Evaluating environmental effects of the adoption of automatic milking systems in Norway

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Abstract

In Norwegian dairy farming, the usage of automatic milking systems (AMS) has increased during the last decades. AMS is primarily a productivity increasing and labor reducing technology, but previous research shows that AMS can have other (secondary) effects that could impact the environmental performance of farms. Effects of AMS-adoption found, include increased total production, increased farm size, changes in grazing patterns and feed mix and changes in energy consumption. This paper aims to study the hypothesis that AMS-adoption, through these secondary effects, affect farm-level GHG-emissions. Using a difference-in-difference approach, we provide evidence of the presence of secondary effects and shows that AMS-adoption negatively affects farms' eco-efficiency, particularly by increasing enteric fermentation. The causal effect is identified by considering adopting farms and non-adopting farms observed at two periods in time. Apart from providing this empirical result, the paper also presents a general procedure of how to go about evaluating farm-level effects of technology adoption.

Keywords Eco-efficiency, milking robots, Norway, agricultural innovations

JEL code Agriculture Q1

1 Introduction

Farm-level consequences of having adopted a new technology can be complex and diverse. Farms might adopt a novel technology because they aim to reach a certain objective. However, apart from that objective, structural and behavioural changes induced by technology adoption are likely to occur. Given that those changes are usually not the objective we refer to these as "secondary effects". Previous research has pointed to the presence of secondary effects, but when evaluating economic or environmental impacts of technology, these remain largely unexplored. When evaluating consequences of technology adoption, secondary effects are important to consider since they might affect the outcome of the evaluation. One technology where existing literature has shown the presence of secondary effects is AMS (automatic milking system). The primary objective of AMS is to decrease labour costs. However, adopting AMS also allows farmers to intensify production (Oudshoorn et al. 2012; Lessire et al. 2020). Since there is a trade-off between grazing and intensification (Lessire et al. 2020), farms that intensify after AMS-adoption also need to decrease grazing and feed the cows more high-energy feed (Oudshoorn et al. 2012; Bijl, Kooistra, and Hogeveen 2007; Schewe and Stuart 2015). Further, AMS has been associated with increased energy usage (Steeneveld et al. 2012) and with expansion as a motivation for adoption (Vik et al. 2019), to achieve economic viability after adoption (Rønningen, Magnus Fuglestad, and Burton 2021) or to recoup the investment (Castro et al. 2012). In other words, AMS has been found to have secondary effects. These secondary effects likely impact farm economic and environmental performance, but an evaluation of what the effect AMS-adoption has on farm performance is lacking. To assess the overall impact of AMS adoption it is required to account for those secondary effects.

To deal with the trade-off between economic and environmental performance we employ the concept of eco-efficiency. On one hand, some changes might have positive implications for sustainability, such as expansion which have been associated with higher eco-efficiency (Soteriades et al. 2020), or intensification (Gołaś et al. 2020). On the other hand, the consumption of more high-energy feed increases enteric fermentation per cow, and the increased consumption of energy also has a negative impact on farms' GHG emissions. Thus, it is not clear what the overall effect of AMS-adoption on farms' eco-efficiency is. Further, it is unclear how important the different effects are relative to each other. To assess this, the aim of this paper is to identify how the adoption of AMS affects eco-efficiency and to identify what structural and behavioural changes associated with AMS-adoption drive those changes in eco-efficiency.

For our empirical analysis we focus on conventional Norwegian dairy farms where we use the Norwegian FADN dataset to empirically study how AMS-adoption changes farms' eco-efficiency. Norwegian dairy farms have one of the highest shares of milk produced using AMS (Vik et al. 2019) and by including data on the milking technology, the Norwegian FADN data provides a unique opportunity to study the usage of AMS in relation to economic and environmental indicators. The dataset contains information on farms over several years, which enables a study of the effects of AMS-adoption over time. Having computed eco-efficiency scores for each farm, propensity score matching and weighting is employed together with a difference-in-difference methodology to answer to the aim of evaluating the effects of AMS-adoption.

The paper highlights the importance of considering secondary effects when evaluating consequences of technology adoption. Further, we propose and apply a general procedure based on the concept of eco-efficiency, which can also be applied to other technologies and settings. Highlighting and quantifying the importance of secondary effects when evaluating technology-adoption is an important contribution to the AMS literature but also for other technologies where those effects are largely ignored. The remainder of the paper is structured as follows; first a literature review is provided of previous efforts of evaluating consequences of technology in general and AMS in particular, then the methods are presented in detail before presenting and discussing the results.

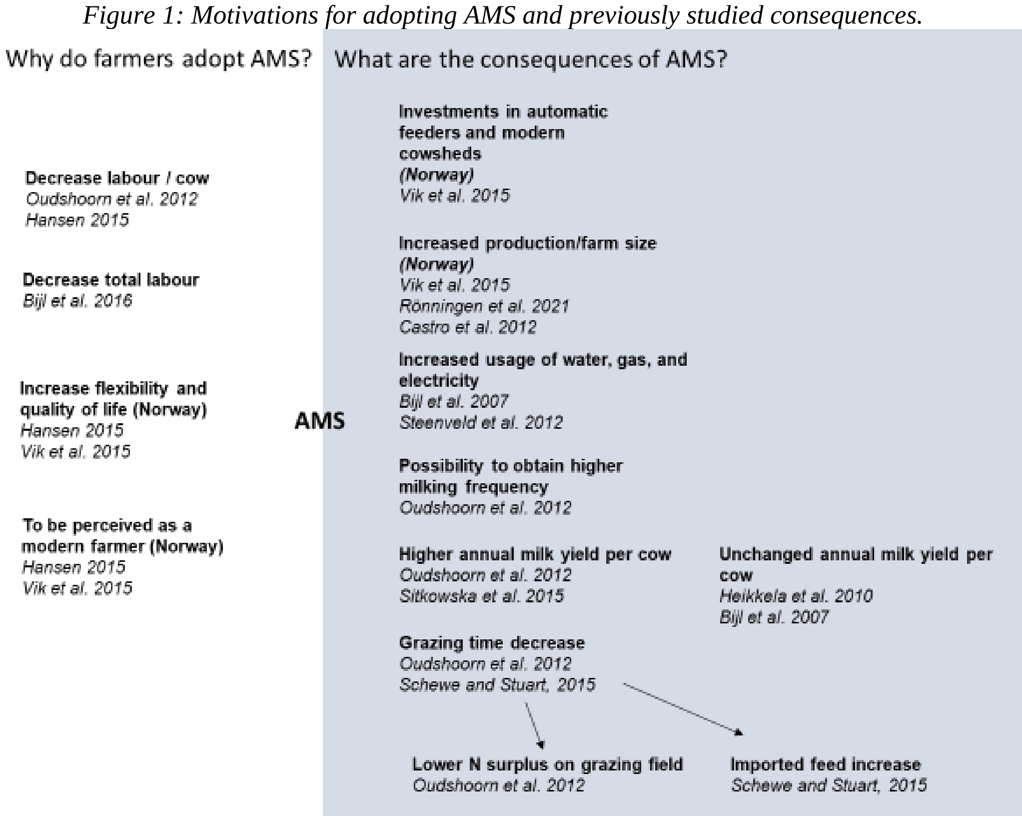
2 Literature review and conceptual framework / Consequences of technology

