy operators use these technologies to breed for higher milk yields, improved feed conversion efficiency, and enhanced disease resilience. Indeed, prior work attributes selective breeding and genetic gains as drivers of the sustained productivity growth in dairy production (DeJarnette et al., 2004; Njuki, 2022). The ARMS Phase 3, Dairy surveys collect information on the usage of artificial insemination (AI), embryo transplant (ET), and sexed semen at US dairy farms. Clearly, these technologies have high breeding/health benefits because that is their primary purpose. Panel B of Table 2 also shows that breeding technologies overall provide medium benefits, as they allow for some digitalization (e.g., via the maintenance of pedigree and genomic records) and automation (by eliminating labor and safety risks associated with maintaining bulls for natural service).

The final technology class data (decision support) systems. These PDF technologies gather and provide data or decision support to dairy operators. Technologies in this class use computerized

systems to provide operators with 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. The ARMS Phase 3, Dairy surveys collect information on the use of individual cow production records, nutritionists to design diets, and computerized feed delivery systems. As shown in panel C of Table 2, data technologies produce high levels of breeding/health benefits, as they contribute to proper diets and feed efficiency. And computerized feed delivery systems, in particular, contribute to knowledge and data creation for individual cows and automation in the feeding process.

We create our first primary regressor by taking these individual classes of PDF technologies and constructing a dummy variable that indicates if the operation had adopted a combination of more than one class of technologies in each year. For example, this dummy equals one for an operation-year observation that adopts at least one non-robotic milking technology and at least one breeding technology. And it equals zero if the operation-year observation adopts only one type of non-robotic milking technology.

The analysis relies on an aggregated combination dummy rather than individual dummies for two reasons. First, prior work suggests that precision technologies are often complementary; their marginal benefits are maximized when implemented as a suite, either due to cost-saving synergies or commercial bundling by suppliers (Lambert et al., 2015; Schimmelpfennig, 2016; McFadden et al., 2023). Second, we follow the literature and create an aggregated adoption measure (e.g., Schimmelpfennig, 2016) because individual technology adoption choices are highly correlated and thus, inclusion of several choices in a single regression comes with multicollinearity concerns. McFadden and Raff (2026) show this to be particularly important in US dairy production using data like ours. In our variable construction, we remain agnostic as to why operators adopt certain combinations of technologies more frequently than others (e.g., McFadden, 2023). But consolidation in US dairy production and the corresponding economies of size have been shown to associate with greater technological adoption, especially for more complex combinations of technologies (MacDonald et al., 2020).

Primary regressor: Robotic milking. RMS represent a transformative PDF. Robotic milking automates nearly all steps underlying the milking process, including the preparation and harvest of milk. We distinguish between two RMS configurations: voluntary milking systems (i.e., box robots), which are typically used in free stall barns and can milk between 55 and 70 cows per day; and robotic carousel parlors, which can automatically milk hundreds of cows per day. There is very little diffusion of fully robotic carousel parlors in the US, so we rely on a dummy variable of box robot adoption that we gather from the ARMS Phase 3, Dairy data. Panel D of Table 2 highlights the high digitalization, breeding/health, and automation benefits of robotic milking adoption, as robotic milking systems gather much data, tailor diets and feed, and fully automate the collection of milk. However, these benefits come with sizable installation and maintenance costs, which may non-linearly affect the impact of adoption on dairy net returns.[11]

[11] There exists much interest in the financial components of robotic milking (Bach and Cabrera, 2017; Prendergast et al., 2024; Salfer et al., 2017; Sauer and Zilberman, 2012; Steeneveld et al., 2012; Tse et al., 2018; Zulovich et al., 2018). It is important to note that the benefits of these systems come with considerable costs. Box robots cost roughly $200,000 per robot, with maintenance costs of $20,000 to $25,000 per year (Urbanz and Cardoso, 2023).

Other analysis factors. We include in our analysis three categories of control factors that we gather from the ARMS Phase 3, Dairy data. We briefly describe the variables that we use from ARMS here, while describing them fully below. The first category of variables are operation-level financial variables. From the commodity costs and returns dataset we include expenses on allocated overhead, labor, veterinary and medicine, and operating costs. Directly from the ARMS Phase 3, Dairy data we include government payments and operator's net equity. Second, we include operation type, size, and infrastructure factors. From ARMS, we gather information on herd size, operated acreage, and parlor usage. Finally, we include in our analysis operator characteristics and demographics. We gather information on operator age, retirement status, educational attainment, internet access.

Construction of analysis samples

We create two samples from the ARMS Phase 3, Dairy surveys. Although technologies and management practices in dairy production have evolved from 2000 to 2021, the core technological adoption questions remained consistent across survey waves. But robotic milking is a relatively new technology, and the ARMS only recently began collecting information on its adoption. Our samples differ then based on their temporal coverage and primary technological adoption variables. We construct a first sample for our analysis of technology combination adoption. This sample is a repeated cross section of operation-year level observations for the ARMS Phase 3, Dairy waves of 2000, 2005, 2010, 2016, and 2021. Our second sample, which we use for our analysis of RMS adoption, is again a repeated cross-section of operation-year observations, but is restricted to the 2016 and 2021 survey waves.

Statistical summaries

The technology combination sample (all ARMS Phase 3, Dairy years) contains 6,723 observations and the robotic milking sample (ARMS Phase 3, Dairy 2016 and 2021 waves) contains 2,209 observations. Table 3 provides summary statistics for our regression measures for each sample. The primary outcome of interest for our analysis is dairy net returns, which we measure in $/cwt of milk produced. Mean net returns in the technology combination sample are -$12.77/cwt and for the robotic milking sample are -$9.40/cwt. These negative values are consistent with the broader landscape of US dairy production, where costs frequently exceed the gross value of dairy production, especially since our net returns measure includes opportunity costs such as unpaid labor (USDA-ERS, 2023). These means also suggest an increase in average operation-level net returns over the past several decades, as the newer robotic milking sample has higher average net returns by over $3/cwt.

Next, Table 3 presents summary statistics for our main regressors of interest, which are the PDF technology adoption dummies. Nearly 72% of observations in the technology combination sample have adopted two or more of the classes of technology that we describe above (non-robotic milking, breeding, and data). Dairy operations in the US adopt RMS more infrequently with only 3.1% of observations experiencing adoption.

Finally, Table 3 contains statistical summaries for other regression measures. We include in our analysis several sets of controls, such as financial characteristics and operator demographics.

Table 3. Summary statistics

	Technology combination		Robotic milking	
Variable	Mean	SD	Mean	SD
Net returns ($/cwt)	-12.77	25.45	-9.396	18.42
Technology combination	0.719	0.450		
Robotic milking			0.031	0.174
White operator	0.989	0.103	0.999	0.030
Middle aged operator	0.491	0.500	0.587	0.493
Acres quartile, first	0.280	0.449	0.185	0.388
Acres quartile, second	0.389	0.488	0.379	0.485
Allocated overhead expenses ($/cwt)	19.97	17.53	17.23	14.39
Herd size <50 head	0.210	0.408	0.174	0.379
Retired operator	0.025	0.156	0.029	0.168
At least HS education	0.786	0.410	0.769	0.421
Internet access	0.851	0.357	0.821	0.383
Unpaid labor expenses ($/cwt)	9.432	12.96	7.790	11.07
Parlor usage	0.716	0.451	0.748	0.434
Government payments (000s)	26.40	61.28	34.95	85.71
Net worth (000s)	3,695	6,807	5,110	8,906
Veterinary expenses ($/cwt)	0.968	0.924	0.869	0.955
Operating expenses ($/cwt)	19.79	16.35	18.68	10.35
Observations	6,723		2,209	

Notes: Summary statistics are at the operation-year level and tabulated for all measures used in the regression analysis. For ease of interpretation, measures are not weighted. Technology combination means that the operation uses PDF technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (decision support).

Operators both samples are predominantly white, roughly half are middle-aged, and very few are retired. Educational attainment in both samples is high: over three quarters of observations have operators with at least a high school education. Importantly, high speed internet access is frequent in both samples (85% in the technology combination sample, 82% in the robotic milking sample). The literature shows that this infrastructure is important for many precision agriculture technologies to function properly (e.g., McFadden et al., 2023). Table 3 shows that operations in our sample face sizable costs in dairy production, as mean allocated overhead, operating expenses, and unpaid labor sum to nearly $50/cwt in each sample (in the final year of our sample period the average all-milk price in the US was $23.65/cwt).

