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Smart Farming Technology and the Environmental and Social Efficiency of European Agriculture

Dissertation

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As I write this, it feels unreal that I am approaching the end of my doctorate. Throughout the past years, I have celebrated the graduations of many dear colleagues by walking down Nussallee, scrambling old metal cookie boxes filled with stones while trying to keep up with the new doctor and the fast supervisor pulling the wagon. Now it is my turn.

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Kurzfassung

Der Agrarsektor steht unter wachsendem Druck. Die steigende Nachfrage nach Lebensmitteln muss gesättigt und gleichzeitig Umweltschäden begrenzt werden. Hierbei müssen Landwirte und die ländliche Bevölkerung ebenfalls bedacht werden. In den aktuellen politischen Debatten in der EU wird der Schwerpunkt darauf gelegt, die landwirtschaftlichen Produktionssysteme auf hohe Ansprüche an sozialen Wohlstand und ökologische Nachhaltigkeit auszurichten. Trotz der verstärkten Konzentration auf die Verbesserung der ökologischen und sozialen Nachhaltigkeit fehlt es jedoch an geeigneten Instrumenten zur gemeinsamen Bewertung der Leistung in den Bereichen Umwelt und sozialer Wohlstand. Ein wichtiges Instrument, um mehr Nachhaltigkeit zu erreichen, sind neuartige Smart Farming Technologien (SFTs). Darüber hinaus sind die Auswirkungen von SFTs bisher kaum untersucht worden und müssen besser verstanden werden, um sicherzustellen, dass der Einsatz von SFTs zur gewünschten Entwicklung beiträgt.

Diese Dissertation zielt darauf ab, Einblicke in die derzeitige ökologische und soziale Effizienz der landwirtschaftlichen Produktion zu geben und das Potenzial von SFT für positive Veränderungen auf Betriebsebene in Europa zu analysieren. Zuerst untersuchen wir den Status quo der landwirtschaftlichen Produktion in der EU. Wir betrachten eine regionale Perspektive und bewerten die miteinander verknüpften ökologischen und sozialen Effizienzwerte in den EU-Regionen mithilfe der Data Envelopment Analysis (DEA). Wir liefern empirische Erkenntnisse darüber, wie die regionale landwirtschaftliche Produktion in der EU ein Gleichgewicht zwischen ökologischer und sozialer Effizienz herstellt, und empfehlen die DEA als praktikables Instrument zur Bewertung des Status quo. Zweitens analysieren wir die Auswirkungen der SFT auf Betriebsebene, indem wir untersuchen, welche strukturellen und verhaltensbezogenen Veränderungen die Technologie hervorrufen kann. Wir folgen der gleichen Methodik der Effizienzanalyse wie im ersten Teil, aber dieses Mal studieren wir die Auswirkungen der SFT auf Betriebsebene. Konkret bewerten wir die Auswirkungen von automatischen Melksystemen (AMS) auf norwegischen Milchviehbetriebe, einschließlich der durch SFT induzierten strukturellen und verhaltensbezogenen Veränderungen, die wiederum die Umwelteffizienz der Betriebe beeinflussen können. Zum besseren Verständnis der durch SFT induzierten Struktur- und Verhaltensänderungen betrachten wir Wirtschaftstheorie und die bisherige Forschung zum Thema, um zur Entwicklung eines konzeptionellen Bewertungsrahmens beitzutragen. Dieses Konzept kann in zukünftigen Studien zur Bewertung der Auswirkungen von SFT auf Betriebsebene verwendet werden, wobei der Schwerpunkt auf den durch SFT ausgelösten Struktur- und Verhaltensänderungen in den Betrieben liegt.

Die Ergebnisse dieser Dissertation liefern wertvolle Erkenntnisse für die nachhaltige Entwicklung des europäischen Agrarsektors und die Rolle der SFT bei diesem Wandel. Unsere Ergebnisse zeigen, dass die Politik dazu beitragen muss, den Zielkonflikt zwischen ökologischer und sozialer Effizienz zu überwinden, um eine nachhaltige landwirtschaftliche Entwicklung zu gewährleisten. Damit SFT Teil einer Strategie zur Überwindung dieses Zielkonflikts sein können, müssen die durch SFT induzierten strukturellen und verhaltensbezogenen Veränderungen besser verstanden und gesteuert werden, so dass SFT eine nachhaltige Entwicklung fördert, ohne unerwünschte und nachteilige Auswirkungen zu verursachen.

