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Are Milking Management Technologies Increasing the Labor Efficiency, Productivity, and Profitability of Pasture-Based Dairy Farms? Evidence from Ireland

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Pasture-based dairy farmers currently face increasing seasonal workload in addition to declining workforce availability. Milking management technologies have the potential to improve labor efficiency with a consequent increase in productivity and profitability. However, there is a lack of evidence of the effects of these technologies on dairy farm performance. Using farm-level data from Ireland and a propensity score matching approach, we found that milking management technologies did not significantly impact labor efficiency. However, we did find a positive impact on milk yield and milk solids, which translated into increased gross output and in turn gross margin per hectare.

Key words: automation technologies, farm performance, impact evaluation, milking management technologies

Introduction

Since the abolition of EU milk quotas in 2015, some European countries—including Ireland—have experienced a dairy farm expansion that has led to larger dairy herds with greater requirements for labor input (Deming et al., 2018). Simultaneously, the number of people working on farms is declining in most developed countries (Hogan et al., 2023), and the attraction and retention of suitably trained and qualified people has become a challenge within the dairy industry (Eastwood et al., 2020; Kelly et al., 2020). The declining workforce available to work on dairy farms might be due to the fact that dairy farming is both very labor intensive and not very flexible. It requires high levels of physical work and allows limited free time due to twice-daily milking duties, which can have a significant impact on dairy farmers' quality of life (Contzen and Häberli, 2021). Additionally, pasture-based dairy systems—such as those present in Ireland, New Zealand, and some parts of Australia—exhibit workload increases during the spring and summer seasons (Deming et al., 2018) because calving periods need to be matched with the seasonal feed supply of grass. The intense

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seasonal workload has led to dairy farmers experiencing high levels of stress (Brennan et al., 2022) and mental health issues (Lunner Kolstrup et al., 2013).

In this context, automation technologies have been increasingly promoted on dairy farms to reduce labor requirements, ease labor, and improve the management of dairy herds (Gargiulo et al., 2018). They have the potential to either reduce pressure on labor or improve labor efficiency by helping to perform tasks previously undertaken manually by farm operators. The Irish government has recognized the benefits of these technologies in improving the competitiveness of the agricultural sector and since 2015 has incentivized the adoption of automation technologies through a series of schemes that subsidize dairy farm technology investments (Department of Agriculture, Food and the Marine, 2023). From the wide range of technologies available, automation-based technologies used in the milking parlor (also referred to as "in-parlor technologies") are particularly important because the milking process and its associated tasks account for approximately 33% of total annual farm labor in Irish pasture-based dairy farms (Deming et al., 2018). The clearest example of in-parlor automation technology is the automatic milking systems (AMS) or milking robots, which utilize data coming from a wide number of sensors to autonomously milk cows (Shalloo et al., 2021). Another example is the automatic cluster removers (ACR) that can automatically identify the optimal termination point to detach the milking units during the milking process (Wieland et al., 2020).

Despite the potential of in-parlor automation technologies to reduce labor demand and the government financial support to invest in these technologies, their rate of adoption remains low (Yang et al., 2021; Palma-Molina et al., 2023b). This may be that the value added of some technologies or combinations of technologies remains unclear to dairy farmers (Edwards et al., 2020). There is a lack of evidence regarding their physical and economic performance (Gargiulo et al., 2020). Most of the literature available on the effects of in-parlor automation technologies on farm performance have focused on the use of milking robots (Bijl, Kooistra, and Hogeveen, 2007; Steeneveld et al., 2012; Shortall et al., 2016; Gargiulo et al., 2020). Shortall et al. (2016) evaluated the profitability of milking robots in an Irish pasture-based system compared to conventional milking systems and found a 36% reduction in labor demand associated with milking robots but no impact on profitability, irrespective of farm size. Similar results were found by Gargiulo et al. (2020) on pasture-based Australian farms and Bijl, Kooistra, and Hogeveen (2007) and Steeneveld et al. (2012) on dairy farms in the Netherlands, showing no significant differences between dairy farms with milking robots and conventional milking systems on performance indicators.

Few studies have investigated the relationships between other in-parlor technologies (besides milking robots) and farm performance indicators. Edwards et al. (2020) investigated relationships between individual in-parlor technologies (automatic teat spraying, automatic cluster removers and automatic drafting) and milking (cows milked per hour) and labor efficiency (cows milked per person-hour). They found that automatic teat sprayers were associated with greater labor efficiency and work routine time, while automatic cluster removers were associated with higher throughput (cows milked per hour). Dela Rue et al. (2020) investigated the association between technologies used in the milking parlor on labor efficiency and found that a combination of automatic cluster removers, automatic teat spraying, and automatic drafting was associated with 43% higher labor efficiency (cows milked per person-hour) in the milking process. Hogan et al. (2022b) researched the work practices and technologies associated with labor efficiency on Irish dairy farms and found that automatic cluster removers offered the largest labor savings (reduction of 2.55 hours per cow) among technologies. Garcia-Covarrubias et al. (2023) explored the role of automation technologies used in the milking parlor (automatic parlor feeders, automatic cluster removers, automatic scrapers, and automatic washers) and found a heterogeneous effect on Irish dairy farms' technical efficiency. This means that automatic cluster removers were associated with higher technical efficiency on smaller, less intensive farms, while the adoption of automated parlor feeders was associated with higher technical efficiency on larger, more intensive farms. Although these studies estimated correlations, they were not able to attribute a causal link between use of the technologies and labor requirements.

Moreover, to our knowledge, there are no studies that empirically assess the simultaneous effect of in-parlor automation technologies on labor efficiency, productivity, and profitability. This study contributes to the existing body of knowledge on the impacts of in-parlor automation technologies on the performance of dairy farms by using causal inference methods and farm-level data on a wide range of farm performance indicators. Specifically, we use a unique nationally representative farm survey and a propensity score matching (PSM) approach to determine the impacts of adopting a group of three in-parlor automation technologies (automatic cluster removers, automatic washers, and automatic parlor feeders)—hereafter referred to as milking management technologies—on labor efficiency, productivity, and profitability. Based on the literature, we hypothesize that adopting milking management technologies would significantly improve labor efficiency on dairy farms by reducing the number of labor hours the operators spend per cow on the farm. In theory, this should decrease labor costs, which would lead to increased profitability. Additionally, we expect that the adoption of milking management technologies would lead to increased milk yields and milk solids due to an improvement in parlor management (better feed allocation and better milking equipment hygiene). The increased milk yield and milk solids might also increase profitability.

The results of our study will inform policy makers, dairy processors, and dairy farmers on the labor and economic outcomes of investing in milking management technologies. This information is key to provide evidence of their benefits (if any) to increase the adoption of these technologies or to identify areas of improvement (if there were not significant impacts) on the use of current and future milking management technologies.

Background and Conceptual Framework

Dairy farming is considered to be very labor intensive. It has been reported that dairy farmers work 50.4 hours/week compared with the national average workweek of 35.7 hours/week in Ireland (Central Statistics Office, 2015). Additionally, pasture-based dairy farms exhibit increased workloads during spring and summer seasons (Deming et al., 2018), when most of the milking, calving, and calf care tasks of the farm occur (Hogan et al., 2023). Consequently, dairy farmers have a higher probability of experiencing stress and mental health issues compared to operators of other farm systems (Brennan et al., 2022). The intense seasonal workload, combined with increased dairy herd sizes and the current challenges of finding qualified people to work on farms (Kelly et al., 2020), has led to labor efficiency and productivity becoming an increasingly important issue on pasture-based dairy farms (Hogan et al., 2022a). In this context, technological innovation, specifically automation, has been identified as an important approach to reducing work hours and increasing flexibility, adaptability, and productivity (Edwards et al., 2020; Yang et al., 2021). Digital technologies, including automation technologies, have been recognized as a priority for Irish research and innovation (Teagasc, 2016). Furthermore, the Irish government has incentivized on-farm capital investment through the Targeted Agricultural Modernisation Schemes (TAMS). The TAMS, which is in its third iteration (TAMS 3), has a total allocated budget of €370 million and includes a specific scheme (Dairy Equipment Scheme) to subsidize investment in the most-up-to-date technologies available (Department of Agriculture, Food and the Marine, 2023).