Difference-in-means of key economic variables

We next examine the differences-in-means of key economic variables between PDF technology adopters and nonadopters. These correlations provide insights into the benefits of technological adoption in improving revenues and reducing costs as described in a previous section. Table 4 presents means of key economic variables for adopters and nonadopters of our technology combination dummy (columns 1 and 2) and robotic milking (columns 3 and 4). The economic variables

Table 4. Operator expenses, production, and dairy net returns by PDF technology combination and robotic milking adoption

	Technology combination		Robotic milking	
Variable	Adopter	Nonadopter	Adopter	Nonadopter
Panel A. 10-49 head [average herd size]	[37 head]	[31 head]	[(D)]	[33 head]
Paid labor	0.71**	0.46	(D)	0.52
Unpaid labor	13.63***	20.43	(D)	15.22
Feed	14.38*	12.80	(D)	12.98
Capital recovery	8.29	8.61	(D)	7.09
Veterinary and medicine	1.16***	0.79	(D)	0.85
Milk production (cwt/cow)	178***	156	(D)	172
Outcome: Net returns ($/cwt)	-18.97*	-23.60	(D)	-17.74
Panel B. 50-149 head [average herd size]	[84 head]	[78 head]	[84 head]	[77 head]
Paid labor	1.38**	1.04	1.27	1.01
Unpaid labor	6.85***	9.45	4.91	6.70
Feed	12.35	12.28	8.01**	12.39
Capital recovery	6.35**	7.30	4.83**	6.13
Veterinary and medicine	1.11***	0.78	0.87	0.84
Milk production (cwt/cow)	199**	175	227	202
Outcome: Net returns ($/cwt)	-9.34***	-12.91	-4.15**	-9.49
Panel C. 150-499 head [average herd size]	[257 head]	[239 head]	[263 head]	[238 head]
Paid labor	2.29***	1.92	1.27***	2.23
Unpaid labor	2.18****	2.88	1.58	1.88
Feed	11.74	11.82	11.69	11.49
Capital recovery	4.82	6.17	6.21	5.46
Veterinary and medicine	1.09***	0.70	0.98	0.89
Milk production (cwt/cow)	215***	178	247	233
Outcome: Net returns ($/cwt)	-3.53	-4.74	-4.86	-4.55
Panel D. >500 head [average herd size]	[1,407 head]	[1,204 head]	[1,681 head]	[1,234 head]
Paid labor	2.24	1.78	1.98	2.23
Unpaid labor	0.34	0.40	0.27	0.26
Feed	11.17	10.88	9.73	11.20
Capital recovery	3.09	2.95	3.77	3.43
Veterinary and medicine	0.83	0.63	0.66	0.70
Milk production (cwt/cow)	233	220	262	245
Outcome: Net returns	2.11	0.77	2.08**	-0.24

Note: All costs are measured in $/cwt. Technology combination treatment means that the operation uses PDF technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (decision support). Delete-a-group jackknife variance estimator with replicate weights used to produce difference-in-means tests. (D) represents a disclosure issue, where there are insufficient observations for analysis.

include costs (paid and unpaid labor, feed, capital recovery, and veterinary and medicine), revenues (via milk production), and net returns. Importantly, Table 4 also accounts for the herd size of the operation, which is important for costs, revenues, and technological adoption (MacDonald et al., 2020; Gillespie et al., 2024).

Table 4 first highlights the differences in costs between small and large operations. Dairy operations with herd sizes between 10 and 149 head expend considerably more on unpaid labor than operations with more than 150 head. This structure flips for paid labor, as the two larger size categories expend more on paid labor than unpaid labor. Table 4 also shows differences in costs between adopters and nonadopters of the technology combination and robotic milking. For the technology combination, adopters for all operations except the largest (>500 head) have lower unpaid labor expenses than nonadopters, suggesting automation benefits of adoption. For operations with between 10 and 49 head, all costs but unpaid labor and capital recovery are significantly higher for adopters. For robotic milking adopters, feed and capital recovery costs are significantly lower for 50-149 head operations, which previous work suggests is the ideal size for box robot use (Urbanz and Cardoso, 2023). Interestingly, there are no significant differences in mean costs for operations with >500 head.

We also examine productivity per cow, which we measure as cwt of milk produced per cow per year, to examine the revenue-side benefits from technological adoption. From 2000 to 2021, average milk production per cow per year for all operations was roughly 169 cwt/year (184 cwt/year for 2016 and 2021). These means are significantly different for adopters and nonadopters nearly across the board. For adopters of the technology combination, mean milk production per cow is 178 cwt/year (10-49 head), 199 cwt/year (50-149 head), 215 cwt/year (150-499 head), and 233 cwt/year (>500 head). Mean production for nonadopters is lower for all categories, although the difference for the >500 head category is not statistically different from zero. The scale of differences are similar for robotic milking adopters and nonadopters, although the differences are not statistically significant.

Finally, Table 4 presents summaries for our outcome of dairy net returns. For all but the largest size category, mean net returns for adopters and nonadopters of both technology dummies are negative, which means that the gross value of milk production in both samples is less than total costs.[12] As operation size increases, net returns increase for all groups, regardless of technology adoption status. Net returns are significantly higher for (or less negative) technology combination adopters <150 head, and robotic milking adopters between 50 and 149 head and >500 head.

Effect of PDF technology adoption on net returns: OLS and matching

This section contains the first set of empirical analyses. Here, we examine the effect of PDF technology adoption on dairy net returns using OLS regression and PSM. We first provide the empirical framework, which includes our regression specification. Then, we discuss the relationships between operation-level observable characteristics and the technological adoption decision. Finally, we present the OLS and PSM estimation results.

Framework

[12] 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 three years with positive annual dairy net returns. However, operating profits, which do not include allocated overhead expenses, have been positive for all years since 2000.

Recall that each dairy operator chooses their level of technological adoption ψ_t to maximize profit, $\pi_t(\psi_t)$, and that optimal adoption satisfies the FOC of equation (4). We now wish to take this adoption decision and estimate its effect on profitability, which we measure using dairy net returns. To match prior notation, we denote net returns $NR_t(\psi_t) = \pi_t(\psi_t) = R_t(\psi_t) - C_t(\psi_t)$. We know that adoption affects net returns through reductions in input costs, increases in revenue, and off-farm income additions. The structural effect of PDF technology adoption on net returns is:

$$\Delta NR_t(\psi_t) = NR_t(\psi_t) - NR_t(0). \tag{5}$$

It is trivial to econometrically approximate this effect using a linear equation:

$$NR_t = \delta + \theta\psi_t + \boldsymbol{X_t}'\rho + \varepsilon_t, \tag{6}$$

where $\boldsymbol{X_t}$ is a vector of characteristics that affect net returns for the operation in period t and ε_t is the error term. θ is the parameter of interest that identifies the effect of PDF technology adoption on net returns.

However, technological adoption is an endogenous choice regressor. Unobservable characteristics such as operator skill or social networks can lead to adoption. As such, $\mathbb{E}[\varepsilon_t|\psi_t] \neq 0$, and naïve OLS estimation of equation (6) produces biased estimates. To arrive at consistent estimates of θ, it may be possible to control for these unobservable characteristics through operation fixed effects. However, our ARMS sample is a repeated cross-section, with few repeat respondents during the sample period. As a result, we proceed in the following ways. First, as a baseline, we estimate the following linear specification:

$$f(NR_{ist}) = \alpha + \beta T_{ist} + \boldsymbol{X_{ist}}'\gamma + \mu_t + \eta_s + \varepsilon_{ist}, \tag{7}$$

where the outcome is arcsinh-transformed total net returns ($/cwt) for dairy operation i in state s in period t. We transform the outcome using the inverse-hyperbolic sine function because this allows us to retain zero and negative values, of which there are many. The regressor of interest, T_{it}, is a dummy indicating technological adoption, which we operationalize in two ways. First, we model the adoption of what we call a technology combination. This measure indicates if the operation has adopted more than one of the three main types of PDF technologies captured in the ARMS Phase 3, Dairy data: 1) non-robotic milking, 2) breeding, and 3) data. The omitted category is therefore operations that have adopted zero or one of these types of technologies. Second, T_{it} represents the adoption of RMS. As mentioned, we focus on box robot adoption because fully robotic milking parlors are extremely rare in the US. The impact of T_{it}, β, is the coefficient of interest, which is positive if PDF technologies increase net returns.