Schlüsselwörter*: Data Envelopment Analysis (DEA), Ökologische Effizienz, Soziale Effizienz, Smart Farming Technologien, Agrartechnologie, Strukturänderungen*

Abstract

The agricultural sector faces growing pressure to meet the increasing demand for food while mitigating environmental damage and being fair to farmers and rural populations. Current policy debates in the EU emphasise steering agricultural production systems towards achieving high social welfare and environmental sustainability. However, despite the increased focus on improving environmental and social sustainability, we lack appropriate tools to jointly evaluate performance in the environmental and social dimensions. One important tool for reaching increased sustainability is novel smart farming technology (SFT). Furthermore, the effects of SFT have scarcely been studied and need to be better understood to ensure that using SFT will contribute to the desired development.

This dissertation aims to provide insights into the current environmental and social performance of agricultural production and explore the potential of SFT to generate farm-level change in Europe. First, we examine the status quo of EU agricultural production. We consider a regional perspective and assess interrelated environmental and social efficiency scores in EU regions using Data Envelopment Analysis (DEA). We contribute empirical insights into how regional agricultural production in the EU balances environmental and social efficiency and suggest DEA as a feasible tool to assess the status quo. Second, we investigate the farm-level effects of SFT, considering what structural and behavioural changes the technology can induce. We follow the same efficiency analysis methodology as in the first part, but this time, we analyse the effects of SFT at the farm level. Specifically, we assess the effects of Automatic Milking Systems (AMS) on Norwegian dairy farms, including SFT-induced structural and behavioural change, which, in turn, can affect farms' environmental efficiency. To further understand SFT-induced structural and behavioural change, we use economic theory and previous literature to contribute a conceptual framework. This framework can be used in future studies assessing the farm-level effects of SFT, emphasising the structural and behavioural change SFT triggers on farms.

The findings in this dissertation provide valuable insights for guiding the sustainable development of the European agricultural sector and the role of SFT in this change. Our results show that policy needs to contribute to overcoming the trade-off between environmental and social efficiency to ensure sustainable agricultural development. For SFT to be part of a strategy to overcome this trade-off, SFT-induced structural and behavioural changes must be better understood and managed so that SFT promotes sustainable development without creating unwanted and adverse effects.

Keywords: Data Envelopment Analysis (DEA), eco-efficiency, social efficiency, smart farming technology, agricultural technology, structural change

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Abbreviations

AMS	**A**utomatic **M**ilking **S**ystem
ASC	**A**gri **S**ustainability **C**ompass
ATT	**A**verage **T**reatment effect for the **T**reated
CAP	**C**ommon **A**gricultural **P**olicy
DEA	**D**ata **E**nvelopment **A**nalysis
EE	**E**co-**E**fficiency
EoSc	**E**conomies of **Sc**ope
EoSi	**E**conomies of **Si**ze
EU	**E**uropean **U**nion
FE	**F**ixed **E**ffects
GHG	**G**reenhouse **G**as **E**missions
IPCC	**I**ntergovernmental **P**anel on **C**limate **C**hange
OLS	**O**rdinary **L**east **S**quares
PS-DID	**P**ropensity **S**core weighted **D**ifference-**I**n-**D**ifference
RMSE	**R**oot **M**ean **S**quare **E**rror
S&B	**S**tructural and **B**ehavioural
SD	**S**tandard **D**eviation
SE	**S**ocial **E**fficiency
SFT	**S**mart **F**arming **T**echnology
UAA	**U**tilised **A**gricultural **A**rea
UAV	**U**nmanned **A**erial **V**ehicle
VRA	**V**ariable **R**ate **A**pplication

Chapter 1
Overview of the thesis

1.1 Motivation and general research question

The agricultural sector faces increasing pressure to feed a growing population while mitigating environmental damage. To rise up to this challenge, sustainable intensification of agricultural production is needed. Sustainable intensification can be defined as a development towards increased food production while minimising, or at the least not increasing, environmental damage (Caiado et al. 2017; Gadanakis et al. 2015; Lindblom et al. 2017; Weltin and Hüttel 2019). Alternatively, sustainable intensification can be defined as satisfying the demand for food while ensuring environmental sustainability (Bonfiglio et al. 2017). However, achieving sustainable intensification is complex due to the many stakeholders involved, multifaced uncertainties related to agricultural production, and high environmental and social costs should the policy fail to achieve sustainability gains (Firbank 2020).