Among dairy farm duties, milking has been found to be the most time-consuming task (Hogan et al., 2022a). According to Deming et al. (2018), milking and its associated tasks (e.g. pre- and post-milking herding, post-milking washing of the equipment) account for 33% of total annual farm labor in Ireland. Edwards et al. (2020) estimated that at peak lactation, milking represents 43%–58% of a conventional 40-hour work week in New Zealand. The longer working hours and increased workloads at peak times has been found to be one of the most important sources of stress among dairy farmers and dairy operators (Brennan et al., 2022). Considering the importance of milking on labor demand, the adoption of in-parlor automation technologies appears to be a key strategy to reduce labor requirements and to overcome current social sustainability challenges around workload and work–life balance.

Automation refers to the development and adoption of new technologies that substitute capital for labor in a range of tasks (Acemoglu and Restrepo, 2019). In-parlor automation technologies have been developed and promoted to facilitate the management of dairy herds by improving labor efficiency, reducing physical efforts, or allowing a decrease in work hours while maintaining or increasing productivity (Yang et al., 2021). According to the capital labor substitution theory (Arrow et al., 1961), this is because there is a displacement effect, where capital takes over tasks previously performed by labor (Acemoglu and Restrepo, 2019). According to Acemoglu and Restrepo's (2019) task-based conceptual framework, automation technologies also have a productivity effect, wherein they increase productivity by allowing a more flexible allocation of tasks that contribute to the demand for labor in nonautomated tasks (a reinstatement effect). Therefore, the net impact of automation technologies on labor demand will depend on how the displacement and productivity effects weigh against each other (Acemoglu and Restrepo, 2019). In this case, if in-parlor automation technologies substitute for the operator in the milking tasks the operator will no longer be necessary (displacement of labor) or their number of labor hours will be greatly reduced, which will facilitate time for new tasks (reinstatement effect) for which they did not previously have time (e.g., calf care or grassland management). By improving other areas of dairy farm management, the dairy farm could increase milk yield (productivity effect), which—if it is considerable enough—could eventually increase labor demand. Additionally, with the use of in-parlor technologies, the operator could handle more cows during milking (Steeneveld et al., 2012), which would also increase milk yield.

It has been reported that the main motivation for dairy farmers to adopt automation technologies is to allow more free time, provide more flexibility and require less manual labor (Mathijs, 2004). Additionally, they are expected to provide economic benefits in terms of labor cost savings and increased production per cow (Wade et al., 2004). Pasture-based dairy systems in New Zealand have increasingly relied more on technologies to deal with the industry labor issues to improve labor productivity with a particular focus on milking tasks (Deming et al., 2018). In Ireland, the uptake of automation technologies on dairy farms has been slower than expected (Teagasc, 2016), which may be due to the smaller herd size or insufficient evidence of the added value of some technologies or combinations of technologies (Edwards et al., 2020). The decision to adopt an automation technology represents a significant investment for a dairy farmer, and the effect of an unproductive investment could be severely detrimental; therefore, these investments are approached with caution (Borchers and Bewley, 2015). Technology performance must be evaluated to demonstrate investment efficacy and inspire producer confidence (Wathes et al., 2008). Most of the literature available has focused on the economic effects of milking robots (Bijl, Kooistra, and Hogeveen, 2007; Steeneveld et al., 2012; Shortall et al., 2016; Gargiulo et al., 2020), with a few that have explored the effects of other in-parlor automation technologies (e.g., automatic washers or automatic cluster removers) on labor efficiency (Dela Rue et al., 2020; Edwards et al., 2020; Hogan et al., 2022b). Although these studies are based on detailed data of labor input (labor hours recorded per task), they only estimate associations between labor efficiency and technology adoption. Using general labor data reported by dairy farmers, the present study is able to estimate the causal effect of the adoption of milking management technologies on total labor hours per cow, milk productivity, and financial return.

Empirical Approach

There are several challenges when estimating the impacts of a binary treatment on an outcome variable (Imbens and Wooldridge, 2009). First, the object of interest is a comparison of the two outcomes for the same unit when exposed, and not, to the treatment. However, we can typically observe only one of these outcomes for each observation unit. This is called the fundamental problem of causal inference (Holland, 1986). In other words, farmers either adopt or do not adopt a technology, they cannot do both in a given period. The standard framework in evaluation analysis to formalize this problem is the Rubin causal model (Rubin, 1973). Rubin's approach interprets causal statements as comparisons of two potential outcomes, denoted as $Y_i(1)$ and $Y_i(0)$. If farmer i adopts a technology, $Y_i(1)$ denotes the realized outcome and $Y_i(0)$ denotes the outcome that would have been realized by the same farmer if he or she had not adopted the technology (the counterfactual outcome). If, on the other hand, farmer i does not adopt the technology, $Y_i(0)$ will be realized and $Y_i(1)$ will be the *ex post* counterfactual. Since estimating the individual treatment effect is not possible, population average treatment effects (ATE) are estimated, which is simply the difference of the expected outcomes with (Y_1) and without (Y_0) treatment (Caliendo and Kopeinig, 2008):

$$\tau_{ATE} = E_{(\tau)} = E\left[Y_1 - Y_0\right]. \tag{1}$$

Nevertheless, the most important evaluation parameter is the so-called average treatment effect on the treated (ATT), which focuses explicitly on the effects on those for whom the treatment is intended:

$$\tau_{ATT} = E\left[Y_1 \mid T = 1\right] - E\left[Y_0 \mid T = 1\right]. \tag{2}$$

A second challenge when estimating treatment effects is that estimations are generally hampered by endogeneity or self-selection bias, the initial differences between adopters and nonadopters farmers (e.g., level of education, age, managerial skills) that can influence not only the decision to adopt a technology but also farm performance outcomes (Imbens and Wooldridge, 2009). For example, factors such as herd size, farmer's age and the region where the farm is located have been found to influence the adoption of milking management technologies (Palma-Molina et al., 2023b). These farm and farmer characteristics, among other factors, have also been associated with the efficiency (Bradfield et al., 2021) and profitability (Hennessy and Heanue, 2012; Hanrahan et al., 2018) of pasture-based dairy farms. If these factors are not considered, simply comparing the outcomes between adopters and nonadopters of technologies would lead to differences due to reasons other than technology adoption being falsely attributed as a technology impact, and as such the impact of the technology may be over- or underestimated. The problem is exacerbated by the fact that reliable data before and after the exposure to a treatment are often not available and a comparable counterfactual group is difficult to identify (Läpple and Hennessy, 2015).

There are several methodological approaches to evaluate the impact of technology adoption while controlling for self-selection bias, including panel data, instrumental variables, difference-in-differences and matching methods (Imbens and Wooldridge, 2009). The choice of methodology will generally depend on the available data. In the absence of panel data or credible instruments, Propensity score matching (PSM) has become a popular approach in agricultural studies (Läpple and Hennessy, 2015; Balaine et al., 2020). PSM is a nonparametric method widely employed to evaluate the impacts of technology adoption on farm outcomes (Balaine et al., 2020; Palma-Molina et al., 2023a), particularly when selection bias is an issue. As a nonparametric technique, it does not require specification of a functional form or distribution assumptions. The basic concept of PSM is that selection occurs only on observable variables, and adopters and nonadopters with the same probability, p, of adopting a technology—given a set of covariates X—can be compared and matched (Rosenbaum and Rubin, 1983). Therefore, the impact of the technology can be estimated by averaging within-matched-pair differences in outcomes (Imbens and Wooldridge, 2009):

$$ATT_{PSM} = E\left[Y_1 \mid T = 1, p\right] - E\left[Y_0 \mid T = 0, p\right], \tag{3}$$

where ATT_{PSM} is the average treatment effect on the treated or, in this case, the effect of milking management technology adoption on farm performance (productivity, labor, and profitability). T is the treatment variable, indicating whether the technology has been adopted ($T = 1$) or not ($T = 0$), Y_1 is the outcome variable in a state where the farmer adopts the technology ($T = 1$), and Y_0 is the outcome variable in a state where the farmer does not adopt the technology ($T = 0$), the control or counterfactual.