Next, $\boldsymbol{X_{it}}$ is a vector of control variables that are correlated with PDF technology adoption and plausibly impact net returns. We include these controls to reduce bias and improve the precision of our estimates. Because we do not have a panel dataset (and therefore cannot use operation fixed effects), we include many control variables that fall into three groups. First, we include in $\boldsymbol{X_{it}}$ operation-level financial variables: allocated overhead expenses, labor expenses, veterinary expenses, operating expenses, government payments, and equity. We hypothesize a negative relationship between the expenses and dairy net returns, because additional expenses necessarily take

away from net returns. We include these expenses as controls to isolate the mechanism through which precision technologies affect net returns (Schimmelpfennig 2016). Any impact on net returns from PDF technology adoption will be through R_t if we hold these expenses constant. Likewise, if milk revenue correlates with government payments, potentially through price or demand effects, they could have an impact on dairy net returns.[13] We hypothesize a positive relationship between net worth (equity) and net returns for the opposite reason. Second, we include operation type, size, and infrastructure controls: a dummy for herd size <50 head, operated acreage quartiles, and parlor usage. We hypothesize that herd size, operated acreage, and parlor usage are all positively associated with net returns given the economies of size present in dairy production and increased efficiency from parlors. Finally, $\boldsymbol{X_{it}}$ contains operator characteristics and demographics controls: dummies for middle-aged operator, retired operator, at least a high school degree, and high speed internet access. We hypothesize that younger, more 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.

Finally, equation (7) contains two sets of fixed effects that control for other unobserved variation that may bias our estimation. μ_t are year fixed effects that control for events that all operations in our sample experience, such as changes in national dairy markets and federal dairy policies. And η_s are state fixed effects that control for state-level characteristics that impact dairy net returns, such as state-level policies or the general structure of a state's dairy industry. Finally, ε_{ist} is the exogenous error term.

We again note that estimation of equation (7) using OLS likely produces biased estimates of β. Nevertheless, we provide results for this estimation as a baseline. We then extend our analysis using PSM, which can help to reduce bias if operators make PDF technology adoption decisions in systematic ways given observable factors, i.e., there exists selection on observables. For example, prior work has shown that large dairy farms adopt precision technologies at higher rates than small farms (MacDonald et al., 2018; McFadden and Raff, 2026). If this selection into adoption exists, OLS produces biased estimates. To account for this possible bias, we implement PSM by matching adopters of the technology combination and robotic milking with their nearest nonadopting neighbor. This procedure creates an alternate control group that is statistically like the treated group, thus allowing for proper comparisons and reducing bias from selection on observables. We use three PSM techniques. First, we match treatment and control observations using the optimal caliper of Austin (2011). This procedure ensures that nearest neighbors are strong matches, rather than simply the closest match. Second, we adjust the optimal calipers to represent one order of magnitude different. Third, we use standard nearest neighbor matching, regardless of distance.

Because we arcsinh-transform the net returns outcome, we must back-transform the coefficients of interest to obtain the correct marginal effects. We follow Bellemare and Wichman (2020) and calculate the marginal effects (in levels) as $\sinh\left(\boldsymbol{X'_{ist}}\widehat{\boldsymbol{\gamma}} + \hat{\beta} + \hat{\varepsilon}_{ist}\right) - \sinh(\boldsymbol{X'_{ist}}\widehat{\boldsymbol{\gamma}} + \hat{\varepsilon}_{ist})$, where $\boldsymbol{X'_{ist}}\widehat{\boldsymbol{\gamma}} + \hat{\beta}$ are the predicted values from the regression, $\hat{\beta}$ is the coefficient on the technology

[13] ERS's Costs of Production team does not use government payments to calculate dairy net returns. But a large literature exists on the capitalization of agricultural subsidies into farmland rental values (Ciaian et al., 2021). 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).

regressor of interest (the technology combination or RMS indicator), and $\hat{\varepsilon}_{ist}$ are the residuals. We perform this calculation for each observation in each of the analysis samples, resulting in a distribution of predicted values for both technology measures. We report the medians of these distributions as the marginal effects in the tables below and focus our discussion of the results on these values.

Observable characteristics of PDF technology adopters

Before we present the OLS and matching estimates, we examine the observable characteristics that correlate with PDF technology adoption. The decision to adopt PDF technologies depends on several factors, such as operational structure, operator personal characteristics, and expected shifts in the cost-revenue frontier (Daberkow and McBride, 2003; Pierpaoli et al., 2013; USGAO, 2024). This analysis serves as the foundation for the matching procedure but also provides useful information on the types of dairy operations that adopt our PDF technologies of interest.

Table 5 presents logit and probit estimation results for separate regressions of technology combination and robotic milking adoption on a series of operator and operation observable characteristics. We first discuss results for the technology combination dummy. Estimation results show that operator characteristics are important in adopting a complex bundle of PDF technologies. Middle-aged and retired operators are significantly less likely to adopt than their younger counterparts, while highly educated operators with high-speed internet access exhibit a significantly higher likelihood of adoption. These findings align with those of the literature (e.g., McFadden et al., 2023), and suggest that connectivity and education lower the information-gathering costs associated with PDF technology adoption. Further, operations with a larger herd size and more acres operated adopt technology combinations at higher rates than smaller operations. Conversely, allocated overhead and unpaid labor expenses are negatively correlated with adoption, likely indicating that liquidity constraints or a surplus of family labor reduce the incentive or capacity for capital-intensive investments.

In contrast, Table 5 shows that fewer observable factors are statistically related to RMS adoption. This lack of significance likely reflects the nascent state of robotic adoption during the survey period. Nevertheless, higher educational attainment remains a positive and significant predictor, while high unpaid labor expenses again correlate with a lower adoption probability. This reinforces that RMS primarily serve as a capital-for-labor substitution that is economically difficult for smaller operations to afford.

OLS and PSM estimation results

Table 6 provides estimation results from the OLS and matching regression analyses of the effects of the technology combination and robotic milking on net returns. Column (1) presents the weighted OLS estimates, while columns (2)-(4) report PSM results with varying match strictness: the Austin (2011) optimal caliper (column 2), a reduced caliper for robustness (column 3), and nearest neighbor matching (column 4). The covariate set (including state and year fixed effects) remains the same across all columns. As above, we first discuss results for the effects of the technology combination on dairy net returns.

Table 5. Relationship between operation-level observable characteristics and PDF technology adoption

	Technology combination		Robotic milking	
Variable	(1)	(2)	(3)	(4)
White operator	0.422	0.255		
	(0.295)	(0.171)		
Middle aged operator	-0.197***	-0.117***	-0.358	-0.150
	(0.062)	(0.036)	(0.258)	(0.116)
Acres quartile, first	-0.203***	-0.123**	-0.447	-0.211
	(0.091)	(0.053)	(0.498)	(0.212)
Acres quartile, second	-0.004	-0.001	0.088	0.035
	(0.081)	(0.046)	(0.291)	(0.130)
Allocated overhead expenses	-0.153	-0.101*	-0.393	-0.178
	(0.096)	(0.054)	(0.318)	(0.145)
Herd size <50 head	-0.440***	-0.283***		
	(0.080)	(0.049)		
Retired operator	-0.757***	-0.434***	0.738	0.300
	(0.184)	(0.108)	(0.548)	(0.270)
At least HS education	0.581***	0.348***	1.420***	0.548**
	(0.073)	(0.044)	(0.622)	(0.230)
Internet access	0.401***	0.239***	0.104	0.046
	(0.079)	(0.047)	(0.369)	(0.160)
Unpaid labor expenses	-0.519***	-0.291***	-0.322*	-0.142*
	(0.059)	(0.032)	(0.177)	(0.079)
Constant	1.871***	1.105***	-2.863***	-1.512***
	(0.377)	(0.216)	(1.068)	(0.453)
Estimation method	Logit	Probit	Logit	Probit
State FE	X	X	X	X
Year FE	X	X	X	X
Pseudo R^2	0.143	0.788	0.071	0.072
Observations	6,723	6,723	2,209	2,209