In the EU, agricultural policies increasingly focus on jointly improving environmental and social sustainability. This is reflected in the current Common Agricultural Policy (CAP) period of 2023-27, which positions itself as "a greener and fairer CAP", emphasising its dual focus on improving the conditions for farmers while mitigating environmental impact (European Commission 2022). The combined emphasis on environmental and social sustainability is also reflected in the recent policy initiative for a strategic dialogue of EU agriculture, which brings together stakeholders to contribute policy advice for improved environmental and social sustainability (Strohschneider et al. 2024; European Commission 2024a).

Chapter 1: Overview of the thesis

Smart farming technology (SFT)[1] - a more data-driven approach to farming (Wolfert et al. 2017) - is one important tool to achieve sustainable intensification with the potential to also increase social welfare. SFT is becoming increasingly important for agricultural production (Storm et al. 2024; Finger 2023). The digitalisation and automatization of agriculture, including SFT, are frequently referred to as the Fourth Agricultural Revolution or Agriculture 4.0 (Klerkx and Rose 2020; Rose and Chilvers 2018; Walter et al. 2017). This reflects the significant impact smart farming is expected to have on the agricultural sector. SFT has the potential to, among other things, increase resource use efficiency, reduce labour requirements and lower production costs (Duckett et al. 2018; Finger et al. 2019; Martin et al. 2022; Walter et al. 2017). Thereby, SFT is expected to improve all aspects of sustainability, i.e., the economic, environmental, and social dimension (Finger et al. 2019).

Despite the increased focus on simultaneously improving environmental and social sustainability through policy and SFT, joint performance evaluation in both dimensions is rare. Additionally, the effects of SFT are poorly studied. These two research gaps become evident in the study by Sparrow and Howard (2021), who show that the social effects of SFT are often overlooked in previous research. Furthermore, Sparrow and Howard (2021) state that the actual effects of future SFT will not depend on whether farmers use the technology but rather on how they use it, implying a need for studies on the realised farm-level effects of SFT.

Regarding joint evaluations of environmental and social performance, previous research has noted the scarcity of studies on this matter. For example, Harrison et al. (2021) discuss the myopic focus on GHG emissions when evaluating the effects of carbon mitigation projects in livestock farming, criticising previous evaluations for overlooking potential synergies or spill-overs on other sustainability dimensions. This is in line with the findings by Sparrow and Howard (2021) on the omission of social aspects when assessing the effects of SFT. To assess environmental and social performance, efficiency analysis can prove useful. Specifically,

1 Throughout this dissertation, we define SFT as a technology with at least one of the features of gathering and providing information, enabling for or conducting variable rate application or being a fully automated system, following the definition we provide in Chapter 4.

efficiency analysis enables accounting for several indicators simultaneously and provides insights into units' performance in jointly supporting high environmental quality with high welfare (Huppes and Ishikawa 2005). However, previous research has focused on environmental and economic performance, while the social dimension was only recently quantified (Chambers and Serra 2018; Ait Sidhoum et al. 2020). While these previous contributions provide important methodological insights, efficiency scores reflecting performance in the agricultural sector on a broader geographical scale and with stronger connections to sustainability targets are still lacking.

Regarding the effects of SFT, it is still not sufficiently understood how farmers use the technology on their farms (Klerkx et al. 2019). Further, realised effects of SFT on environmental and social conditions in agricultural production are rarely studied. Instead, several studies use experimental data or modelling predictions without considering observed farm-level outcomes (Finger et al. 2019). Consequently, we lack knowledge of what changes SFT might generate on the farm level and, thus, how aggregate adoption will affect agricultural practices (Daum, 2021). Particularly, due to the lack of studies assessing the farm-level effects of SFT, insights into how SFT affect farm structures and farmers' decisions are insufficient.