The use of PSM involves several practical steps before estimating the ATT (Balaine et al., 2020). First, we estimate propensity scores, $p_i = P(T = 1)|X_i$, for each farmer i with a logit model, where X_i represents a set of farm and farmer' characteristics that simultaneously affect technology adoption and on farm performance (outcome variables) but are not impacted by adoption status, the covariates, or confounding variables. Second, we select and perform a suitable matching algorithm, like nearest neighbor (NN) matching, which matches adopters to their closest nonadopters in terms of propensity score value. This method requires the selection of the number of matches for each adopter farm and whether to match with or without replacement (if nonadopter farms are allowed to be matched once or more than once). Finally, we evaluate the matching quality by checking that the matching process successfully removed the differences in the observed characteristics between adopters and nonadopters. This assessment is based on the standardized differences of the covariates across groups of adopters and nonadopters (Balaine et al., 2020).

The MatchIt package (Ho et al., 2011) in R was used to pre-process and match the samples of adopter and nonadopter farms. To reach the best trade-off based on our sample size (Balaine et al., 2020), we chose NN matching on the propensity score algorithm, with replacement where two matches were used (nonadopter or control farms) per treated unit (adopter farms) with the "weights" argument (to scale down the overmatched observations when running the model). The covariates selected for analysis were farm and farmer characteristics that have been identified in the literature as being associated with precision technology adoption (Palma-Molina et al., 2023b) and farm efficiency (Bradfield et al., 2021) and profitability (Hanrahan et al., 2018). The differences in means between adopter and nonadopter farms of these variables were tested (two-sample *t*-test) to identify those that might cause selection bias (Table 1). Based on the literature and the results of the *t*-test and the matching quality balance, the covariates included in the technology adoption decision model (logistic regression) to estimate the propensity scores were farm size, herd size, herd size2, agricultural education, and specialization.

Sensitivity Analysis

As a robustness check, we estimated ATTs with alternative treatment effect methods, including a different matching algorithm (Malahanobis matching distance) and inverse probability weighting (IPW). Malahanobis matching distance (Cochran and Rubin, 1973) estimates ATT by matching each treated unit (adopters) with the closest control unit (nonadopters) in terms of their Mahalanobis distance. The Mahalanobis distance M is estimated as

$$\mathrm{M}(X_i,X_j) = \sqrt{(X_i - X_j)' S^{-1} (X_i - X_j)}, \tag{4}$$

where S^{-1} is the sample covariance matrix of X (set of covariates), X_i are the covariates of the treated units, and X_j are the covariates of the control units.

One potential downside of matching is that we discard all data that is not matched. Using IPW allows us to assign every observation some probability of receiving the treatment and then weight each observation by its inverse probability. Additionally, we tested for how sensitive the results are to hidden bias using a Rosenbaum (2002) bounds sensitivity test from the rbounds package in R (Keele, 2010).

Data

The analysis was based on farm-level data collected from the 2018 National Farm Survey (NFS). The NFS is a survey conducted annually in Ireland by Teagasc as part of the Farm Accountancy Data Network (FADN) of the European Union (Dillon et al., 2021). A stratified random sample of approximately 800 farms is selected each year in conjunction with the Central Statistics Office to ensure that the surveyed farms represent different farm systems and farm sizes nationally. The data

Table 1. Characteristics of Irish Dairy Farms by Milking Management Technologies Adoption Status

Variable	Mean Adopters (N = 41)	Mean Nonadopters (N = 232)	Mean All Farms (N = 273)	t-Statistic	p-Value
Herd size (avg. number of cows)	153.2 (56)	80.3 (46)	91.3 (54)	−7.78	<0.001
Farm size (UAA)	101.4 (37)	63.3 (32)	69.1 (36)	−6.12	<0.001
Age (years)	51.3 (10)	53.2 (10)	52.9 (10)	1.09	0.2745
Household members (number)	3.8 (1.5)	3.3 (1.5)	3.4 (1.5)	−1.85	0.0659
Agricultural education[a]	0.92 (0.3)	0.80 (0.4)	0.82 (0.4)	−2.56	0.0123
North-west region[b]	0.04 (0.2)	0.17 (0.4)	0.16 (0.4)	3.02	0.0032
Mid-east region[c]	0.31 (0.5)	0.15 (0.4)	0.18 (0.4)	−2.03	0.0472
South-west region[d]	0.63 (0.5)	0.66 (0.5)	0.66 (0.5)	0.36	0.7132
Soil quality[e]	0.68 (0.5)	0.55 (0.5)	0.57 (0.5)	−1.51	0.1307
Stocking rate	2.32 (0.4)	2.06 (0.5)	2.10 (0.5)	−3.39	0.0011
Specialization[f]	0.68 (0.1)	0.65 (0.1)	0.66 (0.1)	−1.79	0.0769
Concentrate use	1,141.9 (683)	1,107.5 (506)	1,112.6 (535)	−0.31	0.7595

Notes: Values in parentheses are standard deviations.
[a]Categorical variable, = 1 if the farmer has some level of agricultural education; 0 otherwise.
[b]Categorical variable, = 1 if the farm is in the north-west region (counties Louth, Leitrim, Sligo, Cavan, Donegal, Monaghan, Galway, Mayo, or Roscommon).
[c]Categorical variable, = 1 if the farm is in the mid-east region (counties Dublin, Kildare, Meath, Wicklow, Laois, Longford, Offaly, Westmeath).
[d]Categorical variable, = 1 if the farm is in the south-west region (counties Clare, Limerick, Tipperary, Carlow, Kilkenny, Wexford, Waterford, Cork or Kerry).
[e]Categorical variable, = 1 if the farm has good quality soil; 0 otherwise.
[f]Percentage of dairy units of the total livestock units in the farm.
Source: Teagasc National Farm Survey (Dillon et al., 2018).

are provided voluntarily by farmers and collected by professional data recorders through several face-to-face farm visits per year. Each farm is assigned a weighting factor, or population weight, so that the results of the survey represent the national population of farms with a standard output above €8,000 (approximately 85,000 farms). The weighting factors are defined according to farm area (size) and system using annual aggregation factors from the national agriculture census. More information on how the samples were selected and how the weighting factors created can be found in the 2018 NFS Report (Dillon et al., 2018). Farms are classified into one of six farming systems based on the dominant enterprise on the farm: dairy, cattle rearing, cattle other, sheep, tillage, and mixed livestock (Dillon et al., 2021). A total of 897 farms were surveyed in 2018, of which 311 were specialized dairy farms. The 311 surveyed dairy farms represent a total population of 16,146 dairy farms in Ireland.