Notes: Outcome is operation-level adoption of a technology combination (i.e., the operation uses technologies from at least two of the three main PDF technology categories: non-robotic milking, breeding, and data (support)) or robotic milking. All regressions are weighted to ensure that results are representative of the quantity of US milk production. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Across estimation strategies, results for technology combination adoption indicate a modest but consistent profitability advantage. The OLS estimate implies a positive association, statistically significant at the 10% level, between adoption of the technology bundle and dairy net returns. And the implied marginal effect of this adoption is $0.65/cwt. The PSM estimates are similar in sign and slightly larger in magnitude, with statistically significant effects for all matching specifications. The implied marginal effects are $0.66/cwt or $0.88/cwt, depending on matching criteria. This robustness is consistent with the view that precision technologies often operate as complements. The profitability effects are more likely to emerge when operations deploy multiple tools

Table 6. Effect of PDF technology adoption on dairy net returns, OLS and matching

Variable	(1)	(2)	(3)	(4)
Panel A. Technology combination sample				
Technology combination	0.076*	0.102**	0.077*	0.102**
	(0.042)	(0.048)	(0.045)	(0.045)
Marginal effect ($/cwt)	$0.65	$0.88	$0.66	$0.88
Estimation method	OLS	Matching, optimal caliper	Matching, adjusted caliper	Matching, nearest neighbor
State FE	X	X	X	X
Year FE	X	X	X	X
Controls included	X	X	X	X
R^2	0.724	0.721	0.721	0.721
Observations	6,723	6,084	5,991	6,084
Panel B. Robotic milking sample				
Robotic milking	0.142***	0.352***	0.356***	0.261***
	(0.045)	(0.059)	(0.058)	(0.042)
Marginal effect ($/cwt)	$0.99	$2.55	$2.59	$1.85
Estimation method	OLS	Matching, optimal caliper	Matching, adjusted caliper	Matching, nearest neighbor
State FE	X	X	X	X
Year FE	X	X	X	X
Controls included	X	X	X	X
R^2	0.697	0.788	0.787	0.753
Observations	2,209	131	132	361

Notes: Each column presents regression results from a separate specification of equation (7), where the outcome is operation-level arcsinh-transformed dairy net returns. Column 1 results are from OLS estimation. Columns 2-4 present matching results, with the following differences: column 2 results exclude nearest neighbor matches outside of the Austin (2011) optimal caliper, column 3 results exclude nearest neighbor matches outside of 1 order of magnitude different than the optimal caliper, and column 4 results include all nearest neighbor matches. All regressions are weighted to ensure that results are representative of the quantity of US milk production. Technology combination treatment means that the operation uses PDF technologies from at least two of three main technology categories: non-robotic milking, breeding, and data (decision support). Regressions include controls for middle-aged operator, acreage quartiles, allocated overhead expenses, retired operator, at least high school education, internet access, unpaid labor expenses, government payments, equity, parlor usage, veterinary expenses, and operating expenses. Bootstrapped standard errors are in parentheses. Marginal effects are reported as the median of the distribution of marginal effects calculated across observations in the analysis samples. *** p<0.01, ** p<0.05, * p<0.1.

that jointly support data collection, monitoring, and management decisions. Prior evidence in US dairy similarly emphasizes the prevalence of bundled adoption patterns and the importance of farm scale and management capacity in shaping both adoption and returns (e.g., Khanal et al., 2010). More recent work reinforces that higher-intensity PDF technology adoption correlates with herd

size, labor organization, and human capital measures (Palma-Molina et al., 2023). PSM is designed to balance exactly these factors across adopters and comparable nonadopters.

We present the robotic milking estimates in panel B of Table 6. The point estimates indicate a larger implied profitability differential than the technology combination, but potentially also greater sensitivity to common-support restrictions. In the full sample, the weighted OLS regression yields a positive and statistically significant coefficient. Matching estimates remain positive and are larger in magnitude under the caliper restrictions (approximately 0.35), while the nearest-neighbor specification remains sizeable (0.261). The implied marginal effects range from \$0.99 (column 1) to \$2.59 (column 3). However, the matched samples are substantially smaller under the caliper-based specifications, falling from 2,209 observations in the OLS sample to 131 and 132 under the caliper rules (and 361 under nearest neighbor matching). These declines underscore that the PSM estimates for robotic milking should be interpreted as local average treatment effects on the treated for the subset of robot adopters that can be credibly matched to observationally similar nonadopters.

Substantively, the positive effects of robotic milking on net returns are consistent with a large literature characterizing automatic milking systems as a capital–labor substitution where realized returns hinge on labor savings, throughput per robot, and complementary management changes.[14] At the same time, findings in the literature remain heterogeneous: some comparisons report higher capital costs and no average differences in labor costs or net output for robotic milking adopters (Steeneveld et al., 2012). This reinforces the importance of farm-specific constraints and management adjustments when interpreting the magnitude of the robotic milking coefficients.

Effect of PDF technology adoption on net returns: Two-stage control functions

In this section, we present the primary set of analyses, which use a two-stage CF method. We first describe the empirical framework. Then, we provide estimation results for both the first and second stages.

Framework

We extend the OLS and matching analysis using a two-stage CF approach (Terza et al., 2008; Wooldridge, 2015). We must use a two-stage approach to consistently estimate our parameter of interest and to account for the endogenous nature of the primary choice variable. In our case, there are two possible two-stage procedures that we can use. First, we can use standard linear two-stage least squares (2SLS) with at least one exogenous instrument. In the terminology of Terza et al. (2008), this method is the "two-stage predictor substitution" (2SPS), in that it replaces the endogenous variable in the second-stage equation with the predicted residuals from the first stage. Second, we can use a two-stage CF method, which Terza et al. (2008) call the "two-stage residual inclusion" (2SRI) method, which again includes at least one exogenous instrument. Instead of replacing the endogenous variable in the second stage, the CF approach retains the endogenous variable and includes the first-stage generalized residuals as endogeneity "controls". Wooldridge

[14] For example, simulation evidence emphasizes sensitivity of AMS profitability to milking labor costs and milk production (Salfer et al., 2017), with additional empirical analyses similarly highlighting the role of milk harvested per robot and labor use in determining financial outcomes (e.g., Martinsson et al., 2024).

(2015) shows that in the case of a linear first-stage regression, i.e., the endogenous variable (which is the outcome) is continuous, two-stage least squares and the CF produce identical estimates. However, in the case of a non-linear endogenous variable, the CF produces consistent estimates, while linear two-stage least squares does not. In our setting, the PDF technology adoption decision is a non-linear choice, and thus, we wish to estimate the first-stage non-linearly (e.g., using a probit model). We therefore proceed using a two-stage CF approach, like prior studies examining technological adoption in agriculture (e.g., Wechsler and Smith, 2018; McFadden et al. 2022; Gajbhiye et al., 2026).

This estimation strategy now accounts for the endogenous nature of the technological adoption parameter (ψ_t). We use the structural equation (5) and model the adoption decision:

$$\psi_t = g(X_t, Z_t, \varphi_i, \xi_t), \tag{8}$$

where X_t is as before, Z_t is a vector of characteristics that identify the marginal cost of adoption of PDF technologies, φ_i is the skill of the dairy operator, and ξ_t is a factor for technological shocks. To consistently estimate the effect of this technology adoption choice on net returns, we must identify at least one exogenous factor to instrument for the primary source of endogeneity, φ_i. We use as our instrument a measure of the concurrent, state-level adoption of the PDF technology combination and robotic milking variables, while leaving out the observation itself (i.e., a leave-one-out mean). We argue that this is a relevant and exogenous instrument. First, state-level adoption is strongly correlated with adoption at the individual-operation level, as it signals technological diffusion in the area. When there is high state-level adoption of PDF technologies, there exists the necessary infrastructure for individual operations to adopt the technologies as well. For example, high state-level adoption suggests a robust network of local dealers and technicians that can market, sell, and support the technologies. And this infrastructure represents economies of scale for the technology dealers, resulting in decreased adoption costs for individual farms. State-level adoption also increases farmer social networks, which have been shown to be important in agricultural production decisions (e.g., Maertens and Barrett, 2013). Second, this instrument satisfies the exclusion restriction, as it affects operation-level net returns only through the technological adoption choice. Aggregate state-level PDF technology adoption represents a market-level metric that does not directly influence an individual operation's production.

Empirically, we estimate the following non-linear first-stage regression equation:

$$k(T_{ist}) = \alpha_0 + \alpha_1 State_{ist} + \boldsymbol{X_{ist}}'\alpha_3 + \mu_t + u_{ist}, \tag{9}$$

where T_{ist} is the PDF technology adoption choice, $State_{ist}$ is the exogenous state-level adoption instrument ($\mathbb{E}[\varepsilon_t | State_t] = 0$), and u_{ist} is the error term. $\boldsymbol{X_{ist}}$ is a vector of factors that plausibly affect operation-level net returns, and includes the same factors described above.