Understanding the status quo of European agricultural production and what developments SFT might spur is crucial for steering agricultural production towards sustainability. To this end, this dissertation aims to address two research objectives. First, we assess the status quo to provide insights into the current environmental and social performance of agricultural production (Chapter 2). Second, we explore the potential of SFT to generate farm-level change in Europe (Chapters 3 and 4). Figure 1.1 illustrates how the three main chapters of this dissertation contribute to our overarching research aim.

Chapter 1: Overview of the thesis

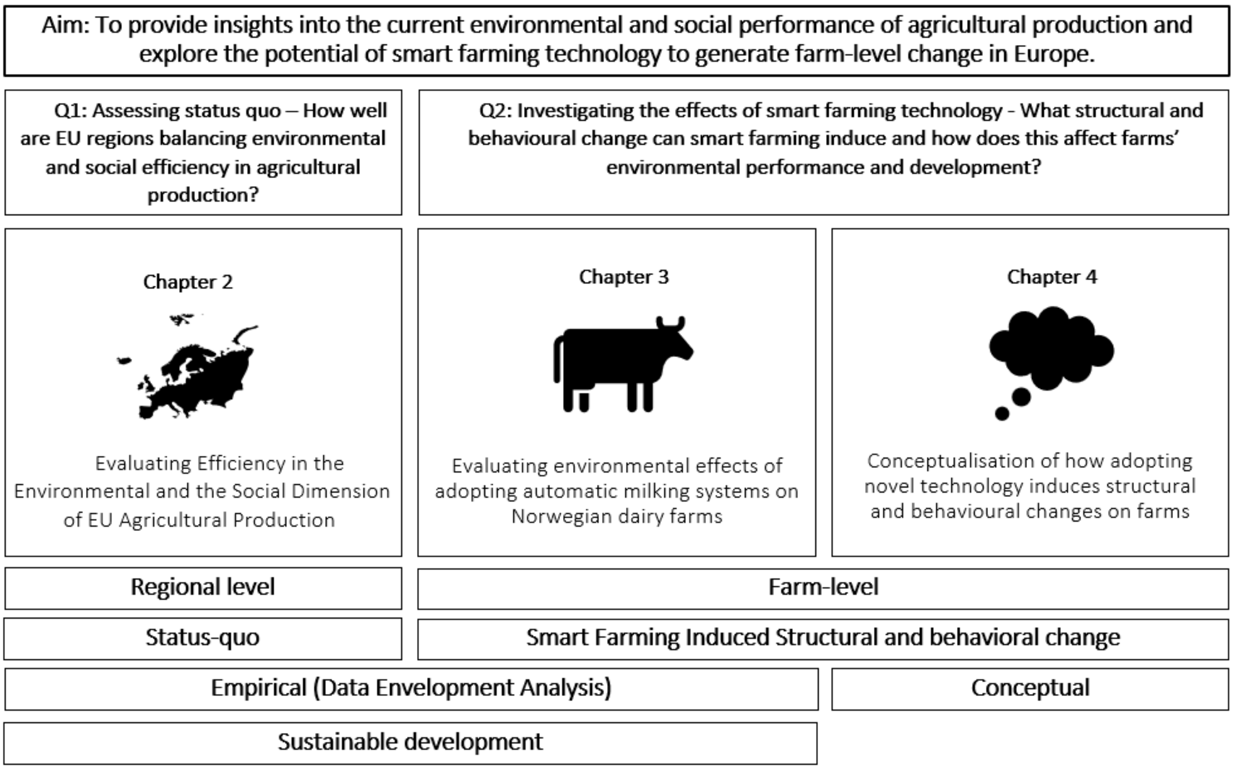

Figure 1.1: Illustration of research synthesis
Source: Own illustration

As illustrated in Figure 1.1, the overarching aim of this dissertation can be divided into two general research objectives:

1. To assess how well EU regions balance environmental and social efficiency in agricultural production and thereby outline paths for sustainable development **(Chapter 2)**.
2. To assess what structural and behavioural change smart farming technology can induce and how this affect farms' environmental performance and development **(Chapters 3 and 4)**.