One well-studied secondary effect of technology adoption is rebound effects, where expected gains in efficiency are absent due to contradicting secondary effects. Rebound effects from technological advancements are commonly studied for energy efficiency (Herring and Roy 2007), but has also been found for e.g. water irrigation technologies, where increases in water efficiency leads to an increased water-demand due to changes towards more water intensive crops (Sears et al. 2018). (Schieffer and Dillon 2015) use simulations to show that implementation of precision farming technologies allows for increasing application of nitrogen to increase yields, and thus could decrease farmers' responsiveness to GHG-taxes. Secondary effects can also be induced by policies, where Harrison et al. (2021) conclude that GHG mitigation policies have implications for economic, social and other environmental aspects. One example is where a policy to convert annual crops to permanent pasture might decrease GHG-emissions but also decrease the need for labour (Harrison et al. 2021).

Research on evaluating consequences of robotic technologies is scarce, since much of the emerging technologies which will play an important role in the future of agriculture has not been widely adopted yet. Duckett et al. (2018) provides and overview of environmental benefits and an outline of future outlooks and trends of agricultural robotics. Balafoutis et al. (2017) lists some smart farming technologies with potentials to decrease GHG-emissions and (Finger et al. 2019) specifies in what way smart farming has the potential to provide benefits for farmers. However, while these predictions and future outlines provide important insights, there is a lack of empirical evaluations of smart farming technologies.

Secondary effects are important to include when assessing how technologies and innovations affect farm sustainability, but rarely included in evaluations. Some difficulties in assessing consequences of technology adoption are attributing changes on farms to adoption of one specific technology and a lack of information on what technologies are implemented when on farms. Often, the adopters of a technology are not fully aware themselves of the extent of consequences the adoption of the new innovation leads to (Rogers 2003). Aiming to evaluate all consequences of a technology is a major task, but by first forming a hypothesis of what secondary effects a technology might have, an evaluation can be conducted covering identified relevant aspects. In this paper, the hypothesis is that AMS-adoption affects GHG-emissions. There are indications that AMS affects GHG-emissions, through e.g. increasing production (Rønningen, Magnus Fuglestad, and Burton 2021), increasing the usage of electricity (Steeneveld et al. 2012), and increasing enteric fermentation by intensifying production (Oudshoorn et al. 2012). While the focus of this paper is on GHG-emissions, AMS-adoption likely also affect other aspects of sustainability, for example biodiversity when grazing intensities are affected. This has previously been studied in organic farms by (Oudshoorn and de Boer 2008). An overview of some motivations for adopting AMS and some identified consequences are presented in figure 1. Despite indications that AMS has an environmental impact, studies of this are largely scarce in the literature.

Figure 1: Motivations for adopting AMS and previously studied consequences.



3 Method and data

The aim of this paper is to assess how AMS-adoption changes farm-level eco-efficiency and to estimate what farm-level factors drive those changes. The farm level factors tested for are potential secondary effects of AMS-adoption. The aim is operationalized into two objectives: 1) Assessing how AMS-adoption affects eco-efficiency, and 2) Assessing what structural and behavioural changes drive the impact of AMS on eco-efficiency. Eco-efficiency is evaluated with a focus on GHG-emissions, aiming to cover the trade-off between economic value and farm-level GHG-emissions. While this paper focuses on GHG-emissions, the used eco-efficiency measure has the potential to study several environmental aspects simultaneously (Kuosmanen and Kortelainen 2005). Three indicators are included in the eco-efficiency calculation to reflect farm-level GHG emission: energy consumption, fertilizer expenditures and enteric fermentation. The impact of AMS-adoption is evaluated by contrasting the change in eco-efficiency among adopters to the change in eco-efficiency among non-adopters in a two-period difference-in-difference (DiD) framework. To enable a comparison between adopters and non-adopters and attribute the changes in eco-efficiency to AMS, propensity scores are used. Further, variations in the impact of AMS-adoption over time relative to adoption on eco-efficiency is assessed in a fixed effects regression.

The analysis is conducted on conventional farms observed over at least two years between 2013-2019. Farms not adopting AMS are used as a control group. Farms adopting AMS are all observed at least one period before adoption such that the time of adoption is known. The dataset used for the analysis consists of 43 farms adopting AMS sometime between 2014-2019 and 266 farms not adopting AMS. In total, these farms add up to 1525 observations.

3.1.1 Eco-efficiency

Integrating economic and environmental aspects into one measure of efficiency is important to satisfy the increasing demand for various goods while maintaining a reasonable environmental quality (Huppes and Ishikawa 2005). The most straightforward measure of intensification in agriculture is the ratio of output to input (Barnes and Thomson 2014), and when adding the dimension of environmental sustainability; the ratio of output to environmental damage. Eco-efficiency is about minimizing the environmental damage caused by a given amount of production and is defined as the ratio of economic value added to emissions or other environmental damage (Kuosmanen and Kortelainen 2005). Eco-efficiency, also referred to as sustainable intensification, can be achieved by raising yield, increasing input use efficiency, or in other ways reduce the environmental impact while increasing or keeping the generated economic value constant (Firbank et al. 2013; Gadanakis et al. 2015; Smith et al. 2017). In agricultural research, the most common application of eco-efficiency is on farm-level (Zhou et al. 2018), which is also the focus of this paper.

To assess eco-efficiency, data envelopment analysis (DEA) (Charnes, Cooper, and Rhodes 1978) is applied. DEA is a deterministic approach evaluating each unit towards an efficiency frontier constructed of the most efficient units in the sample. Many applications of farm-level DEA eco-efficiency is on cross-sectional samples (Pérez Urdiales, Lansink, and Wall 2016; Martinsson and Hansson 2021; Gómez-Limón, Picazo-Tadeo, and Reig-Martínez 2012). In this paper eco-efficiency is assessed on a panel-dataset.