In addition to standard FADN data on the technical and financial performance of the farm business and sociodemographic information on the farm operator and household, the NFS includes an additional survey that collects various farm management information yearly. The NFS additional survey is usually completed voluntarily at the end of the original NFS; therefore, some farmers might choose not to continue with the additional questions. The 2018 additional survey was completed by 273 of the 311 specialized dairy farms surveyed by the NFS. In 2018, the NFS additional survey included questions regarding technology adoption, specifically information on the adoption of nine technologies on dairy farms (Palma-Molina et al., 2023b), including automation technologies used in the milking parlor: automatic parlor feeders, automatic cluster removers, and automatic milk washers. Milking robots were also included in the survey, but there were insufficient observations to be considered for analysis. Previous research has found that farmers tend to adopt PLF technologies in groups or clusters of technologies (Palma-Molina et al., 2023b). Specifically, Palma-Molina et al. (2023b) estimated that dairy farmers using automatic parlor feeders were approximately 5.3 times more likely to use automatic cluster removers and approximately 3.4 times more likely to use automatic washers. Dairy farmers using ACR were approximately 6 times more likely to use automatic washers (Palma-Molina et al., 2023b). The strong association between technologies and the fact that they are all used to reduce labor and ease management in the milking parlor supported the decision to group them into a group called milking management technologies. The milking management technologies variable would equal 1 if the dairy farmer adopted automatic parlor feeders, automatic cluster removers, and automatic milk washers, and 0 otherwise. There were 41 adopter dairy farms (treatment group) and 232 nonadopter dairy farms (control or counterfactual group) of milking management technologies. Table 1 presents descriptive statistics of selective farm and farmers characteristics, classified by technology adoption status.

To assess the effects of milking management technologies adoption on labor efficiency, we used the total labor hours per cow as an indicator, which we estimated by adding the labor hours of family (unpaid) and paid labor hours of all workers on the farm and dividing them by herd size. To assess the effects of milking management technologies adoption on farm productivity we focused on two indicators: milk component yield as kilograms of fat-protein corrected milk (FPCM) per hectare and per cow, and milk solids as kilograms of milk solids per hectare and per cow. Milk component yields and milk solids are included because dairy farmers are compensated based on milk fat, true protein, and other dairy solids; therefore, they directly influence the profitability of dairy farms (Wieland et al., 2020). Additionally, to assess whether the adoption of milking management technologies had an effect on pasture growth and utilization, we included kilograms of grazed grass dry matter (DM) per hectare as an indicator. To assess the effects of milking management technologies adoption on farm profitability, we utilized three indicators: gross output per hectare, gross margin per hectare, and net margin per hectare. Moreover, we included direct costs per hectare and fixed costs per hectare in the financial analysis. Table 2 presents descriptive statistics of the outcome variables from the NFS included in the analysis.

Empirical Results

Table 1 presents descriptive statistics and the differences in means (two-sample *t*-test) of farm and farmer variables by selected technology adoption status. From Table 1, it appears that there are initial differences between adopter and nonadopter farms of milking management technologies that might cause selection bias. Specifically, adopter farms had larger dairy herds ($p < 0.001$) and were of a larger farm size ($p < 0.001$), farmers operators were more likely to have attained higher agricultural education ($p = 0.012$), were more likely to be located in the mid-east region of Ireland ($p = 0.047$) and less on the north-west region of Ireland ($p = 0.003$), compared to nonadopter farms. Additionally, adopter farms tend to have higher stocking rates and were more specialized in dairy than nonadopter farms. Conversely, nonadopter farms tend to have lower herd and farm size, to be operated by farmers with less formal agricultural education, to be located more in the north-west

Table 2. Outcome Variables Description and Descriptive Statistics for Sampled Dairy Farms

Variable	Description	Mean Adopters (*N* = 41)	Mean Nonadopters (*N* = 232)	Mean All Farms (*N* = 273)	*p*-Value
Productivity					
FPCM/ha	Kg of fat-protein-corrected milk per hectare	15,473.1 (3,505)	11,826.3 (3,842)	12,374 (4,006)	<0.001
FPCM/cow	Kg of fat-protein-corrected milk per cow	6,761.1 (1,077)	5,753.0 (1,128)	5,904.6 (1,176)	<0.001
Solids/ha	Kg of milk solids per hectare	1,113.2 (250)	838.5 (281)	879.7 (293)	<0.001
Solids/cow	Kg of milk solids per cow	486.7 (78)	407.6 (85)	419.5 (89)	<0.001
Grazed pasture/ha	Kg of grazed grass DM per hectare	8,450.6 (1,861)	6,992.8 (2,048)	7,211.8 (2,084)	<0.001
Labor efficiency					
Labor/cow	Total labor hours per cow	36.3 (13)	54.7 (33)	52.0 (32)	<0.001
Profitability					
GO/ha	Gross output per hectare	5,397.7 (1,401)	4,102.7 (1,364)	4,297.2 (1,443)	<0.001
DC/ha	Direct costs per hectare	2,351.7 (753)	1,749.1 (663)	1,839.5 (709)	<0.001
GM/ha	Gross margin per hectare	3,045.9 (915)	2,353.7 (893)	2,457.7 (928)	<0.001
FC/ha	Fixed costs per hectare	1,919.5 (501)	1,493.3 (554)	1,557.3 (567)	<0.001
NM/ha	Net margin per hectare	1,126.4 (892)	860.4 (786)	900.4 (807)	0.0516

Notes: Values in parentheses are standard errors.
Source: Teagasc National Farm Survey (Dillon et al., 2018).

region of Ireland, and to have lower stocking rates than adopter dairy farms. Farm size, herd size, herd size squared, agricultural education, and specialization were included in the logistic model to estimate propensity scores.

Table 2 presents the results from the differences in means of labor efficiency, productivity, and profitability indicators by technology adoption status. Dairy farms that adopted milking management technologies tend to be more productive in terms of milk yield per hectare ($p < 0.001$) and per cow ($p < 0.001$) and milk solids per hectare ($p < 0.001$) and per cow ($p < 0.001$). Adopter farms also had higher use of grazed grass per hectare ($p < 0.001$) compared to nonadopter farms. There were also significant differences in labor efficiency between adopter and nonadopter farms. Specifically, adopter farms had fewer total labor hours per cow ($p < 0.001$) than nonadopter farms. Moreover, the results suggest that adopter farms had higher gross output ($p < 0.001$), direct costs ($p < 0.001$), gross margin ($p < 0.001$) and fixed costs ($p < 0.001$) than nonadopter farms.

Table 3 presents the results from the logistic regression that estimated the propensity scores. Larger herd sizes were positively correlated with the adoption of milking management technologies, while farm size, agricultural education, and specialization did not appear to be related to technology adoption. The assessment of the matching covariate balance is presented in Appendix Table A1.

Table 3. Results of the Adoption Decision Model (logit regressions) Used to Estimate the Propensity Scores

Covariates	Estimate	*p*-Value
Farm size	−0.006 (0.01)	0.527
Herd size	0.073 (0.02)	<0.001
Herd size^2	−0.0001 (0.00)	<0.001
Agricultural education	0.738 (0.71)	0.299
Specialization	1.97 (2.31)	0.393
Intercept	−9.1 (2.1)	<0.001
Akaike information criterion	173.97	

Notes: Values in parentheses are standard errors.
Source: Teagasc National Farm Survey (Dillon et al., 2018).

The results showed that the standardized differences between adopter and nonadopter farms became close to 0 for all covariates after matching, which indicates a successful covariate balance.

Table 4 presents the estimations of the average treatment effect of the treated (ATT) or, in this case, the effect of milking management technology adoption on labor efficiency, productivity, and profitability. The table reports the unmatched comparison of the outcome variables between adopter and nonadopter farms (naïve correlation) and the ATT estimations using PSM, Mahalanobis distance matching, and IPW. The results from the PSM suggested that after controlling for selection bias using PSM, the adoption of milking management technologies tend to increase milk yield by 1,650 kilograms of FPCM per hectare ($p < 0.05$) and by 565 kilograms of FPCM per cow ($p < 0.05$) on average in 2018. These results were robust to the use of different estimation methods (Mahalanobis matching and IPW). The PSM results also indicated that the adoption of milking management technologies tends to increase milk solids by 120 kilograms per hectare ($p < 0.05$) and 41 kilograms per cow ($p < 0.05$) on average, in 2018. These results were similar across the other two approaches. Additionally, the results showed no impact of technology adoption on the use of grazed grass per hectare. In terms of labor efficiency and contrary to priori expectation, the results showed that after controlling for selection bias, the adoption of milking management technologies had no significant effect on total labor hours per cow. Financially, the adoption of milking management technologies tends to increase gross output by €647 per hectare ($p < 0.05$) and gross margin by €415 per hectare ($p < 0.05$) on average in 2018. However, there were no statistically significant effects on net margin per hectare. The results were robust to the use of different estimation approaches.