In this first stage, we estimate the PDF technology combination adoption choice and the robotic milking adoption choice differently. Recall that our measure of technology combination adoption comprises several sets of PDF technologies: non-robotic milking, breeding, and data (decision support) technologies. We create a dummy "treatment" indicator that indicates if the operation adopts technologies from more than one of these categories (the omitted category is therefore

operations that adopt technologies from zero or only one of these categories). With three classes of precision technologies, we create the technology combination indicator from eight possible adoption bundles (e.g., zero technologies, breeding technologies only, non-robotic milking and breeding technologies, all three classes). We wish to use this richer set of categories in the first-stage outcome to capture variation in technological adoption pathways that is not possible to measure using a collapsed dummy outcome (e.g., Bourguignon et al., 2007). For the technology combination measure, then, we estimate equation (9) using multinomial logit regression. We consider as the omitted category the adoption of zero classes of PDF technologies. We also estimate the first stage for robotic milking adoption non-linearly by using a probit regression, as we have a single dummy variable for the adoption of this technology.

Next, we incorporate generalized residuals from our first-stage estimation into a second stage to control for the endogeneity of the PDF technology adoption choice. Our outcome is operation-level arcsinh-transformed dairy net returns, so we estimate the following equation using OLS:

$$f(NR_{ist}) = \beta_0 + \beta_1 T_{ist} + \boldsymbol{X_{ist}}'\beta_2 + \widehat{\boldsymbol{u_{it}}}'\beta_3 + \mu_t + \eta_s + \varepsilon_{ist}, \quad (10)$$

where notation follows that of equation (7). New to this equation, $\widehat{\boldsymbol{u_{it}}}$ is the vector of first-stage generalized residuals. For the technology combination regression, we simply use the residuals from the multinomial logit regression. We calculate the generalized residuals using the methodology of Wooldridge (2015) for the probit regression on robotic milking adoption:

$$T_{it} \times m(\boldsymbol{z_{it}}\hat{\alpha}) - (1 - T_{it}) \times m(-\boldsymbol{z_{it}}\hat{\alpha}), \quad (11)$$

where $m(\cdot) = \phi(\cdot)/\Phi(\cdot)$ is the inverse Mills ratio, $\boldsymbol{z_{it}}$ is the vector of exogenous covariates explaining technological adoption, T_{it} is the technological adoption outcome, and $\hat{\alpha}$ are the coefficients from the first-stage probit regression of technological adoption.

For the technology combination second-stage regression, there are seven sets of residuals, one for each individual PDF technology adoption dummy except the omitted category of zero adoption. The robotic milking regression includes only one set of generalized residuals. The CF uses these generalized residuals to control for endogeneity when estimating the effect of PDF technology adoption on net returns in the second stage.

CF estimation results

First-stage estimates. Table 7 provides both sets of first-stage regression estimates. Columns (1a)-(1g) show results from the first-stage weighted multinomial logit regression of the technology combination categorical variable on the instrument and set of controls.[15] Note that columns (1a)-(1g) contain the individual technology type coefficients: breeding only, milking only, data only, breeding and milking, breeding and data, milking and data, and all three technology types (respectively). Column (2) contains the results of the first-stage weighted probit regression for robotic milking. The key excluded instrument in both first stages is the concurrent state-level adoption

[15] Because of collinearity issues, we cannot include state fixed effects in the first-stage multinomial logit regression modeling the component technologies.

Table 7. First-stage coefficients, PDF technology combination and robotic milking adoption

Variable	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)	(2)
State-level adoption	1.754*	4.113***	2.927***	4.115***	5.276***	5.444***	7.603***	1.027***
	(1.006)	(1.310)	(1.105)	(1.548)	(0.877)	(1.012)	(0.942)	(0.126)
White operator	16.36***	-1.623**	0.412	-2.241**	0.045	-0.632	-1.519**	---
	(1.214)	(0.657)	(0.711)	(0.895)	(0.700)	(1.276)	(0.742)	
Middle aged operator	-0.093	-0.037	-0.330	0.097	-0.295	-0.229	-0.391*	-0.013*
	(0.250)	(0.366)	(0.264)	(0.390)	(0.207)	(0.274)	(0.226)	(0.008)
Acres quartile, first	0.203	-0.193	0.418	0.561	0.915***	-0.145	0.169	-0.020
	(0.431)	(0.443)	(0.404)	(0.862)	(0.332)	(0.477	(0.358)	(0.013)
Acres quartile, second	0.273	-0.074	-0.025	0.386	0.703**	-0.117	0.361	-0.008
	(0.332)	(0.447)	(0.331)	(0.551)	(0.275)	(0.373)	(0.292)	(0.009)
Allocated overhead expenses	-0.090	-0.749	-0.393	-0.080	-0.828*	-0.366	-1.230***	-0.018*
	(0.437)	(0.657)	(0.451)	(0.647)	(0.444)	(0.449)	(0.423)	(0.010)
Herd size <50 head	-0.027	-1.745***	-0.074	-1.260**	-0.567**	-1.090**	-1.112***	---
	(0.253)	(0.625)	(0.264)	(0.615)	(0.224)	(0.463)	(0.308)	
Retired operator	-0.402	0.870	0.191	0.164	-0.898*	-0.891	-0.986**	0.023
	(0.505)	(0.588)	(0.511)	(0.914)	(0.468)	(0.733)	(0.460)	(0.022)
At least HS education	0.382	0.003	0.190	1.606***	0.243	1.000***	0.827***	0.023**
	(0.312)	(0.391)	(0.301)	(0.512)	(0.255)	(0.334)	(0.292)	(0.011)
Internet access	0.441	0.618	0.173	-0.094	0.556**	0.417	0.883***	0.003
	(0.281)	(0.474)	(0.267)	(0.579)	(0.240)	(0.357)	(0.282)	(0.010)
Unpaid labor expenses	-0.010	0.036	-0.139	-0.588*	-0.357	-0.700***	-0.766***	-0.004
	(0.252)	(0.355)	(0.262)	(0.354)	(0.242)	(0.260)	(0.231)	(0.006)
Government payments	-0.000	0.00001	0.00001**	0.00001	0.00001*	0.00001**	0.00002***	0.00001
	(0.001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Net worth	0.000	0.000**	0.000	0.000	0.000	0.000*	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parlor usage	-0.577**	1.984***	0.201	0.976**	-0.821***	1.738***	0.833***	-0.043***
	(0.240)	(0.505)	(0.279)	(0.465)	(0.217)	(0.381)	(0.243)	(0.010)
Veterinary expenses	0.528*	-0.076	0.564*	0.748	1.448***	0.675*	2.224***	0.004
	(0.303)	(0.443)	(0.342)	(0.570)	(0.273)	(0.354)	(0.304)	(0.008)
Operating expenses	-0.113	-0.198	-0.342	-0.288	0.104	-0.171	-0.128	---
	(0.242)	(0.325)	(0.317)	(0.359)	(0.210)	(0.344)	(0.248)	
Constant	-17.67	-0.119	-0.184	-1.894	-0.672	-1.991	0.437	0.082
	(34.52)	(1.762)	(1.496)	(2.555)	(1.384)	(1.880)	(1.449)	(0.057)
Year FE	X	X	X	X	X	X	X	X
State FE								X
Observations	6,638	6,638	6,638	6,638	6,638	6,638	6,638	2,209
Log-likelihood	-294,468	-294,468	-294,468	-294,468	-294,468	-294,468	-294,468	830
Wald X^2	39,355***	39,355***	39,355***	39,355***	39,355***	39,355***	39,355***	175***

Notes: Columns 1a-1g present multinomial logit regression results from the estimation of equation (9), where the outcome is the categories of technology combination adoption. The columns represent results for the following technology combinations: column 1a is breeding only, column 1b is milking only, column 1c is data only, column 1d is breeding and milking, column 1e is breeding and data, column 1f is milking and data, and column 1g is all 3 technology types. The omitted category is no technology adoption. Column 2 presents probit regression results from the estimation of equation (9), where the outcome is robotic milking adoption. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

rate of the relevant technology measure, which we motivate as capturing diffusion-related infrastructure and learning effects.