Using panel data with DEA efficiency comes with several options. Common alternatives are to evaluate separate frontiers for each year (Latruffe and Desjeux 2016; Bonfiglio, Arzeni, and Bodini 2017) or calculating the change over time using Malmquist productivity index (Forleo et al. 2021; Chen, Si, and Chen 2020). A Malmquist index type of eco-efficiency scores was formulated by (Kortelainen 2008). For the purpose of this paper, eco-efficiency scores are computed relative to an intertemporal efficiency-frontier (Tulkens and Vanden Eeckaut 1995) by pooling the observations together and assessing all farms at all times towards the same frontier. Pooling observations together into this intertemporal efficiency frontier facilitates comparisons across units and over time (Avkiran 2009). Further, as AMS-adoption takes place in different years for different farms, evaluating the changes in eco-efficiency towards the same efficiency frontier facilitates the interpretation of the eco-efficiency change. The panel data is thus treated as a cross sectional and the same methodology can be applied as in previous papers using cross sectional observations. Following the notation used by (Kuosmanen and Kortelainen 2005), eco-efficiency for farm n is expressed as $EE_n = \frac{V_n}{D(Z_n)}$ where V_n denotes net income and $D(Z_n)$ is a function of environmental pressures $D(Z_n) = w_1Z_1 + w_2Z_2 + \cdots + w_MZ_M$ where there are Z_m environmental pressures each assigned an individual weight w_m. With DEA, weights are determined to generate the highest eco-efficiency score possible for each observation. To obtain linearity, the inverse of the maximization problem is calculated as:

$$\begin{aligned}
&\min_{w} EE_n^{-1} = w_1\frac{Z_{n1}}{V_n} + \cdots + w_M\frac{Z_{nM}}{V_n} \\
&s.t. \\
&w_1\frac{Z_{11}}{V_1} + \cdots + w_M\frac{Z_{1M}}{V_1} \geq 1, \qquad (1) \\
&\dots \\
&w_1\frac{Z_{N1}}{V_N} + \cdots + w_M\frac{Z_{NM}}{V_N} \geq 1
\end{aligned}$$

Given that we want to evaluate the effect of AMS-adoption between two periods, the focus is on changes in eco-efficiency. The change for farm n is computed as $\Delta EE_n = EE_{t=1,n} - EE_{t=0,n}$ where t=1 denotes the first time a farm is observed and t=0 denotes the last time a farm is observed.

One critique of DEA eco-efficiency is that it is highly dependent on the sample selection, where the omission or inclusion of farms can change the eco-efficiency scores. To decrease the influence that the sample selection has on the eco-efficiency scores and adjust for this bias, a bootstrap procedure is performed (Simar and Wilson 1999) which adjusts the scores by drawing 500 pseudo samples and recalculating the scores for each.

To obtain a finite solution to equation (1), all values of V and Z need to be strictly positive. This is sometimes referred to as the positivity property of DEA (Bowlin 1998). To satisfy this positivity property, values equal to or smaller than zero can be replaced with a small arbitrary number (Bowlin 1998). However, this only works for the environmental pressures in this model as values of net income close to zero always will generate eco-efficiency scores close to zero. Due to this restriction, 12 farms observed with negative net income in at least one period are removed.[1] Among these farms five are AMS-adopters and are observed with these negative values of net income right after AMS-adoption. Thus, the analysis is limited to assessing effects of AMS-adoption on farms which do not suffer negative economic consequences of the adoption. Investigating what determines negative economic net income after AMS-adoption is outside the scope of this paper. Negative values for the environmental pressures are observed for energy and fertilizers. This indicate that nothing is consumed of that indicator that year, but rather that the farm has more energy or fertilizers than what is used on the farm that year, which motivates the replacement of a small number so that the farm can achieve higher eco-efficiency for that year[2]. The third environmental indicator, enteric fermentation is a composite indicator which is positive for all observations.

To assess the drivers of eco-efficiency, a linear regression is used. Using this procedure to assess determinants of DEA efficiency-scores have been criticised since the efficiency scores are serially related and limited to values between 0 and 1 (Simar and Wilson 2007). However, where this paper deals with changes in eco-efficiency, the boundary problem is not as urgent as with absolute levels of efficiency scores; the changes in eco-efficiency can range from +1 to -1. Further, it has been shown that

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[1] Farms observed with negative net income at any period in time are omitted from the analysis, as this might indicate that these farms react differently from the farms not facing negative net incomes after adoption. Only omitting the years where negative net income are observed introduce bias in the results as reactions to AMS are overlooked. Further, only omitting the years observed with negative net income create gaps in the data which makes it difficult to analyze.

[2] A total of 14 observations are found with negative values for any of the environmental pressures. None of the negative observations coincides, which could have pointed to other underlying changes on the farm.

the method proposed by (Simar and Wilson 2007) generate similar results as linear OLS regression when explaining eco-efficiency (Latruffe, Davidova, and Balcombe 2008). Using OLS regression to explain DEA efficiency scores has also been advocated for from a theoretical point of view by (Hoff 2007; McDonald 2009).

3.1.2 Propensity scores and difference-in-difference

DiD with propensity score (PS) weighting is used to trace out the causal effects of AMS-adoption on eco-efficiency. We are interested in the average treatment effect (ATE) where treatment refers to AMS-adoption and the outcome of interest is changes in eco-efficiency. If AMS adoption would have been randomly assigned, the ATE is simply the difference in outcomes between adopters and non-adopters when observed in the time periods after treatment, namely; $ATE = E(Y_i(1) - Y_i(0) \,|T = 1) = E(Y_i(1) \,|T = 1) - E(Y_i(0) \,|T = 1)$, where $Y_i(1)$ is the outcome for adopters in the post-treatment period (when T=1) and $Y_i(0)$ is the outcome for non-adopters in the same period. However, as AMS-adoption is not randomly assigned, this approximation of the ATE is biased. To control for this bias, we use propensity scores which creates as statistical comparison group of non-adopters either by matching or weighing observations according to their likelihood of adoption. Propensity scores are estimated based on observed covariates. Using propensity scores is motivated by the assumption that the only source of selection bias is from the observed covariates. However, AMS adoption also depends on unobserved farmer characteristics. By assuming that these unobserved farmer characteristics remain constant over time, this can be indirectly controlled for using the DiD framework to assess changes over time for the two groups of farms.

Having estimated propensity scores based on covariates, effects of AMS-adoption are computed by either using matching or weighting. When conducting the matching, there are several matching algorithms to consider. In this paper, a full matching is applied using the Matchit package in R (B. B. Hansen and Klopfer 2006). In our setting the full matching approach achieves the highest balance of covariates between the adopters and non-adopters. The optimal full matching is conducted by creating subclasses where the distance between control and treated units in each subclass is minimized. From this, weights can be generated which are included in the DiD regression. As a sensitivity analysis, inverse probability weights (IPW) are applied using the following equation (Horvitz and Thompson 1952):

$$W\ IPW_i = \frac{Adoption_i}{P(X)_i} + \frac{1 - Adoption_i}{1 - P(X)_i} \qquad (2)$$

Where P(X) are the propensity score based on the covariates X and adoption is a binary variable indicating if the farm is in the group of adopters or not. Using either a full matching or IPW are usually good options when estimating the ATE (Stuart 2010). In the case of propensity scores close to one, weighting approaches might lead to imprecise inference procedures (Khan and Tamer 2010).