Discussion

Adopters and Nonadopters of Milking Management Technologies

The results of the analysis of characteristics of adopters and nonadopters of milking management technologies (Table 1) showed that dairy farms that adopted milking management technologies significantly differed from nonadopter dairy farms in terms of herd size, farm size, agricultural education, the region where the farm is located, and stocking rates. These differences are important to consider when estimating causal effects because of the possibility of selection bias. Additionally, they give us some insights into the factors that might influence technology adoption. Consistent

Table 4. Estimation of the Average Treatment Effects of the Treated (ATT)

Outcome Variable	Naïve Correlation	PSM	Mahalanobis Matching	IPW
Sample sizes				
Treated units	41	41	41	41
Control units (matched)	232	48	52	232
Productivity				
Milk yield (kg of FPCM/ha)	$3,646.8^{***}$ (642.9)	$1,650.5^{**}$ (699.8)	$1,886.8^{**}$ (756.4)	$1,518.1^{***}$ (413.7)
Milk yield (kg of FPCM/cow)	$1,007.9^{***}$ (189.9)	565.0^{**} (228.5)	737.3^{***} (225.1)	574.1^{***} (127.7)
Milk solids (kg/ha)	274.7^{***} (46.8)	119.7^{**} (50.7)	137.5^{**} (54.9)	111.1^{***} (29.9)
Milk solids (kg/cow)	79.1^{***} (14.3)	41.1^{**} (17.1)	54.2^{***} (16.8)	42.3^{***} (9.5)
Grazed grass/ha	$1,457.8^{***}$ (342.6)	705.6 (358.9)	628.6 (379.9)	518.8^{**} (235.3)
Labor efficiency				
Total labor (hours/cow)	-18.3^{***} (5.3)	2.4 (3.1)	0.8 (3.1)	3.9^{**} (1.7)
Profitability				
Gross output (€/ha)	$1,294.9^{***}$ (232.1)	647.1^{**} (272.5)	737.5^{**} (282.1)	594.1^{***} (158.8)
Direct costs (€/ha)	602.6^{***} (114.3)	232.1 (154.5)	244.5 (155.5)	181.5^{**} (84.9)
Gross margin (€/ha)	692.2^{***} (151.8)	415.0^{**} (169.4)	493.0^{***} (178.8)	412.7^{***} (103.4)
Fixed costs (€/ha)	426.1^{***} (92.7)	236.7^{**} (108.0)	270.1^{**} (109.3)	221.9^{***} (61.3)
Net margin (€/ha)	266.1 (136.1)	178.4 (162.8)	222.9 (170.8)	199.8^{**} (96.2)

Notes: Values in parentheses are standard errors. Double and triple asterisks (**, ***) indicate significance at the 5% and 1% level, respectively.

with other studies (Gargiulo et al., 2018; Balaine et al., 2020; Palma-Molina et al., 2023b), the results showed that adopters of milking management technologies tend to have larger herd sizes than nonadopters of milking management technologies. In addition to herd size, Palma-Molina et al. (2023b) found that proportion of hired labor, age, number of household members, and the region where the farm is located also influenced the adoption of milking management technologies. Balaine et al. (2020) found that nonadopter farms were less specialized in dairy (estimated as the proportion of dairy cows of the total livestock units in the farm) and had less agricultural education and fewer household members than dairy farms that had adopted milk meters in Ireland. In addition to farm and farmer structural factors, previous research has found that the technology adoption decision process among Irish dairy farmers is also influenced by financial considerations and characteristics of the technology (e.g., usefulness and ease of use) (McDonald et al., 2016). Moreover, the results show that there are initial differences in terms of productivity, labor efficiency, and profitability between adopter and nonadopter farms that might suggest that technology adopters are more productive, efficient, and profitable than nonadopters.

Impacts of Milking Management Technologies on Labor Efficiency

The main goal of adopting automation technologies in milking parlors is to reduce the labor associated with milking tasks, which may in turn lead to quality-of-life improvements for farmers and possible reduced stress levels. Our findings suggest that although initially adopter farms were more labor efficient than nonadopter farms, after controlling for selection bias there was no significant impact of milking management technologies on labor efficiency. Specifically, the adoption of automatic cluster removers, automatic parlor feeders, and automatic washers did not significantly reduce total labor hours per cow. These results differ from what we expected and from previous research on the use of ACR and other automation technologies. Edwards et al. (2020) found that having automatic cluster removers and automatic drafting improved labor efficiency at peak lactation compared with having no technology. Dela Rue et al. (2020) found that dairy farms with a combination of automatic cluster removers, automatic teat spraying, and automatic drafting were associated with 43% higher labor efficiency than those without all three technologies. Hogan et al. (2022b) reported that having automatic cluster removers offered one of the greatest time savings by reducing labor by 2.55 hours per cow. Studies on the use of robotic milking have estimated a reduction in labor demand that ranges from 29% (Bijl, Kooistra, and Hogeveen, 2007) to 36% (Shortall et al., 2016) compared to conventional milking systems. However, these studies estimate correlations or are based on scenario modeling; hence, they do not attribute causality or control for selection bias. Additionally, they included different in-parlor automation technologies than those considered in our study.

The absence of a causal effect suggests that the combination of milking management technologies used in our study (automatic cluster removers, automatic parlor feeders, and automatic washers) were not achieving their expected labor-saving potential. This might have different explanations. First, the labor data collection method may have limitations. In accordance with FADN methodology, the NFS labor input data are based on estimations of farmers and not on daily recorded data; therefore, they might be less accurate than data used in other labor efficiency studies, albeit carried out in a smaller number of farms (Hogan et al., 2022a). Additionally, the 232 control farms used in the analysis included dairy farms that might have adopted one or two combinations of milking management technologies; therefore, they could be affecting the differences between adopter and nonadopter farms and thus the impact estimations. Second, in addition to milking management technologies, other factors could influence labor efficiency, such as the type of parlor installed in the dairy farm or work practices (Hogan et al., 2022b, 2023). According to Hogan et al. (2023), an effective work organization on the farm (i.e., how tasks are organized and coordinated within the context of an overarching work system) can also have a beneficial impact on labor input and labor efficiency. Therefore, in addition to milking management technologies, adopter dairy farms might also be adopting better work organization on the farm, resulting in better labor efficiency outcomes. Edwards et al. (2020) reported that rotary parlors are associated with greater labor efficiency than herringbone parlors. This is mainly because in a rotary parlor cow loading and exiting can be automated using technology that translates into a shorter work routine time for the operators attaching milking units. Moreover, if both automatic teat spraying and ACRs are included in a rotary parlor, the parlor can operate without an operator in the cluster-removing position (Edwards et al., 2020). In herringbone parlors, the effect of ACR may not be as strong since the operator must still pick up and swing the cluster over from the middle of the pit, reducing the potential time saving (Edwards et al., 2020). In our sample, 78% of adopter farms had herringbone milking parlors and none had rotary parlors.

An additional explanation for the absence of significant impacts is that farm operators might be expending time in learning how to use milking management technologies. According to a recent survey, 50% of Irish dairy farmers do not feel very confident in using precision technologies (Irish Farmers Association, 2019) therefore, when adopting a technology, they might need additional time to acquire the necessary knowledge and skills to effectively use it. This could lead to a temporary increase in working hours during the early stages of adoption that could hide the real effect on labor efficiency.