When addressing the status quo in Chapter 2, we consider a regional level, which is necessary for capturing social dynamics and enabling a broad geographical coverage of Europe. On the contrary, Chapters 3 and 4 focus on the farm level to capture farmer behaviour and reactions to the novel technology. In Chapters 2 and 3, we use Data Envelopment Analysis (DEA) to assess efficiency, highlighting what aspects can be improved (Chapter 2) and how SFT affect farm-level efficiency (Chapter 3). Both Chapters 2 and 3 contribute, apart from empirical insights, innovative applications of efficiency analysis. In Chapter 4, we use economic theory to provide a conceptual framework that can be used as a foundation for studying SFT that is not yet widely diffused or still under development.

Chapter 2 studies the status quo of EU regions' environmental and social performance, improving knowledge of how agricultural production balances these two objectives. Specifically, we assess relative performance by computing interrelated scores of environmental and social efficiencies (EE and SE). Chapter 2 also provides implications for how EE and SE can be improved by considering whether relative efficiency can be improved by less efficient regions learning from regions with high joint EE and SE or whether there is an absence of regions performing well in both dimensions. The latter scenario, an absence of high-performing regions in both EE and SE, would imply that a system shift is required for production to become more sustainable in EE and SE jointly. Considering that SFT can increase the efficiency of already existing production systems or enable system redesign by creating new farming systems and agricultural landscapes (Finger 2023), insights into the status quo efficiency can guide the implementation of SFT and other policy interventions to jointly increase EE and SE where it is most needed.

SFT encompasses a wide range of technologies with different readiness and adoption rates. Where autonomous technology such as Unmanned Aerial Vehicles (UAVs) are only recently being adopted by farmers, other SFTs have been used on farms for decades (Khanna et al. 2024). For example, Automatic Milking Systems (AMS) are already widely implemented in the livestock sector (Eastwood et al. 2019; Martin et al. 2022). The long tradition of using AMS, particularly in northern Europe (Jacobs and Siegford 2012), makes it a good case study of the farm-level effects of SFT. In Chapter 3, we assess the effects of AMS on farm structural and behavioural factors on Norwegian dairy farms, thereby investigating the scarcely studied phenomena of farm-level secondary effects of technology, which we also refer to as SFT-induced structural and behavioural (S&B) change. Further, we study how the AMS-induced structural and behavioural change, in turn, affects farms’ eco-efficiency, focusing on GHG emissions (GHG emissions efficiency).

The findings in Chapter 3 highlight the importance of understanding the processes triggered on farms as a novel SFT is adopted. Accounting for such processes is crucial to ensure that the novel technology spurs a development towards increased farm sustainability without generating adverse or contradictory effects. Previous studies have discussed the effects of specific SFTs and summarised these findings to enable conclusions about the general effects of smart farming and the robotisation of agriculture (Sparrow and Howard 2021; Martin et al. 2022). However, to enable evaluations of how SFT can trigger farm-level change once the technology is adopted, we need a better understanding of the mechanisms driving S&B change and what outcomes this will result in on farms. To this end, Chapter 4 provides a conceptual framework contributing to a better understanding of SFT-induced S&B change.

In the remainder of this chapter, we provide more detail on the studies constituting this thesis and elaborate on how each study contributes to the overarching aim and the respective objective. In Chapter 1.3, we summarise the findings and conclude, outlining the limitations and highlighting the potential for future research that this dissertation invites. Finally, in Chapter 1.3.2, we suggest some concrete policy implications that can be derived from the results of the included studies.

1.2 Contribution of the thesis

In this section, we summarise each chapter of the dissertation. We provide the background to each chapter in light of the dissertation’s overarching aim, the methodologies used, and the main results. Finally, we discuss how each chapter's main findings contribute to the dissertation's aim and objectives.