Some recent works using propensity score techniques when estimating farm-efficiency are (Lindlbauer, Schreyögg, and Winter 2016; Sariful et al. 2020; Bravo-Ureta et al. 2021). In the context of AMS, Bijl, Kooistra, and Hogeveen (2007) used matching when assessing the profitability of AMS compared to conventional milking systems using year of investment (in either AMS or the conventional system), milk production, and intensity of land-use as matching covariates. Callaway and Sant'Anna (2021) suggests IPW as a feasible utilization of propensity scores when assessing a DiD with variation in treatment timing and effects.

3.1.3 Assessing the impact of AMS-adoption

The impact on AMS-adoption are assessed using a set of linear regressions outlined in Table 1. Using these regression specifications, we obtain information on how AMS-adoption change eco-efficiency compared to if farms had not adopted, how the eco-efficiency of farms adopting AMS changes for each year relative to adoption, how AMS-adoption affects factors chosen as potential secondary effects and finally how the potential secondary effects drive eco-efficiency changes.

Table 1: Overview of regressions

How does AMS affect eco-efficiency?	
(1) $\Delta EE_i = \alpha_i + \beta_1(adoption_i) + e_i$	To test the effect of AMS-adoption on changes in eco-efficiency. Where adoption is a binary indicator of whether a farm belongs to the group of farms adopting AMS or not.
(2) $EE_{it} = \alpha_i + \varphi_t + \beta_1(years\_since\_adoption_i) + \sum_{n=-4}^{4} \beta_n dummy\_year\_since_{it} + e_{it}$	A time- and farm-fixed effects regression to assess variation in effects of adopting AMS. Dummies are included for each period relative to adoption to enable an estimation of effects specific for each period.
What structural and behavioural changes associated with AMS-adoption drive the changes in eco-efficiency?	
(3) $\Delta factor_i = \alpha_i + \beta_1(adoption_i) + e_i$	To test the effect of AMS-adoption on structural and behavioural factors. This regression is specified once for each factor tested for as a potential secondary effect. Adoption is binary.
(4) $\Delta EE_i = \alpha_i + \sum \beta_k(\boldsymbol{factor}_{i,k}) + e_i$	To test how structural and behavioural factors a affects eco-efficiency. All k factors are included in the same regression to obtain a marginal effect keeping all other included factors constant.

Regression 1 and 3 are essentially two-period DiD regressions where the effect of a binary treatment, AMS-adoption, is assessed for two groups observed at two periods in time. Regression (4) also makes use of the first and the last time each farm is observed. As the panel is unbalanced, the time between the first and the last period of observation differs between being up to six years to being the difference from one year to another. Further, farms adopt AMS in different time periods and are thus observed in different periods relative to adoption. While some farms have used AMS for four years when observed for the last time in the dataset, some farms have just adopted AMS that same period. As we are interested in the average effect, this is not an issue. The two-period DiD implicitly impose an assumption that the effect of adopting AMS is constant. The assumption of a constant effect of AMS is tested when running the fixed effects regression depicted in equation 2. Here, the effect of being up to four years before to four years after adoption is estimated.

To obtain the contributing power of each factor to the changes in eco-efficiency induced by AMS-adoption in the two-period formulation, the estimated effect of AMS-adoption on one factor (obtained from regression (3)) are multiplied by that factor's marginal effect on eco-efficiency (from regression (4)). Conducting this procedure for each factor, and adding the contributing power together for all factors, we also obtain estimates of how much of the eco-efficiency change induced by AMS-adoption can be explained by the included secondary effects. Assessing drivers of eco-efficiency in regression (4), the same two-period sample of adopters and non-adopters is used to enable comparisons between the regressions. It is assumed that the drivers of eco-efficiency do not differ between adopters and non-adopters and thus farms' adoption-status is not included here.

The weights obtained from the full matching and the IPW are incorporated in the regressions where adopters and non-adopters are compared, which is regression (1) and (3). Given that the matching manages to control for all differences between adopting and non-adopting farms, this allows to interpret the effects as causal.

3.1.4 Variables

All variables used for the eco-efficiency assessment and tested for as secondary effects are displayed in table 2. Given the two-period setting which is the main focus of the analysis, the variables are expressed as changes over time between the first and last period of observation.

For the eco-efficiency assessment, three indicators for farm-level GHG-emissions are included. The indicators are energy consumption, fertilizer expenditures and enteric fermentation. The economic indicator is net income. Emissions from livestock production originates mainly from four sources; enteric fermentation, manure management, feed production and electricity consumption. The indicators for this eco-efficiency assessment is chosen to reflect this to the best extent possible with the given data. Energy expenditures, available directly in the FADN dataset, is divided by the price of diesel for each year retrieved from nibio (Totalkalkylen, NIBIO). Price-data for fertilizers is not available, and thus this indicator is not transformed, but included as expenditures. Enteric fermentation is calculated using IPCC methods and values for emission factors specifically calculated for Norwegian dairy in the national inventory report (UNFCCC, 2021). Manure management is not considered, despite being a large contributor to farms' GHG emissions. Implications have been found that despite manure contributing to GHG emissions, manure management systems do not differ much in the amount of GHG emissions caused (Soteriades et al. 2019). Since changes in eco-efficiency is used for the analysis, factors causing GHG-emissions but are constant over time does not impact the estimates. Despite this, the lack of knowledge of which manure management system is used is a weakness and gathering this information in the Norwegian FADN dataset would enable a more precise evaluation.

Table 2: Descriptive statistics of the variables included for the analysis. All expressed in changes between the fist and the last observation for each farm.

	Adopters (n=43)		**Non-adopters (n=266)**	
	Mean of change	Sd of change	Mean of change	Sd of change
Eco-efficiency				
Net income *(1000 nkr)*	-9.849	46.96	6.917	30.291
Energy *(litre diesel)*	17.893	33.566	-0.12	18.011
Fertilizers *(nkr)*	275.558	577.574	63.426	276.463
Enteric fermentation *(CH_4)*	1196.985	1319.21	41.824	559.242
Structural and behavioural changes				
Labour per cow	-39.563	39.367	0.299	44.551
Milk per cow *(litre per head)*	993.506	1170.806	55.842	696.726
Income from outside farming *(nkr per total net income)*	5983.644	162628.699	23818.737	153152.537
Number of cows *(heads)*	10.016	10.796	-0.222	2.745
Feed concentrates *(feed units, share of total feed concentrates and roughage)*	0.066	0.116	-0.012	0.075
Crop production per milk output (hectare per milk output)	-0.001	0.001	0	0.001

The propensity score matching is made considering the values the first time each farm is observed; descriptive statistics of these variables are found in table 3 which also displays the differences between adopting and non-adopting farms before the matching. The propensity scores are calculated using covariates related to AMS-adoption and eco-efficiency.