Last, as suggested by Acemoglu and Restrepo (2019), net labor savings could not be as large as expected because of a reinstatement effect that counterbalanced the displacement of labor . This means that milking management technologies might be reducing labor requirements from milking tasks (displacement effect) but the operators are reinstated on new in-parlor tasks (e.g., milk recording) or on different areas of dairy farm management. Similar results were discussed by Steeneveld et al. (2012) and Gargiulo et al. (2020) on the use of milking robots on Dutch dairy farms. In this case, operators might be now focusing on grassland management tasks (e.g., grass measuring, reseeding) or breeding. The results of the study showed that although milking management technologies had no direct impact on grazed grass use, adopter dairy farms had higher growth and use of grazed grass compared to nonadopter farms, suggesting that dairy farms might be allocating more time to grassland management tasks. Unfortunately, the labor data used in the study were not collected for each task on the farm; therefore, a displacement or reinstatement effect was not possible to establish. Future research should include the collection of updated detailed data on the labor requirements per farm task to allow for estimation of displacement and reinstatement effects and to isolate the impact of technology adoption on labor efficiency from the hours farmers spent learning how to use the technology.

Although the absence of a significant effect of technology adoption on labor efficiency can have multiple explanations that need to be further studied, we found no evidence to promote the adoption of milking management technologies as a means to improve the social sustainability (through increased labor efficiency) of dairy farms. However, using only labor efficiency as an indicator of farmer's wellbeing provides a narrow understanding of the social sustainability issues that dairy farmers face. There might be other paths through which technologies can impact farmer's wellbeing (positive or negative). For example, anecdotal evidence from a survey of 19 farmers of Australia, New Zealand, and Ireland shows that farmers primarily invested in automatic milking systems to acquire more flexibility in time management, to reduce the physical efforts on the body from repetitive manual tasks, and because of restricted labor availability (Gargiulo et al., 2020). Future research should include additional indicators of social sustainability that better reflect whether these technologies are effective in improving farmers' wellbeing (e.g., reduced stress and mental health issues) and so supporting evidence-based decision-making around technology adoption.

Impacts of Milking Management Technologies on Productivity

The adoption of milking management technologies had a positive impact on productivity, which was reflected in an increased milk yield and milk solids yield. This partially supports our hypothesis, and it might be explained by the time saved in milking by the use of in-parlor technologies being used in other tasks associated with milking (feed allocation and cleaning of the equipment) or other dairy farm tasks and practices outside milking that increase farm performance. For example, adopter dairy farms had higher grazed grass use than nonadopter farms; therefore, they might be investing more time in grassland management. Moreover, dairy farmers might be also using other technologies that increase milk yield. Due to the high association between technologies, it can be difficult to isolate the impacts of technologies from one another. For example, 58% of adopters of milking management technologies were also adopters of grass measuring or grass management technologies.

Our findings are consistent with other studies focused on in-parlor technologies. Wade et al. (2004) reported that milk production increased by 2% on average after the adoption of milking robots on Dutch dairy farms. Balaine et al. (2020) found that milk-recording technology increased milk yield by an average 406 liters per cow, or 7%. However, more recent studies of the impact of milking robots on pasture-based dairy farms have found no significant differences between milking robots and conventional milking systems on milk yield per cow and per hectare or on milk solids (Gargiulo et al., 2020). This suggest that productivity improvements will depend on the technologies or combination of technologies used and cannot be generalized to all milking management technologies.

Impacts of Milking Management Technologies on Profitability

In addition to evaluating the effect of adopting milking management technologies on labor efficiency, our research aimed to determine the effect of these technologies on profitability. The results suggest a positive impact of milking management technologies on gross output. This is likely driven by the increase in milk yield caused by technology adoption. Additionally, there was a positive impact on gross margin. This means that although milking management technology adoption had no effect on labor efficiency, and therefore on reducing labor costs, the increase in outputs caused by technology adoption (productivity effect) was sufficiently significant to generate an increase in gross margin per hectare. However, the effect on net margin per hectare was not statistically significant; therefore, when accounting for the costs of the technologies (fixed costs), milking management technologies were no longer profitable. Given that the depreciation costs and borrowing costs are reflected in overhead rather than direct costs, these results suggests that there is no positive impact on profit when the full cost of technology is considered. Our results are consistent with other studies on milking robots that have not found impact on profitability (Bijl, Kooistra, and Hogeveen, 2007; Steeneveld et al., 2012; Shortall et al., 2016; Gargiulo et al., 2020).

Policy Implications

The Irish government has identified the investment in new and existing technologies as key to sustainably intensifying production of the agriculture sector (Teagasc, 2016). Through the Targeted Agriculture Modernisation Schemes (TAMS), it has been supporting farmers with grants that allow them to access modern infrastructure and equipment, including up-to-date technologies, with the goal of improving farm sustainability outcomes. The findings of the research provide evidence of the benefits on productivity and, to a limited degree, on economic impact of the adoption of milking management technologies. In terms of labor input, the study found no effect of technology adoption on labor efficiency. This information can be used to target current grant schemes for these types of automation technologies if the goal is to increase the productivity and profitability of dairy farms. However, it is important to highlight that most adopters of milking management technologies are already better-performing farms (in terms of productivity, efficiency, and profitability). Therefore, it is possible that if adoption becomes more widespread, especially among poorer performing farms, the impact of the technologies on profit and labor efficiency may be more significant. Hence, policy interventions that promote such technologies among poorer performing farms may be justified.

Finally, extension services can use the findings of the research to develop training and outreach initiatives that help increase the adoption and use of milking management technologies to their full potential. Based on the results of this research, the adoption of milking management technologies in association with the use of other management practices can help dairy farmers in reaching better performance outcomes.

Conclusion

This study is the first to simultaneously determine the causal effect (controlling for selection bias) of adopting milking management technologies on the labor efficiency, productivity, and profitability of pasture-based dairy farms. Our findings show that although adopter dairy farms are more labor efficient than nonadopter farms, milking management technologies had no effect on labor efficiency (total hours per cow) when self-selection bias was controlled. Therefore, we could not establish an efficient capital labor substitution effect with the adoption of automatic cluster removers, automatic washers, and automatic parlor feeders. It should be noted however, that the approach to labor recording in the dataset used, where hours spent on milking activities are not directly recorded, may impact this finding because farmers may allocate the time released from milking to other productive tasks on the farm or they may temporarily dedicate more working hours to learning how to effectively use the technologies. While it was hypothesized that the technologies considered could reduce labor requirements and contribute to an enhanced quality of life for farmers, the evidence did not support this hypothesis. The results did show however, that milking management technologies had a positive impact on milk yield and milk solids, with a consequent effect on gross output per hectare and gross margin per hectare. Nevertheless, there was no significant effect on net margin per hectare. From a policy perspective, our results confirm the importance of funding schemes that help farmers invest in automation technologies to increase the performance of dairy farms. Additionally, our results also suggest that the effectiveness of in-parlor automation technologies are not generalizable to all technologies; more information of the causal effects of other in-parlor technologies is necessary to tailor funding schemes.

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References

Acemoglu, D., and P. Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33(2):3–30. doi: 10.1257/jep.33.2.3.

Arrow, K. J., H. B. Chenery, B. S. Minhas, and R. M. Solow. 1961. "Capital-Labor Substitution and Economic Efficiency." *Review of Economics and Statistics* 43(3):225. doi: 10.2307/1927286.

Balaine, L., E. J. Dillon, D. Läpple, and J. Lynch. 2020. "Can Technology Help Achieve Sustainable Intensification? Evidence from Milk Recording on Irish Dairy Farms." *Land Use Policy* 92:104437. doi: 10.1016/j.landusepol.2019.104437.

Bijl, R., S. R. Kooistra, and H. Hogeveen. 2007. "The Profitability of Automatic Milking on Dutch Dairy Farms." *Journal of Dairy Science* 90(1):239–248. doi: 10.3168/jds.S0022-0302(07)72625-5.