1.2.1 *Environmental and social efficiency of NUTS2 regions: identifying opportunities for sustainability improvements and necessities for a system change*

If smart farming is to reduce environmental pressures and improve social and economic conditions as promised (Duckett et al. 2018; Walter et al. 2017), efforts for adoption should be focused on where they are most needed. Nevertheless, it has been recognised that productivity gains and technologization benefitting environmental aspects do not guarantee improved social sustainability (Strohschneider et al. 2024; Rose et al. 2021). Thus, the recent policy debate in the EU reflects the need to balance the social and environmental dimensions when formulating policies for the development of agricultural production (Strohschneider et al. 2024). Despite this focus, we lack the tools to jointly evaluate environmental and social performance. Consequently, empirical insights are scarce. To this end, Chapter 2 provides novel insights into the status quo of the joint EE and SE of agricultural production in NUTS2 regions in the EU.

Policies to improve efficiency are more likely to gain public acceptance than policies restricting production (Beltrán-Esteve et al. 2017; Kuosmanen and Kortelainen 2005). However, the social aspect is often overlooked in efficiency evaluations despite its importance for agricultural production and rural communities (Caiado et al. 2017). By evaluating EE and SE interrelatedly, we show whether there are trade-offs or synergies between the two, offering insights into the status quo and potential development paths. Particularly, we provide insights into whether less efficient regions can improve relative efficiency by learning from regions with high combined EE and SE. If no region displays high levels of EE and SE, this implies that a system shift might be required to overcome this trade-off.

We use DEA to jointly assess environmental and social efficiency, ensuring comparability between the two efficiency scores through an interdependency constraint (Boussemart et al. 2020; Dakpo and Lansink 2019). DEA requires that the evaluated units are homogenous in that they perform similar activities and use similar inputs in similar production environments (Dyson et al. 2001). To meet this requirement, we use metafrontiers (O'Donnell et al. 2008).

We implement the meta frontiers by grouping the regions based on three different categories: main specialisation (whether the region produces the main share of output from livestock, arable production or high-value crops), biogeographical region (based on the classification by the European Environment Agency (EEA)), and population density (based on a grouping by (Bianchi et al. 2020). By grouping the regions, we can consider relative performance within the groups and compare performance between groups. As we consider several options for grouping, each region is grouped three times and thus receives three scores of EE and SE respectively. One important feature of DEA is to assign weights to the different indicators, which can take on any positive value. To ensure that no indicator is assigned unreasonable high or low weights, we define assurance ranges (Cooper et al. 1999). We use the Agri Sustainability Compass (ASC) (European Commission 2024b) to select environmental and social indicators to include in the efficiency scores, ensuring the inclusion of indicators which are relevant to EU agriculture.

Chapter 2 contributes to the overarching aim of this dissertation by assessing the joint environmental and social efficiency of EU agriculture and thus providing insights into the current environmental and social performance of agricultural production. To this end, SFT is an important instrument to enable regions to operate with higher environmental and social efficiency. Depending on the considered technology, SFT can contribute to improved efficiency or a system redesign (Finger 2023). However, smart farming is also associated with social risks, such as increased inequality and changes in employment affecting certain individuals (Rose et al. 2021), which further motivates jointly assessing environmental and social efficiency to ensure that improvements in one dimension do not come at the cost of the other.

Chapter 2 identifies a trade-off between environmental and social efficiency that persists in all groupings. This indicates a need for a system redesign to reach high levels of efficiency in both dimensions simultaneously. Additionally, we identify higher heterogeneity in the trade-offs in groups specialising in arable crops, Continental and Atlantic regions, and regions with rural and intermediate population densities. This implies that less efficient regions can learn from the more efficient regions to jointly increase EE and SE in these groups.

1.2.2 *Evaluating environmental effects of adopting automatic milking systems on Norwegian dairy farms*

Chapter 3[2] consists of an empirical study of the effects of AMS on farms' GHG emissions efficiency. Having assessed the status quo of EU agricultural production on a regional level in Chapter 2, Chapter 3 focuses on the farm level, investigating the actual effects of a novel technology once implemented on farms. The joint contribution of Chapters 2 and 3 is important as they both propose using DEA efficiency analysis to assess current performance (Chapter 2) and the effects of technology (Chapter 3). This facilitates comparisons between the development needed in the agricultural sector to increase efficiency and the farm-level effects generated by new technology. The main motivation for this chapter is that novel technology might induce S&B change and that overlooking the effects of such changes can increase the risk that novel technology leads to maladaptation (Pörtner et al. 2022).