Table 3: Descriptive statistics of the covariates used for the propensity score matching. The first time each farm is observed is considered.

	Adopters (n=43)		**Non-adopters (n=266)**	
	Mean	Sd	Mean	Sd
Covariates for propensity score matching				
Years observed	5.86	1.441	4.805	2.244
Hired labour *(share of total)*	0.202	0.114	0.186	0.129
Labour per cow	144.089	46.62	183.96	61.089
Milk per cow *(litre per head*)	6605.752	832.812	6597.898	958.396
Income from outside farming *(nkr per total net income)*	119541.454	125742.635	79600.95	147086.396
Number of cows *(heads)*	28.565	11.796	20.845	8.806
Feed concentrates (*feed units, share of total feed concentrates and roughage)*	0.404	0.091	0.429	0.082
Crop production per milk output *(ha per milk output)*	0.002	0.001	0.003	0.002
Sold roughage *(income per cow)*	1080.986	1295.466	1108.991	1402.04
Beef per milk *(kg/litre output)*	0.019	0.015	0.018	0.011
Energy *(litre diesel)*	60.545	30.327	44.039	26.646
Fertilizers *(nkr)*	744.068	412.644	549.02	312.424
Enteric fermentation *(CH_4)*	3221.127	1543.549	2260.37	1364.854
Net income *(1000 nkr)*	966.059	382.987	824.818	375.146

However, farmers are not only motivated to adopt AMS based on farm sizes and structure, but Norwegian farmers have been found to adopt AMS for reasons such as increased flexibility and to increase their quality of life (Stræte, Vik, and Hansen 2017; B. G. Hansen 2015). As farmer characteristics can be assumed to remain constant over time, they can be differenced out by considering changes over time, which is done throughout the paper.

4 Results

Evaluating eco-efficiency and calculating the change between the first and the last period of observation points to large heterogeneities among farms. For the entire sample (n=309) the mean change in eco-efficiency is close to zero (0.0006) while the largest decrease observed is -0.34. The largest increase is 0.26. Changes in eco-efficiency for adopters and non-adopters are displayed in table 4.

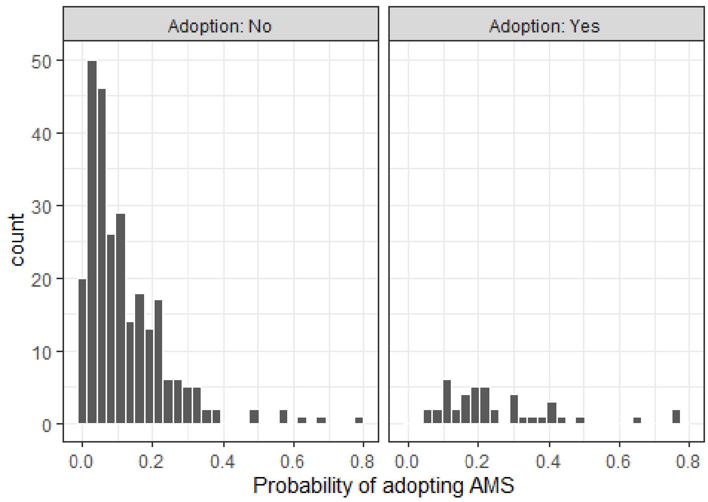
Table 4: Changes in eco-efficiency between the first and the last time of observation.

	Adopters ***(n=43)***	**Non-adopters** ***(n=266)***
mean	-0.049	0.009
max	0.09	0.27
min	-0.28	-0.34
sd	0.07	0.07

Among the non-adopters, eco-efficiency changes are close to zero, while a decrease in eco-efficiency is found for adopters. As eco-efficiency scores are either a value close to 0 (very low eco-efficiency) and 1 (maximum eco-efficiency, the units that constitutes the frontier), the most extreme changes in eco-efficiency possible are if a farm goes from being on the frontier to having a score close to zero resulting in a change close to 1. Or vice versa, which would result in a change close to -1. The largest change observed here is decreasing eco-efficiency by close to a third (non-adopters decrease at most 0.33). Overall, the changes in eco-efficiency during this period are, on average, small. However, there is also a clear difference between adopters and non-adopters where the former has decreased eco-efficiency more over the period, which points to AMS-adoption having some impact on eco-efficiency.

A logit regression is used to calculate propensity scores. The matching fulfils the common support (or overlap) condition as illustrated in figure 2. The lowest propensity score is 0.002 and the highest is 0.78.

Figure 2: Distribution of the propensity scores for adopters and non-adopters separately



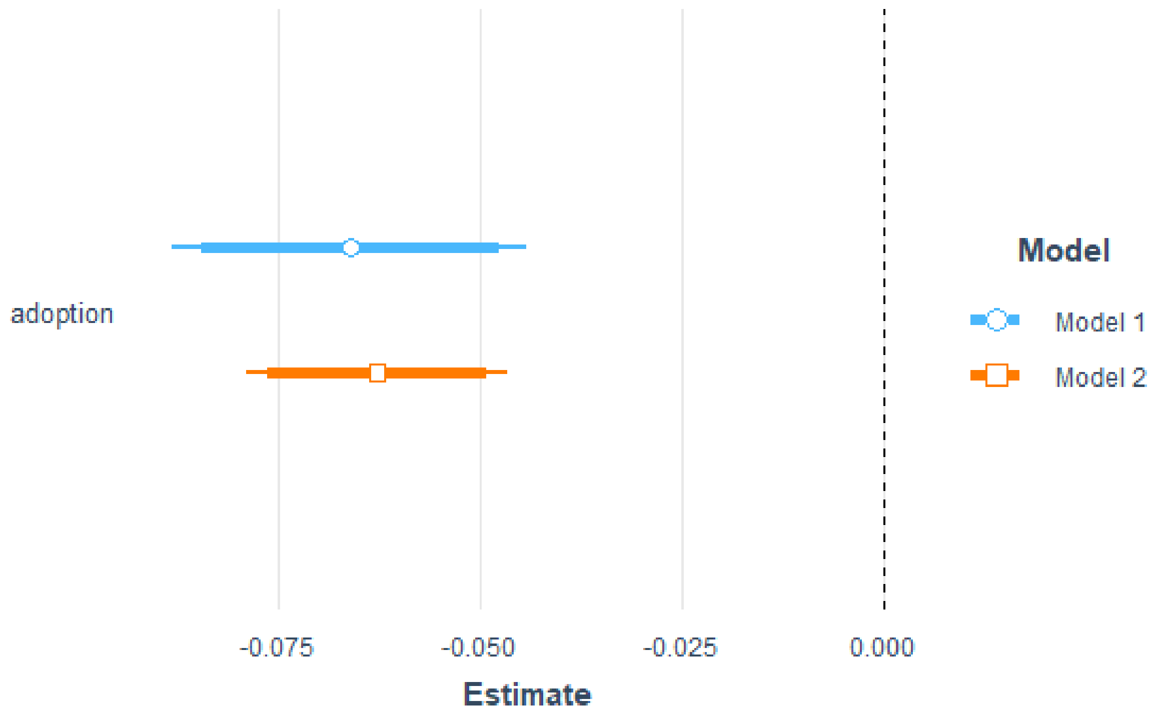
Having computed eco-efficiency changes and propensity scores, the analysis can be conducted to estimate the effect of AMS-adoption on eco-efficiency and assess to what extent the included structural and behavioral changes can explain this effect.