Borchers, M. R., and J. M. Bewley. 2015. "An Assessment of Producer Precision Dairy Farming Technology Use, Prepurchase Considerations, and Usefulness." *Journal of Dairy Science* 98(6): 4198–4205. doi: 10.3168/jds.2014-8963.

Bradfield, T., R. Butler, E. Dillon, T. Hennessy, and P. Kilgarriff. 2021. "The Effect of Land Fragmentation on the Technical Inefficiency of Dairy Farms." *Journal of Agricultural Economics* 72(2):486–499. doi: 10.1111/1477-9552.12413.

Brennan, M., T. Hennessy, D. Meredith, and E. Dillon. 2022. "Weather, Workload and Money: Determining and Evaluating Sources of Stress for Farmers in Ireland." *Journal of Agromedicine* 27(2):132–142. doi: 10.1080/1059924X.2021.1988020.

Caliendo, M., and S. Kopeinig. 2008. "Some Practical Guidance for the Implementation of Propensity Score Matching." *Journal of Economic Surveys* 22(1):31–72. doi: 10.1111/j.1467-6419.2007.00527.x.

Central Statistics Office. 2015. "Quarterly National Household Survey 2015." Government of Ireland. Available online at https://www.cso.ie/en/releasesandpublications/er/qnhs-es/qnhsemploymentseriesq12015/ [Accessed September 1, 2023].

Cochran, W. G., and D. B. Rubin. 1973. "Controlling Bias in Observational Studies: A Review." *Sankhyā: The Indian Journal of Statistics, Series A* 35(4):417–446.

Contzen, S., and I. Häberli. 2021. "Exploring Dairy Farmers' Quality of Life Perceptions – a Swiss Case Study." *Journal of Rural Studies* 88:227–238. doi: 10.1016/j.jrurstud.2021.11.007.

Dela Rue, B. T., C. R. Eastwood, J. P. Edwards, and S. Cuthbert. 2020. "New Zealand Dairy Farmers Preference Investments in Automation Technology Over Decision-Support Technology." *Animal Production Science* 60(1):133. doi: 10.1071/AN18566.

Deming, J., D. Gleeson, T. O'Dwyer, J. Kinsella, and B. O'Brien. 2018. "Measuring Labor Input on Pasture-Based Dairy Farms Using a Smartphone." *Journal of Dairy Science* 101(10): 9527–9543. doi: 10.3168/jds.2017-14288.

Department of Agriculture, Food and the Marine. 2023. "Targeted Agricultural Modernisation Scheme 3 (tams 3), Dairy Equipment Scheme." Government of Ireland. Available online at https://gov.ie/en/department-of-agriculture-food-and-the-marine/services/dairy-equipment-scheme-2/ [Accessed October 6, 2023].

Dillon, E., T. Donnellan, B. Moran, and J. Lennon. 2021. *Teagasc National Farm Survey 2021 Final Results*. Teagasc. Available online at https://teagasc.ie/wp-content/uploads/2025/05/Teagasc-National-Farm-Survey-2021.pdf.

Dillon, E., B. Moran, J. Lennon, and T. Donnellan. 2018. *Teagasc National Farm Survey 2018 Results*. Teagasc. Available online at https://web.archive.org/web/20231129232131/https://teagasc.ie/media/website/publications/ 2019/NFS-2018_final_web.pdf.

Eastwood, C. R., J. Greer, D. Schmidt, J. Muir, and K. Sargeant. 2020. "Identifying Current Challenges and Research Priorities to Guide the Design of More Attractive Dairy-Farm Workplaces in New Zealand." *Animal Production Science* 60(1):84. doi: 10.1071/AN18568.

Edwards, J. P., B. Kuhn-Sherlock, B. T. Dela Rue, and C. R. Eastwood. 2020. "Short Communication: Technologies and Milking Practices That Reduce Hours of Work and Increase Flexibility Through Milking Efficiency in Pasture-Based Dairy Farm Systems." *Journal of Dairy Science* 103(8):7172–7179. doi: 10.3168/jds.2019-17941.

Garcia-Covarrubias, L., D. Läpple, E. Dillon, and F. Thorne. 2023. "Automation and Efficiency: A Latent Class Analysis of Irish Dairy Farms." *Q Open* 3(1):qoad015. doi: 10.1093/qopen/qoad015.

Gargiulo, J. I., C. R. Eastwood, S. C. Garcia, and N. A. Lyons. 2018. "Dairy Farmers with Larger Herd Sizes Adopt More Precision Dairy Technologies." *Journal of Dairy Science* 101(6): 5466–5473. doi: 10.3168/jds.2017-13324.

Gargiulo, J. I., N. A. Lyons, K. Kempton, D. A. Armstrong, and S. C. Garcia. 2020. "Physical and Economic Comparison of Pasture-Based Automatic and Conventional Milking Systems." *Journal of Dairy Science* 103(9):8231–8240. doi: 10.3168/jds.2020-18317.

Hanrahan, L., N. McHugh, T. Hennessy, B. Moran, R. Kearney, M. Wallace, and L. Shalloo. 2018. "Factors Associated with Profitability in Pasture-Based Systems of Milk Production." *Journal of Dairy Science* 101(6):5474–5485. doi: 10.3168/jds.2017-13223.

Hennessy, T., and K. Heanue. 2012. "Quantifying the Effect of Discussion Group Membership on Technology Adoption and Farm Profit on Dairy Farms." *The Journal of Agricultural Education and Extension* 18(1):41–54. doi: 10.1080/1389224X.2012.638784.

Ho, D. E., K. Imai, G. King, and E. A. Stuart. 2011. "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." *Journal of Statistical Software* 42(8):1–28. doi: 10.18637/jss.v042.i08.

Hogan, C., J. Kinsella, M. Beecher, and B. O'Brien. 2023. "The Impact of Work Organisation on the Work Life of People on Pasture-Based Dairy Farms." *Animal* 17(1):100686. doi: 10.1016/j.animal.2022.100686.

Hogan, C., J. Kinsella, B. O'Brien, M. Gorman, and M. Beecher. 2022a. "An Examination of Labor Time-Use on Spring-Calving Dairy Farms in Ireland." *Journal of Dairy Science* 105(7): 5836–5848. doi: 10.3168/jds.2022-21935.

Hogan, C., J. Kinsella, B. O'Brien, A. Markey, and M. Beecher. 2022b. "Estimating the Effect of Different Work Practices and Technologies on Labor Efficiency Within Pasture-Based Dairy Systems." *Journal of Dairy Science* 105(6):5109–5123 . doi: 10.3168/jds.2021-21216.

Holland, P. W. 1986. "Statistics and Causal Inference." *Journal of the American Statistical Association* 81(396):945–960. doi: 10.1080/01621459.1986.10478354.

Imbens, G. W., and J. M. Wooldridge. 2009. "Recent Developments in the Econometrics of Program Evaluation." *Journal of Economic Literature* 47(1):5–86. doi: 10.1257/jel.47.1.5.

Irish Farmers Association. 2019. "Digital Agriculture Technology: Adoption & Attitudes Survey." Available online at https://www.ifa.ie/wp-content/uploads/2020/11/Digital-Ag-Tech-Adoption-Attitudes.pdf.

Keele, L. 2010. *An Overview of Rbounds: An R Package for Rosenbaum Bounds Sensitivity Analysis with Matched Data*. White paper. Ohio State University. Available online at https://www.researchgate.net/publication/251969933_An_Overview_of_Rbounds_An_R_Package_for_Rosenbaum_Bounds_Sensitivity_Analysis_with_Matched_Data.

Kelly, P., L. Shalloo, M. Wallace, and P. Dillon. 2020. "The Irish Dairy Industry – Recent History and Strategy, Current State and Future Challenges." *International Journal of Dairy Technology* 73(2):309–323. doi: 10.1111/1471-0307.12682.