AMS represents an important case study, as this is one of the most extensively used smart farming technologies. Norway is at the forefront of AMS usage (Vik et al. 2019), which motivates our geographical focus. AMS can improve social welfare, and farmers commonly adopt AMS to increase their flexibility and, thus, their quality of life (Hansen et al. 2020; Stræte et al. 2017). However, research has shown that adopting and using AMS is not only linked to changes in farm work and farmer flexibility but also associated with other structural changes on farms (Rønningen et al. 2021; Oudshoorn et al. 2012; Vik et al. 2019). To this background, it is important to ensure that developments spurred by AMS usage do not couple with deteriorated environmental performance. Ideally, AMS can generate joint improvements in both environmental and social sustainability.

[2] Chapter 3 is published as Martinsson, E., Hansson, H., Mittenzwei, K., & Storm, H. (2024). Evaluating environmental effects of adopting automatic milking systems on Norwegian dairy farms. *European Review of Agricultural Economics, 51(1)*, 128-156. DOI: https://doi.org/10.1093/erae/jbad041.

Nevertheless, no previous study has investigated how smart farming can affect farms' environmental performance through changes in farm structure and farmer behaviour. Further, the effect of smart farming on farms' S&B development has received little attention in previous literature. To fill this gap, this chapter aims to assess what change AMS can induce on several S&B factors and how this affects farms' GHG emissions efficiency. Specifically, we consider a sample of Norwegian dairy farms and include labour per cow, milk per cow, off-farm income, number of cows, the share of feed concentrates in the cows' diet and arable land per milk output.

Alongside the empirical results of the effects of AMS on Norwegian dairy farms, this chapter presents a novel methodological procedure for assessing the effects of novel technology on farms' efficiency, accounting for the influence of S&B change. We compute GHG emissions efficiency using DEA, following the approach by Kuosmanen and Kortelainen (2005) with bootstrapping of the efficiency scores to reduce sample bias (Simar and Wilson 2000). Having obtained efficiency scores for each farm, we assess the effects of AMS adoption on farms' GHG emissions efficiency and the included S&B factors. To fully utilise the unbalanced panel data and account for staggered adoption and variations in effects over time, we employ a machine learning matrix completion method for causal identification (Athey et al. 2021). We use a fixed effects regression to assess the association between the GHG emissions efficiency and the S&B factors at the farm level. In the final step, we connect the results by multiplying the effect of AMS on the S&B factors with the correlation between each factor and the GHG emissions efficiency. This procedure allows us to estimate each factor's contributing power to the relation between AMS adoption and GHG emissions efficiency.

Chapter 3 contributes to the second objective of this thesis: to assess how smart farming can induce S&B change and affect farms' environmental performance and development. The contribution is twofold: on the one hand, we provide a novel methodological procedure to assess farms' development after adopting a novel technology, specifically accounting for S&B change and secondary effects on farms' GHG emissions efficiency. On the other hand, we provide empirical results regarding the effects of AMS in Norwegian dairy farming. Our findings imply that the average effect of AMS on GHG emissions efficiency is small but with a large variation, indicating that AMS affect farms heterogeneously. We also identify that the S&B change affects GHG emissions efficiency in contradicting ways. This finding underlines the importance of understanding what farm-level effects are triggered by technology adoption to ensure that technology is used to increase the sustainable development of farms. Through these findings, we demonstrate that the effects of technology initially intended to increase the social well-being of farmers might generate S&B changes, which, in extension, have unintended effects on farms' environmental efficiency. The insights from Chapter 3 emphasise the importance of understanding structural and behavioural change and its potentially contradictory and adverse effects on farm sustainability. This sets the scene for Chapter 4, where we explore smart farming-induced structural and behavioural change further.