4.1 *The effect of AMS-adoption on eco-efficiency*

First, we test the effect of AMS-adoption in our two-period DiD comparing farms adopting AMS to farms that do not. Propensity scores are used as weights in the regression, obtained from a full matching approach. As a sensitivity analysis we also test an alternative matching approach through IPW which delivers very similar results. In the following we present the results of both approaches. Second, we test how AMS-adoption affects eco-efficiency among the adopting farms relative to the time of adoption. This effect is estimated compared to the reference-case of being observed five years before adoption.

The results of the two-period DiD are shown in figure 3. The results show that the two different propensity score methods (full matching weights and the IPW) provide very similar estimation results with estimates of -0.066 (full matching) and -0.063 (IPW).

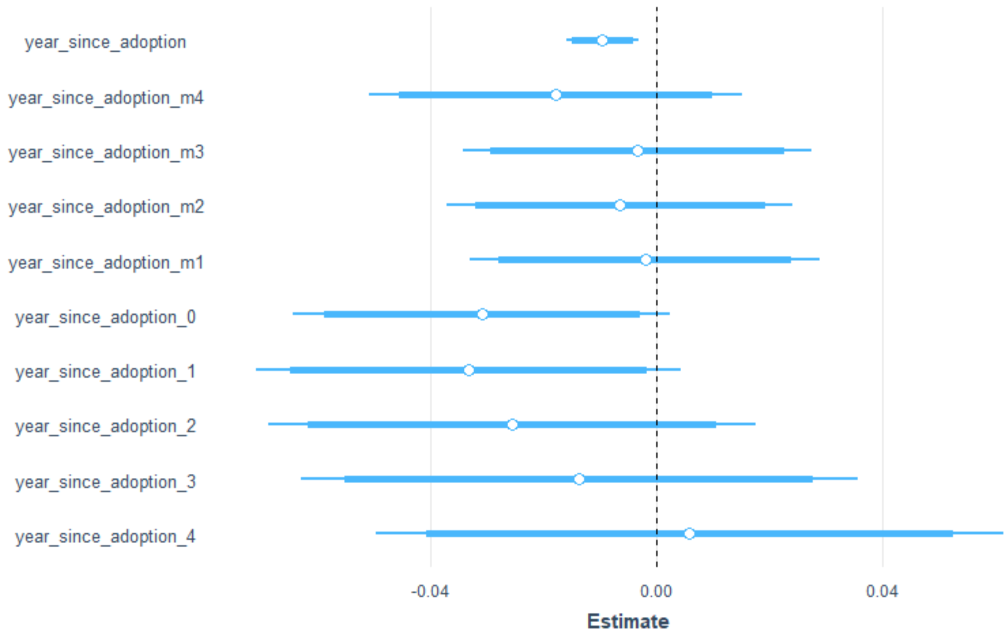
Figure 3: Dependent variable; changes in eco-efficiency. Observations = 309. Displaying confidence intervals of .95 and .9.



AMS-adoption, included here as a binary variable, cause decreases in eco-efficiency by around -0.06 points between the two periods of observation. This confirms our hypothesis that AMS-adoption does actually have implications for farms' eco-efficiency. This finding points to the importance of assessing how new technologies affect farms' eco-efficiency and sustainability, as the adoption of a technology can induce impacts in ways that where not intended, as in the current case. It lends support to the idea that AMS-adoption does induce secondary effects. What potential secondary effects of AMS are that cause this negative impact on eco-efficiency is investigated in chapter 4.1.1. First, however, we use the fixed effects regression (equation 2 in table 1) to assess how effects of AMS-adoption vary over time for the adopting farms.

To further investigate the impact of AMS-adoption, the variable of interest in this fixed effects regression is years relative to adoption. The year relative to adoption a farm is observed ranges from four years before adoption to four years after adoption. The year of adoption, *year_since_adoption_0* in the regression, is identified as the first year a farm is observed using AMS in the dataset. Farm-fixed effects are used to control for unobserved farm characteristics which vary between farms but are constant across time, such as the location of the farm and farmer characteristics. Time-fixed effects are included to control for events which are constant in time and influence all farms in the sample in the same way, such as changes in policies or legislation. In this setting, as AMS-adoption occurs at different years for different farms, such time-fixed effects potentially driving farms to adopt in a certain year are important to include. To enable variations in the effects depending on in which time relative to adoption a farm is observed, dummy variables are included for each value of years since adoption. To avoid multicollinearity and specify a reference, observations five years before adoption are omitted, such that the estimates of each of the dummy indicators are to be interpreted as a change relative to the eco-efficiency five years before adoption.

Figure 4: Dependent variable; Eco-efficiency. Observations; 250. Displaying confidence intervals of .95 and .9.