Läpple, D., and T. Hennessy. 2015. "Assessing the Impact of Financial Incentives in Extension Programmes: Evidence from Ireland." *Journal of Agricultural Economics* 66(3):781–795. doi: 10.1111/1477-9552.12108.

Lunner Kolstrup, C., M. Kallioniemi, P. Lundqvist, H.-R. Kymäläinen, L. Stallones, and S. Brumby. 2013. "International Perspectives on Psychosocial Working Conditions, Mental Health, and Stress of Dairy Farm Operators." *Journal of Agromedicine* 18(3):244–255. doi: 10.1080/1059924X.2013.796903.

Mathijs, E. 2004. "Socio-Economic Aspects of Automatic Milking." In A. Meijering, H. Hogeveen, and C. J. A. M. De Koning, eds., *Automatic Milking, a Better Understanding,* Brill, 46–55. doi: 10.3920/9789086865253_004.

McDonald, R., K. Heanue, K. Pierce, and B. Horan. 2016. "Factors Influencing New Entrant Dairy Farmer's Decision-Making Process Around Technology Adoption." *Journal of Agricultural Education and Extension* 22(2):163–177. doi: 10.1080/1389224X.2015.1026364.

Palma-Molina, P., T. Hennessy, E. Dillon, S. Onakuse, B. Moran, and L. Shalloo. 2023a. "Evaluating the Effects of Grass Management Technologies on the Physical, Environmental, and Financial Performance of Irish Pasture-Based Dairy Farms." *Journal of Dairy Science* 106(9): 6249–6262. doi: 10.3168/jds.2022-23111.

Palma-Molina, P., T. Hennessy, A. H. O'Connor, S. Onakuse, N. O'Leary, B. Moran, and L. Shalloo. 2023b. "Factors Associated with Intensity of Technology Adoption and with the Adoption of 4 Clusters of Precision Livestock Farming Technologies in Irish Pasture-Based Dairy Systems." *Journal of Dairy Science* 106(4):2498–2509. doi: 10.3168/jds.2021-21503.

Rosenbaum, P. R. 2002. "Observational Studies." In *Observational Studies,* Springer Series in Statistics. Springer, 2nd ed., 1–17. doi: 10.1007/978-1-4757-3692-2_1.

Rosenbaum, P. R., and D. B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70(1):41–55. doi: 10.1093/biomet/70.1.41.

Rubin, D. B. 1973. "Matching to Remove Bias in Observational Studies." *Biometrics* 29(1):159. doi: 10.2307/2529684.

Shalloo, L., T. Byrne, L. Leso, E. Ruelle, K. Starsmore, A. Geoghegan, J. Werner, and N. O'Leary. 2021. "A Review of Precision Technologies in Pasture-Based Dairying Systems." *Irish Journal of Agricultural and Food Research* 59(2):279–291. doi: 10.15212/ijafr-2020-0119.

Shortall, J., L. Shalloo, C. Foley, R. D. Sleator, and B. O'Brien. 2016. "Investment Appraisal of Automatic Milking and Conventional Milking Technologies in a Pasture-Based Dairy System." *Journal of Dairy Science* 99(9):7700–7713. doi: 10.3168/jds.2016-11256.

Steeneveld, W., L. W. Tauer, H. Hogeveen, and A. G. J. M. O. Lansink. 2012. "Comparing Technical Efficiency of Farms with an Automatic Milking System and a Conventional Milking System." *Journal of Dairy Science* 95(12):7391–7398. doi: 10.3168/jds.2012-5482.

Teagasc. 2016. *Teagasc Technology Foresight 2035: Technology Transforming Irish Agri-Food and Bioeconomy*. Final report. Teagasc Head Office. Available online at https://www.teagasc.ie/media/website/publications/2016/Teagasc-Technology-Foresight-Report-2035.pdf.

Wade, K. M., M. A. P. M. v. Asseldonk, P. B. M. Berentsen, W. Ouweltjes, and H. Hogeveen. 2004. "Economic Efficiency of Automatic Milking Systems with Specific Emphasis on Increases in Milk Production." In A. Meijering, H. Hogeveen, and C. J. A. M. De Koning, eds., *Automatic Milking, a Better Understanding,* Wageningen, 62–67. doi: 10.3920/9789086865253_006.

Wathes, C. M., H. H. Kristensen, J.-M. Aerts, and D. Berckmans. 2008. "Is Precision Livestock Farming an Engineer's Daydream or Nightmare, an Animal's Friend or Foe, and a Farmer's Panacea or Pitfall?" *Computers and Electronics in Agriculture* 64(1):2–10. doi: 10.1016/j.compag.2008.05.005.

Wieland, M., D. V. Nydam, W. Heuwieser, K. M. Morrill, L. Ferlito, R. D. Watters, and P. D. Virkler. 2020. "A Randomized Trial to Study the Effect of Automatic Cluster Remover Settings on Milking Performance, Teat Condition, and Udder Health." *Journal of Dairy Science* 103(4): 3668–3682. doi: 10.3168/jds.2019-17342.

Yang, W., J. P. Edwards, C. R. Eastwood, B. T. Dela Rue, and A. Renwick. 2021. "Analysis of Adoption Trends of in-Parlor Technologies Over a 10-Year Period for Labor Saving and Data Capture on Pasture-Based Dairy Farms." *Journal of Dairy Science* 104(1):431–442. doi: 10.3168/jds.2020-18726.

Appendix

Table A1. Standardized Differences Between Group of Adopters Before and After Propensity Score Matching

Covariates	Std. Mean Difference Before Matching	Std. Mean Difference After Matching
Farm size	1.0206	0.0083
Herd size	1.2852	0.0576
Herd size^2	0.8859	0.0934
Agricultural education	0.4804	0.0000
Specialisation	0.3253	0.1696
Stocking rate	0.5915	0.1455

2018 NFS Additional Survey Questions

NFS Additional Survey 2018

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Agricultural Economics & Farm Surveys Dept.

FARM CODE		REC	

Dairy only

Q5: Select (tick) the **<u>most used method</u>** of heat detection on your farm. If after 2015 enter **Year** adopted

Timed observation of bulling		Natural service	
Teaser bull + chin ball		Tail strips	
Technology solution (e.g. Moo Monitor+)		Tail paint	
Other (please specify):-		**Please enter year first used**	

Q6: <u>Grassland management practices:</u> Please answer the following (tick)

(a): Have you drawn up a map of your grazing paddocks?	Yes		
	No		
(b): During the main grazing season (March to November), how often do you walk your farm?	Never		
	At least once per week		
	Approximately twice per month		
	Approximately once per month		
	Less than once per month		
(c): During the main grazing season (March to November), how often do you complete a farm grass cover on your farm?	Never		
	At least once per week		
	Approximately twice per month		
	Approximately once per month		
	Less than once per month		
(d): If you answered more than 'Never' to part (c) How do you primarily measure grass? Enter year Started - "X" if pre 2015	*Visual observation*		
	Plate meter or Bluetooth		
	Quadrant and scale		Year
	Enabled plate meter		
(e): On average, how often do you soil test your farm?	I never soil test my farm.		
	Approximately every year		
	Approximately every other year		
	Approximately every 2 to 5 years		
	Less than every 5 years		

Q7: Please indicate if you have the following by putting a tick in *the '**tick if Yes'** box. If installed in 2015 or after, please enter the year it was installed in the Start Year box. If installed before 2015, please leave blank / X*

Code the main reason for the investment

1 = Reduce Labour, 2 = Ease management; 3 = Improve Herd Health; 4 = improve profitability; 5 = Other

	Tick if Yes	**Start Year**		**Tick if Yes**	**Start Year**	**Reason**
Automatic scrapers - housing			Drafting gate -manual			NA
Automatic washers			Drafting gate-automated			NA
Automatic cluster removers			Individual cow activity sensors			
Automatic calf feeding			Milk Meters			
Automatic backing gate			PastureBase / Agrinet			
Automatic feeders - parlour			Other technology –specify			