We first discuss the technology combination first stage. The coefficients on state-level adoption are uniformly positive, large, and statistically significant across all adoption pathways, with especially large effects for more complex technology bundles (e.g., all three technology types). This pattern is consistent with the diffusion intuition motivating our instrument: when adoption is already high at the state level, dairy operations face lower adoption frictions (greater availability of dealers and/or technicians, thicker peer learning networks, and better complementary infrastructure), making it more likely that they move beyond single-category adoption into multi-category bundles.[16] Importantly, the large Wald χ^2 test statistic strongly supports instrument relevance, as it is significantly higher than the chi-squared critical value at the 1% level, in addition to the large implied z-statistics on each of the statewide adoption variables.

Several other first-stage results align with intuition surrounding the adoption of capital- and management-intensive technology bundles. Small operations (<50 head) are significantly less likely to adopt PDF technology types involving milking and multi-category bundles, consistent with fixed-cost and scale-to-amortization arguments. Educational attainment is strongly positively associated with the more complex technology pathways (e.g., breeding and milking, milking and data, and all three categories), reinforcing broader evidence that information-processing capacity and human capital can matter most when technologies are complementary and require managerial integration (see, e.g., Stone, 2020; Palma-Molina et al., 2023). Finally, the parlor-use coefficients suggest intuitive "technology fit": parlor usage is positively associated with milking-intensive technology types (milking only, breeding and milking, and milking and data) but negative for breeding only and the combination involving breeding and data. These results indicate meaningful heterogeneity in adoption trajectories across farm infrastructure types.

The first-stage robotic milking results suggest that, as in the technology combination case, the state-level adoption instrument is positive and highly statistically significant, consistent with diffusion-driven reductions in adoption costs and uncertainty. The associated Wald statistic is also highly statistically significant, supporting instrument relevance for the second-stage robotic milking estimates.[17] The signs on the other covariates are also consistent with the idea that robotic milking is a high-fixed-cost, management-reorganizing investment, lending support to the internal validity of our research design. Adoption is positively associated with operator education and negatively associated with parlor usage, perhaps reflecting that operations adopt RMS as an alternative to conventional parlor-based milking infrastructure rather than as a marginal add-on. These first-stage patterns are also consistent with recent empirical work emphasizing that perceived risk and social networks, as distinct from fundamental attributes like prices and farm size (Ahmed, 2024), shape robotic milking and related PDF technology adoption.

Second-stage estimates. Next, Table 8 presents the second-stage CF estimates of the profitability effects of both technologies. We first discuss the technology combination results (column 1). The

[16] We note that the diffusion-and-infrastructure channel aligns with the network externalities and sequential implementation logic emphasized in other parts of the robotic milking adoption literature; see Sauer and Zilberman (2012).
[17] The implied Wald χ^2 for state-level adoption is approximately 66.4, likely driving the large value of the (joint) Wald test statistic.

Table 8. Second-stage control function estimates, effect of PDF technology combination and robotic milking adoption on dairy net returns

Variable	(1)	(2)
Panel A. Regression coefficients		
Technology combination	0.232**	
	(0.095)	
Robotic milking		0.521*
		(0.292)
Generalized residual, breeding only	0.163	
	(0.168)	
Generalized residual, milking only	0.097	
	(0.128)	
Generalized residual, data only	0.144	
	(0.153)	
Generalized residual, breeding and milking	0.191	
	(0.152)	
Generalized residual, breeding and data	-0.282*	
	(0.154)	
Generalized residual, milking and data	-0.082*	
	(0.044)	
Generalized residual, all technologies	0.041	
	(0.086)	
Generalized residual, robotic milking		-0.153
		(0.301)
White operator	-0.083	
	(0.074)	
Middle aged operator	0.012	0.205***
	(0.031)	(0.016)
Acres quartile, first	0.533***	0.682***
	(0.039)	(0.024)
Acres quartile, second	0.228***	0.149***
	(0.050)	(0.018)
Allocated overhead expenses	-1.833***	-2.118***
	(0.045)	(0.020)
Herd size <50 head	-0.300***	
	(0.098)	
Retired operator	-0.251**	-0.657***
	(0.101)	(0.045)
At least HS education	0.007	-0.287***
	(0.043)	(0.022)
Internet access	-0.081*	-0.209***
	(0.043)	(0.016)
Unpaid labor expenses	-0.279***	-0.329***
	(0.034)	(0.013)
Government payments	-0.000***	0.000
	(0.000)	(0.000)
Net worth	-0.000***	0.000**
	(0.000)	(0.000)
Parlor usage	0.214**	0.260***
	(0.085)	(0.020)
Veterinary expenses	-0.058	-0.981***
	(0.046)	(0.015)
Operating expenses	-2.574***	
	(0.060)	
Constant	13.18***	5.697***
	(0.254)	(0.149)
Panel B. Marginal effects ($/cwt)	$2.09	$3.99
State FE	X	X
Year FE	X	X
R^2	0.725	0.788
Observations	6,723	2,209

Notes: Columns present regression results from the estimation of equation (10), outcome is operation-level dairy net returns. All regressions are weighted to ensure that results are representative of the quantity of US milk production. Bootstrapped standard errors are in parentheses. Marginal effects are reported as the median of the distribution of marginal effects calculated across observations in the analysis samples. *** p<0.01, ** p<0.05, * p<0.1.

second-stage coefficient on the technology combination adoption dummy is positive and statistically significant, with an implied marginal effect of $2.09/cwt. To put this main results into greater context, we note that the average all-milk price in the final year of our sample is $23.65. Thus, the increase in economic gains from the adoption of the technology combination is 8.5% of the price of milk that producers receive, a sizable increase.

Relative to the OLS/PSM magnitudes that we show in Table 6 ($0.65–$0.88/cwt), this larger CF estimate is consistent with the view that selection into adoption is non-random, and that baseline "selection on observables estimates" may understate profitability gains. This could be the case if unobserved managerial ability, information networks, or local diffusion conditions jointly influence both adoption and performance (e.g., Imbens and Wooldridge, 2009). The generalized residual terms corresponding to the breeding and data and milking and data combinations, which are important diagnostics in Table 8, enter negatively and are statistically significant at the 10% level. These significant residuals provide evidence of endogeneity for (at least some) adoption pathways, and the negative signs are consistent with negative selection (i.e., unobservables raising the propensity to adopt those bundles are associated with lower net returns absent adoption), which puts downward bias on naïve estimates, such as those from OLS in Table 6.

The CF estimates for RMS adoption (column 2) also indicate economically meaningful profitability effects, though with less precision. The robotic milking coefficient is positive and significant at the 10% level. The median marginal effect for this technology is $3.99/cwt, or 17% of the average all-milk price in 2021. As with the OLS and PSM analyses, this magnitude is consistent with the broader notion of RMS as a major labor-saving technology (Gallardo and Sauer, 2018). The generalized residual for robotic milking is not statistically different from zero. Although this may suggest weaker evidence of endogeneity after conditioning on the included controls and fixed effects, it more likely points to an issue of limited power given the small share of RMS adopters in the 2016 and 2021 ARMS waves.

Across both sets of results the control variables largely behave as we expect and serve mainly to improve precision. Allocated overhead expenses and unpaid labor expenses are strongly negatively associated with net returns, while operated-acreage quartiles and parlor usage are positively associated with net returns. In the technology combination sample, herd size dummy is negative and statistically significant, consistent with well-documented scale economies in US dairy production (e.g., Mosheim and Lovell, 2009). Some operator-characteristic coefficients, including education and internet access in the robotic-milking regressions, are negative. Given the role of these regressors as controls, the most conservative interpretation is that their primary relationship with profitability operates through channels already captured in the adoption decision, costs, and fixed effects.

Discussion and policy implications

Our analysis provides the first national-scale, causal evidence that the adoption of PDF technologies significantly increases operation-level net returns. With estimated gains of over $2/cwt for technology bundles and nearly $4/cwt for RMS, these technologies represent a transformative shift in the economic structure of the US dairy industry. We present evidence that our findings are the result of both increased productivity (the revenue side) and improved input-use efficiency (the cost

side). While PDF technologies involve significant upfront capital costs, we find that, for the average adopter, the marginal revenue and labor savings more than offset these outlays. This suggests that PDF technologies represent a fundamental shift in the production function of modern dairy operations. Our findings have implications for sectoral consolidation, the design of USDA cost-share programs, and the broader agricultural policy landscape. We discuss each in turn.