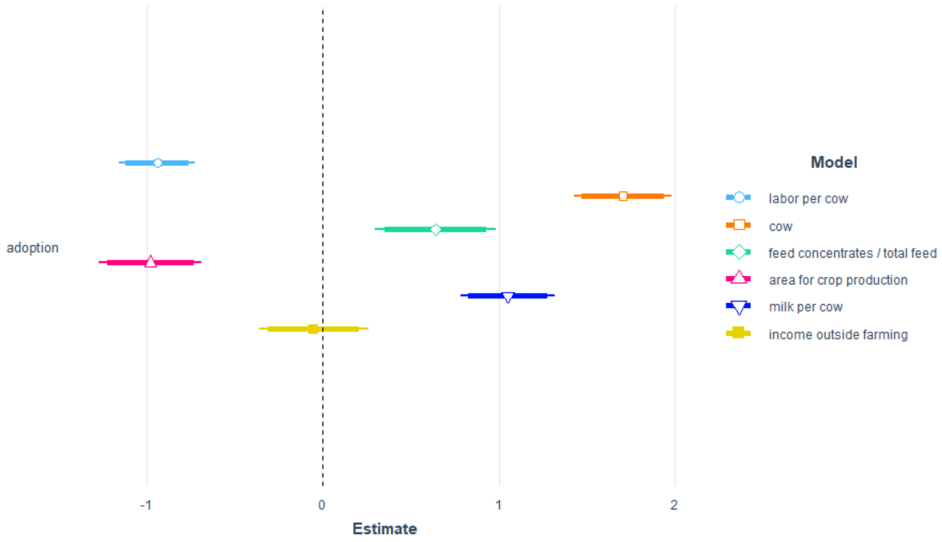


On average, years since adoption has a negative effect on eco-efficiency and it is evident from figure 4 that the negative impact occurs right after adoption rather than before. Approaching adoption does not have a significant effect on eco-efficiency and the estimates are consistently around zero, except for four years before adoption where estimates are a little lower but still insignificant. At the time of adoption and up to two years after we find a negative effect, which gradually seem to diminish the further after adoption a farm is observed. Thus, the negative effect visible right before adoption appears to be temporary and caught up the more time pass after adoption. However, as standard errors are large and only nine farms are observed four years after adoption, we need to be careful in drawing conclusions about the long-term impact of AMS on eco-efficiency. The rest of the paper focuses on the two-period DiD without considering the dynamics of the effects.

4.1.1 The effect of AMS-adoption on structural and behavioural factors

Having shown how AMS-adoption has a negative effect on eco-efficiency, we want to attribute these changes to structural and behavioral factors, to assess what we in this paper refer to as secondary effects. To do this, we assess the impact of AMS-adoption on farm-level secondary effects listed in table 2 using the two-period DiD framework. Before conducting the regression, all factors are standardized to a mean of zero to facilitate comparisons between the different units of measurement. Figure 5 shows the estimates from regression (4) for each of the included variables. Each of the dependent variables are included in separate regressions, all with the binary indicator for adoption on the independent variable. The results reported here are from the full matching, but the results are similar with the IPW which is displayed more in detail in Appendix 1. Figure 5 is a coefficient plot of all regressions of the effect of AMS adoption, which clearly explains how AMS affects the different factors. As the variables are standardized, the estimates are to be interpreted from deviations from the mean and easy to compare in the illustration below.

Figure 5: Dependent variable indicated by the model name. Independent variable; Adoption. Observations; 309. Displaying confidence intervals of .95 and .9.

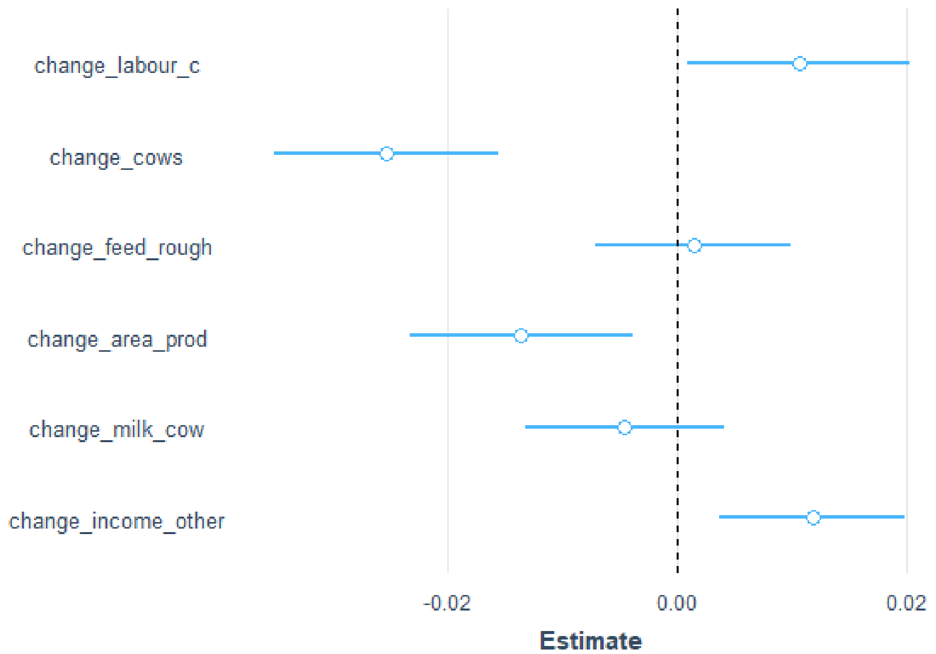


As figure 5 illustrates, the largest impact of AMS-adoption is on the number of cows. This is in line with previous research which has observed that farms with AMS are larger in terms of number of cows than farms without (Vik et al. 2019; Rønningen, Magnus Fuglestad, and Burton 2021). The results here show the adoption of AMS is associated with an enlargement of the herd. Milk yield per cow also shows to increase with AMS-adoption, which is an expected finding as adopting AMS comes with possibilities to milk the cows more often (Oudshoorn et al. 2012). Also, relating to the increased milk yield per cow, is also the share of feed concentrates in the diet. This is, together with milking the cows more often, a decision the farmer can make to obtain a higher milk yield. On the other side of the spectrum lies "area of crop production relative to milk output" and "labor per cow", which is the only of the included factors negatively related to AMS-adoption. This shows that farms, after having adopted AMS, chose to specialize more in dairy production relative to crop. Further, it shows that AMS-adoption decrease labor per cow, which is one of the motives for adopting AMS. To conclude, the effects of AMS-adoption on the included factors are highly in line with findings from previous research.

4.1.2 *The effect of structural and behavioural factors on eco-efficiency*

Having estimated how the structural and behavioural factors included are relating to AMS-adoption, the final step is to estimate how each of these factors affect eco-efficiency. This is done following equation (5). The impact of the factors on eco-efficiency is displayed in table 6.

Figure 6: Dependent variable; Eco-efficiency change, Observations; 309



This is, to our knowledge, the first estimation of drivers of eco-efficiency which include changes in eco-efficiency and changes in potential drivers, rather than levels. This changes the interpretation of the results slightly as it does not pay any regard to the levels. The largest driver of eco-efficiency changes is the number of cows, which is negatively related to eco-efficiency. That is, increasing the number of cows cause eco-efficiency to decrease. This is opposite to previous findings of that farm-size should be positively related to eco-efficiency (Martinsson and Hansson 2021). Further, changes in “income from outside farming” and “labour per cow” is associated with changes in eco-efficiency of around +0.01, while “area produced relative to milk production” is associated with eco-efficiency changes of -0.01. Intensification has been found previously to be positively associated with eco-efficiency (Soteriades et al. 2020).