First, dairy production in the US has undergone a long-term trend of consolidation, driven largely by economies of size. This trend is highly pronounced even in an overall era of consolidation of agricultural production (MacDonald et al., 2018). Our findings suggest that PDF technology adoption may exacerbate this trend. The large upfront costs of advanced PDF tools, especially those with high levels of automation such as RMS, can make them inaccessible to capital-constrained, primarily small, operations. If large dairies are better able to absorb these costs and capture the added returns from adoption, then the productivity gap between small and large operations will widen.

However, we have shown that robotic milking in particular appears best-suited for operations in the 50-500 head range because each box robot milks between 50 and 70 cows per day. For these operations, PDF technology adoption can reduce unpaid labor expenses and presents the opportunity for operations to supplement their household finances with additional off farm income. In this work we remain agnostic as to whether policymakers wish to alter the consolidation trend in dairy production, i.e., keep smaller dairy operations in business. However, consolidation has been linked to environmental disamenities (e.g., Sneeringer, 2010; Raff and Meyer, 2022), negative effects on rural economies (Park and Deller, 2021), and decreased competition (MacDonald, 2017). Thus, if the objective function of policymakers contains a factor for decreasing consolidation in agricultural production, then efforts should be made to determine if PDF technologies can lift up small operations, or if they serve simply as a tool for their exit. If the former, policymakers can design technical assistance or cost-share programs that allow small operations the ability to adopt without facing the large upfront costs of PDF technologies.

Next, the interplay between PDF technology adoption and risk management programs, e.g., USDA's Dairy Margin Coverage (DMC) program, remains an important policy area. 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. However, since both DMC payments and the premiums that producers pay for the coverage are partly based on the operation's productivity, it is unclear a priori how operations that realize efficiency increases through PDF technologies would adjust their participation (if at all). In aggregate, total DMC payments would be expected to increase because of technology-induced productivity increases that are reflected in established production histories, assuming there are no offsetting changes in average margin coverage levels, production coverage percentages, and overall program participation. But such all else equal scenarios may be unlikely. The extent to which the use of PDF technologies boosts dairy profitability could, in theory, influence producers' decisions to enroll in the program and subsequent coverage choices. Technologically sophisticated, highly profitable dairy operations may perceive less need in any given year for program payments but nonetheless desire higher coverage levels on average due to greater value at risk. Along similar lines, if certain PDF technologies are risk reducing (or risk increasing), any

resulting changes in risk levels and producers' risk tolerances could also influence their demand for margin coverage.

In contrast, there exist clear connections between PDF technology adoption and conservation programs like the Environmental Quality Incentives Program (EQIP). Importantly, at least 60% of EQIP financial assistance funds each year must be targeted to conservation practices related to livestock production, including dairy. However, EQIP offers many conservation practices of relevance that dairy operations implement, in part, using PDF technologies. Several of these practices pertain to management of crops used for silage, and their implementation could involve soil testing to determine nutrient needs, variable rate manure applications, and precision pesticide 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. The addition of small grains into cropping plans through conservation crop rotations provides dairy operations with more options for silage or grazing. More generally, automated equipment steering can be used for field operations involving planting, spraying, and harvesting (e.g., silage) as part of implementing many EQIP practices.

Finally, USDA has long supported research and data collection efforts surrounding PA and technological development/adoption. USDA's Agricultural Research Service (ARS) is a leader in this space. ARS conducts research under the umbrella of 15 National Programs (NP), of which the following study PA technologies (among others): Crop Protection and Quarantine (NP 304), Crop Production (NP 305), Water Availability and Watershed Management (NP 211), and Grass, Forage and Rangeland Agroecosystems (NP 215). Additionally, ARS' Annual Reports on Science Accomplishments have documented research breakthroughs in the area of "reducing labor and advancing precision agriculture through automation." Between 2020 and 2022, some of these major accomplishments included development of the first automated peanut sampling system, an efficient apple harvesting robot, and an autonomous robot for high-throughput phenotyping, among many others (USDA-ARS, 2021; USDA-ARS, 2022; USDA-ARS, 2023).

Underlying the PDF dimensions of USDA policies and USDA agency programming are major 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, including dairy. APHIS designs these studies to assist with information needs from specific commodity sectors. In recent decades, the NAHMS unit has been surveying US dairy operations on a recurring basis, with 2014 being the most recent dairy survey year.[18]

In summary, PDF technologies offer a significant pathway to enhanced profitability in the US dairy sector. But these technologies also pose risks of further sectoral consolidation, which may or may not be of interest to policymakers. If it is, then a balanced policy approach would combine expanded cost-share programs for environmental PDF technologies, updated risk management frameworks, scale-neutral technology research, and high-quality data collection efforts. By aligning technological innovation with broader social and environmental goals, USDA and other

[18] Based on recent conversations with APHIS, the timing of the next NAHMS dairy survey and related studies is unclear.

policymakers can help to ensure that the shift toward PDF contributes to the long-term sustainability of the dairy industry.

Conclusion

This paper provides the first nationally representative causal estimates of the effect of PDF technology adoption, including the use of robotic technologies, on operation-level net returns. We distinguish between two distinct forms of PDF technology: 1) bundled non-robotic milking, breeding, and data technologies (i.e., technology combination) and 2) RMS. To address the endogenous nature of the technological adoption decision, our primary estimation strategy employs a two-stage CF approach that instruments for PDF technology adoption using concurrent state-level adoption rates. The CF approach includes in a second-stage regression the adoption variable and generalized residuals from the first stage to control for endogeneity. We find that adoption of either a technology combination or robotic milking increases dairy net returns at the operation level. The marginal effects are $2/cwt (8.5% of the average all-milk price in the final year of our sample period) for the technology combination and $4/cwt (17% of the average all-milk price in the final year of our sample period) for RMS. These values represent meaningful gains for individual operations, especially in an agricultural sector where net returns are consistently negative.

Our findings are important for US dairy producers, commodity groups, and policy stakeholders. The sizable upfront costs of PDF technology adoption create barriers to adoption, particularly for smaller operations, yet we find that adoption is profitable, on average, even for those operations. Financial assistance targeted at PDF technology adoption (e.g., loans for obtaining PDF tools, cost-share programs) may enhance adoption among operators for whom the private benefits outweigh the social costs of subsidization. And PDF technology adoption will likely change labor needs in dairy production by altering the mix of paid versus unpaid labor and potentially supporting the viability of smaller operations via off-farm labor opportunities.

There remains the need for future research in this area. While the ARMS data provide broad spatial and temporal coverage, our samples are repeated cross-sections. Operation-year panel data would allow us to use operation fixed effects to better control for unobserved operation-level heterogeneity. Next, we study one sector of livestock production. Results may not generalize to other livestock systems where market conditions or technological design differ, particularly for sectors where contractual arrangements might specify the kinds of capital equipment required for commodity production. Finally, as PDF technologies continue to evolve, future work should examine the distributional consequences of adoption, including how PDF technology adoption affects sectoral consolidation and rural labor markets.

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Appendix

Description of ARMS Phase 3, Dairy precision technologies and management practices

In this appendix, we describe in depth the technologies and management practices that we examine in the main text.

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.[1] It is therefore necessary to wash the udders of dairy cows and disinfect the teats before milking. The first PDF 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 A3, 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 prevent mastitis. However, teat disinfection—with or without udder washing—is the most important part of the pre-milking cleaning process.

In the U.S., the use of holding pens with udder washers is relatively low and has remained consistent over the past two decades; 5% of dairy farms used the technology in 2000, while 7% of dairy farms used the technology in 2021.[2] 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 (cwt) by operations using the technology. For this and all other technologies that we examine, milk production percentage is higher than the percentage of dairy farms using the technology, reflecting the fact that large dairy operations—that 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% of all-milk production occurred at U.S. dairy farms that used holding pens with an udder washer. In 2021, this percentage increased to 32%.

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,

[1] 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).

[2] The ARMS Phase 3, Dairy surveys only gather data on automatic udder washing in a holding pen. Udder cleaning, and teat disinfectant in particular, are important components of the milking process that are not prohibitively expensive. But many operations in the U.S. 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 pre-milking washing. Wash water often collects bacteria from other parts of the cow, which can then concentrate at the teat while the water drains off.

operators can use milking units with automatic takeoffs (figure A3, 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% of U.S. dairy farms used this technology; the adoption rate increased to 46% in 2021. And 59% of milk was produced at U.S. dairy farms using milking units with automatic takeoffs in 2000; by 2021, that percentage increased to 83%.