Investing heterogeneities in drivers of eco-efficiency is scarcely done and an important topic for future research, as many aspects seems to matter when assessing what affects farms’ eco-efficiency. See e.g. (Martinsson and Hansson 2021) who shows that drivers of eco-efficiency changes, especially the impact of increasing farm sizes, when adjusting the eco-efficiency scores for environmental targets. However, this is outside the scope for this paper. Further, the purpose of this regression is not to fully explain changes in eco-efficiency but rather to assess how the factors of interest relate to eco-efficiency.

4.1.3 Calculating the contributing power of each factor on the effect of AMS-adoption on eco-efficiency

By multiplying the impact of each factor on eco-efficiency, assessed using equation (3), with the impact of AMS-adoption on each factor, assessed with equation (4), we obtain the contributing power of each factor on the overall impact of AMS-adoption on eco-efficiency. To illustrate the procedure, consider the example number of cows. We find that, AMS-adoption change average number of cows on farms by 1.7. Further, from equation (4) we find that increasing number of cows by 1, keeping all other factors constant, decreases eco-efficiency 0.030, as reported in table 7. This implies that the change in number of cows by 1.7 induced by AMS contributes to a change in EE by 1.7 * (-0.037) = -0.063. This procedure is conducted for each factor and the results are displayed in table 7.

Table 5: How structural and behavioural factors constitutes the effect of AMS-adoption on eco-efficiency

Factor	**Change induced by AMS**	**Impact on eco-efficiency**	**Contributing power in the effect on AMS-adoption on eco-efficiency**
Labour per cow	-0.94057	0.0106259	-0.009994403
Cows	1.694	-0.030	-0.05082
Feed concentrates	0.775	0.001	0.000775
Produced area	-0.980	-0.011	0.01078
Milk per cow	1.042	-0.003	-0.003126

Income outside farming	-0.115	0.010	-0.00115
		Total	-0.0535354

Adding the effect of each of the factors together result in an impact on eco-efficiency of -0.054. That is, eco-efficiency changes with -0.053 as a consequence of AMS-adoption caused by these structural and behavioural factors. As the total impact of AMS-adoption on eco-efficiency is -0.066 (for the full matching), most of this can be explained by changes in the secondary factors.

5 Conclusion

In this paper, we present a general procedure of how to go about evaluating effects of a new technology including potential for secondary effects. The procedure includes a novel utilization of eco-efficiency scores to assess the impact on farm economic and environmental sustainability. This paper is, to the best of our knowledge, the first paper that uses eco-efficiency to evaluate the impact of new technology. Specifically, we assess the impact of AMS-adoption on eco-efficiency with a focus on GHG-emissions in Norwegian conventional dairy farms. The result shows that AMS-adoption has a negative impact on farms' eco-efficiency, and that this negative effect occurs right after adoption. We find indications that the negative effect of AMS on eco-efficiency decrease over time, however the available data does not allow to draw strong conclusion about the long-term effects, such that this topic remains an open question for future research. We also attribute the association between AMS-adoption and eco-efficiency to structural and behavioural changes hypothesised to be secondary effects of AMS-adoption. The main secondary effect of AMS-adoption influencing eco-efficiency is increases in the number of cows, which is negatively related to eco-efficiency changes but positively related to AMS-adoption. Of the total effect of AMS-adoption on eco-efficiency, most can be explained by the included factors. This paper is, to our knowledge, the first to identify and empirically show the presence of secondary effects and how these secondary effects induce effects on farm-level sustainability.

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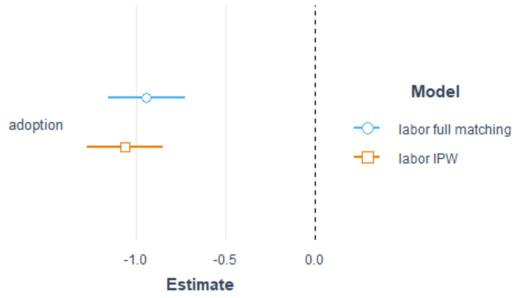
Appendix 1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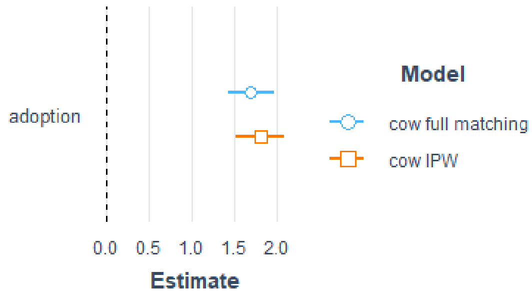
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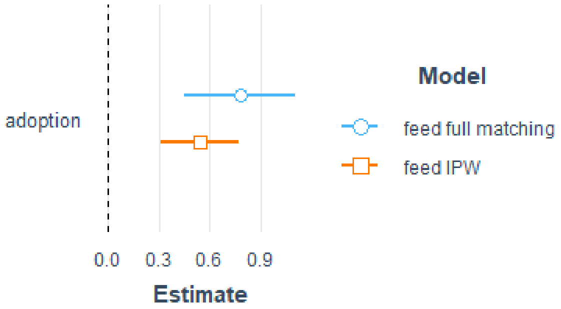
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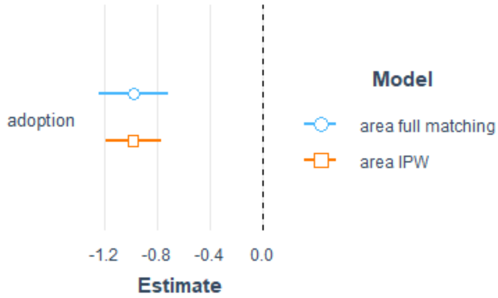
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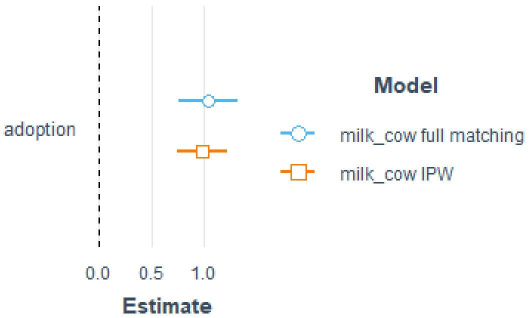
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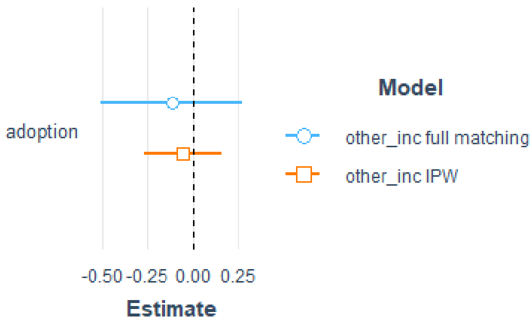
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