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 A3, 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% of dairy farms in 2000 to 13% of dairy farms in 2021. The percentage of milk produced at dairy farms using computerized milking systems is higher, moving from 20% in 2000 to 45% in 2021.

When breeding for replacement animals, the selection of the best-suited sires and ensuring a healthy pregnancy that will occur with minimal effort are imperative. From a productivity and replacement animal perspective, artificial insemination (figure A3, panel D), which allows producers to select sires, is one of the most beneficial PDF 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 makes it so 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 PDF technology (e.g., Ombelet and 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 A3, 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 to 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 non-productive 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—which has sustainability implications—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 breeding beef cross bull calves on dairy farms for sale is financially beneficial for operators. Dairy farms in the U.S. have begun to use sexed semen, which is semen that contains a larger proportion of male (Y) or female (X) chromosomes and is used to selectively breed offspring of the desired sex (figure A3, 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) because it can be cost-effective to use or economically beneficial (e.g., it can reduce the production of calves of the unwanted gender).

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 A3, panel G).[3] 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 number of dairy farms using this practice was 61% in 2005 and 63% in 2021.[4] During that same timeframe, total U.S. milk production at dairy farms using individual cow production records increased from 82% to 90%.

[3] 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.

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

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-APHIS, 2016). 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.[5] Several benefits of TMR feeding include increased milk productivity, the 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 and Kalantari, 2016), but it is infeasible to provide TMRs at the individual cow level.[6]

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 A3, 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% of U.S. dairy farms (2000) to 73% of dairy farms (2021).[7] Total U.S. milk production at dairy farms using a nutritionist to design diets has increased similarly, moving from 83% in 2000 to 94% in 2021.

Second, the ARMS Phase 3, Dairy surveys collect information on the use of computerized feed delivery systems (figure A3, 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% of U.S. dairy farms

[5] In-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 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.

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

[7] The ARMS Phase 3, Dairy questionnaire asks about the practices at each operation during that calendar year. Nearly all dairy operators consult with a nutritionist regarding diets at some point. However, we find that 73% used a nutritionist to design diets during the most recent surveyed period (January 1-December 31, 2021).

used computerized feed delivery systems. This percentage increased 2 percentage points, to 10%, in 2021. However, total U.S. milk production at dairy farms using this technology has seen a larger increase. In 2000, 22% of U.S. milk was produced at operations using computerized feed delivery systems. By 2021, this percentage had increased to over half—52%—of U.S. milk production.[8]

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-cleaning system, teat detection system, robotic arm for teatcup attachment, control system, and milking machine (figure A4, 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 pre-determined 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, SCC) 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 and 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 (e.g., Marques et al., 2023). Nonetheless, there are several thousand box robots in North America, on dairy farms of various size.[9] The ARMS Phase 3, Dairy data from 2021 indicate that 3% of U.S. dairy farms used box robots.[10]

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

[8] 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 given data limitations. It is therefore possible that these data (decision support) systems range in the extent of their technological sophistication and emphasis on individual cow management.

[9] 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 and Karszes, 2023).

[10] The ARMS Phase 3, Dairy surveys 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 paper 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" (e.g., Marques et al., 2023).

of cows (figure A4, panel B).[11] These systems automate all steps of the milking process, and milking (generally non-voluntary) 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.[12]

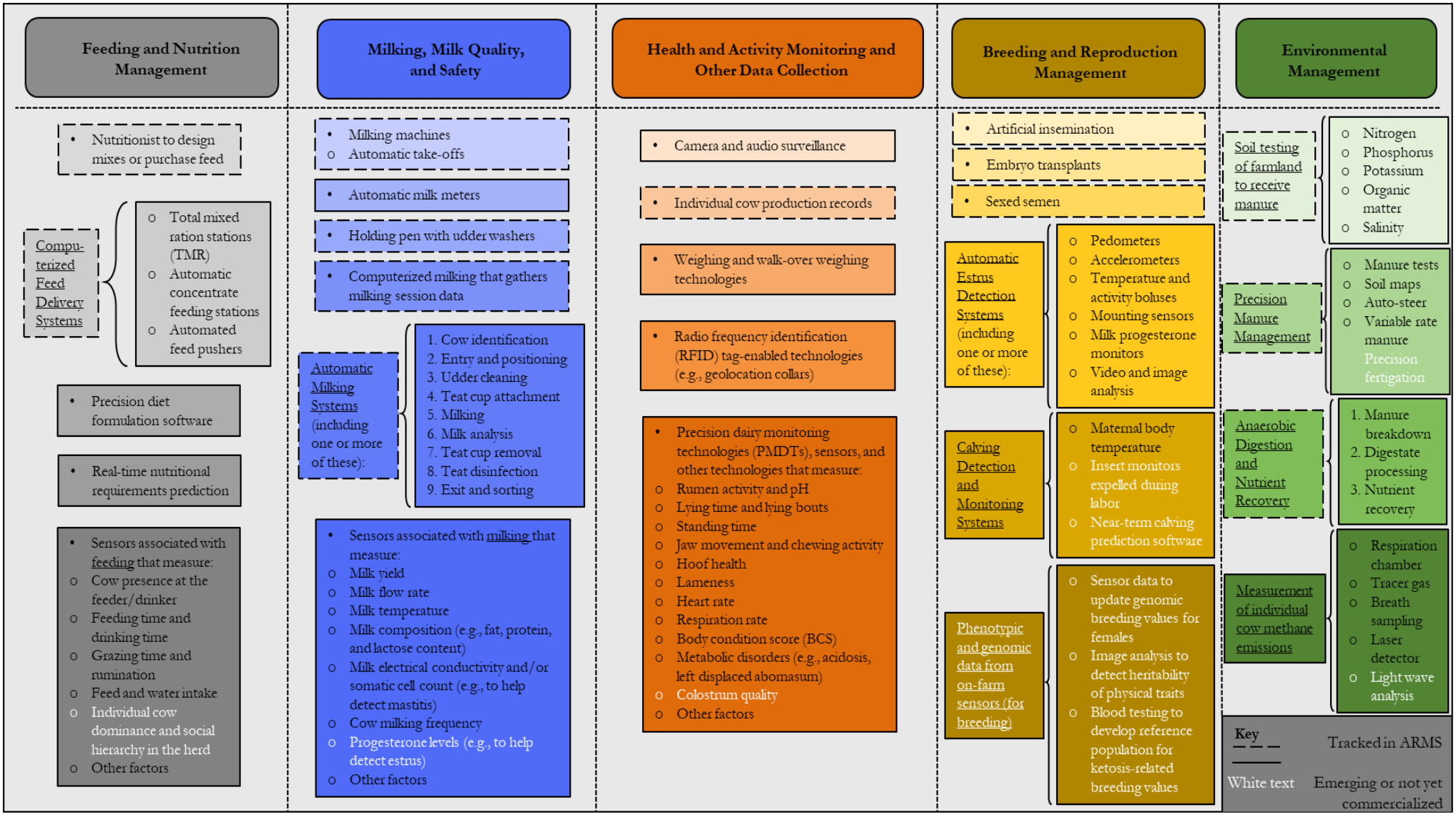
PDF technologies not collected in the ARMS Phase 3, Dairy surveys. A wide range of other precision technologies with various purposes, functionalities, technical sophistication, and availability levels (from pre-commercialization to broadly diffused) exist in the dairy sector, but the ARMS Phase 3, Dairy 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 feeding stations), while others are currently emerging (e.g., precision fertigation, predicting individual cows' methane emissions based on lightwave analyses from milk samples). 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 (Figure A1).

A major line of demarcation across the technology groupings relates to the use and proliferation of sensors that collect and analyze data at the individual cow level (Hogeveen and 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 and 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).

[11] Currently, on large dairy farms (e.g., > 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 (e.g., Zahniser et al., 2018).

[12] 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 are likely fewer than 10 dairy farms in the United States using fully robotic carousel milking technologies, consistent with estimates from the 2016 and 2021 ARMS 3, Dairy data. This paper therefore omits this statistically negligible usage of fully robotic carousel milking when discussing overall robotic milking adoption in the United States.

Figure A1. Types of PDF Technologies



Note: The diagram includes PDF technologies not included in the empirical analysis. In the empirical analysis, we focus on PDF 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.

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