1.2.3 *Conceptualisation of how adopting novel technology induces structural and behavioural changes on farms*

In the final chapter of this dissertation[3], we provide a conceptual framework of induced S&B change generated by smart farming adoption. In contrast to the previous chapters, this chapter does not conduct an empirical efficiency analysis. Instead, we expand on the conceptual understanding of the farm-level effects of SFT. Specifically, we build on the notion of induced S&B change presented in Chapter 3 to construct a theoretical framework. By conceptualising SFT-induced S&B change, Chapter 4 provides a more general understanding of the farm-level effects of SFT. We provide a conceptual framework by using economic theory to derive mechanisms of change triggered by traits of SFT. Additionally, Chapter 4 contributes a literature review to provide examples of how the conceptual framework applies.

This chapter aims to enhance the conceptual understanding of how novel SFT motivates farm-level S&B changes in both arable and livestock farming. The conceptual framework applies to

[3] Chapter 4 is published as Martinsson, E., & Storm, H. (2025). Conceptualization of How Adopting Novel Technology Induces Structural and Behavioural Changes on Farms. *Journal of Agricultural and Resource Economics, 1-26.* DOI: 10.22004/ag.econ.356163

SFT, which is defined as a technology with at least one of the traits of being autonomous, conducting variable rate application (VRA), or gathering and providing information. We consider these traits, together with the initial costs and capacity of the technology, as factors which can induce S&B change.

Previous research has thoroughly investigated the adoption determinants of smart and digital technologies (Gallardo and Sauer 2018; Michels et al. 2020; Shang et al. 2021). However, less attention has been given to the actual effects. After adoption, a SFT might drive farmers to adjust their field structures (Sparrow and Howard 2021), expand production and farm size (Vik et al. 2019) or reorganise farm labour (Martin et al. 2022). However, the mechanisms triggering these changes are poorly conceptualised. Furthermore, previous concepts formulated to study the effects of smart farming, such as activity theory (Lioutas et al. 2019) or responsible research and innovation (Rose and Chilvers 2018), focus on interactions between actors but do not incorporate farm-level S&B adaptations to novel SFT.

In our conceptualisation, we consider changes in Economies of size (EoSi), Economies of scope (EoSc), production and financial risk and increased input use efficiency (triggering rebound effects) as drivers of S&B adaptations to novel SFT. We term these drivers as mechanisms triggered by features of technology which, in turn, lead to various outcomes of S&B change. By connecting technology features to economic theory, we derive processes through which novel SFT induces S&B change. Through the literature review, we identify 27 previous studies where we can derive the mechanisms and outcomes described in our conceptual framework. Of these studies, 16 focus on livestock production, while 11 consider arable production.

Together with Chapter 3, Chapter 4 contributes to the second objective of the thesis: Assessing how smart farming can induce S&B change and thereby affect farms' environmental performance and development. The framework developed in this chapter can support hypothesis formulation and guide research to study the effects of SFT on farms. The framework can also be used to model the upscaling of SFT and provide insights into how to steer increased adoption and usage of technology to contribute to sustainable development and sustainable intensification.

1.3 Conclusion

This dissertation aims to provide insights into the current environmental and social performance of agricultural production and explore the potential of SFT to generate farm-level change in Europe. We contribute to this aim by, on the one hand, assessing the status quo and thus identifying the need for policy and SFT to improve environmental and social efficiency. On the other hand, we investigate the effects that SFT will have once it is implemented on farms. The studies in this thesis contribute both methodological and conceptual insights, as well as novel empirical results.

In Chapters 2 and 3, we present new applications of efficiency analysis and DEA. Specifically, we suggest that efficiency analysis can be a valuable tool in evaluating the performance of agricultural production in its ability to jointly provide high environmental quality and social welfare (Chapter 2). Further, in Chapter 3, we outline a procedure, including DEA, for assessing how novel SFT impacts the environmental efficiency of farms through structural and behavioural change.

In addition to methodological contributions, all chapters in this dissertation enable conclusions relevant for policymakers, farmers, technology developers, and researchers looking to steer towards sustainable development of European agricultural production and better understand the effects of digitalisation and the automatization of farming. Concretely, the results from Chapter 2 provide insights into regions' current performance and development potential, either through improving relative efficiency or indicating the need for a system change. Therefore, Chapter 2 is relevant for policymakers by indicating what steering is required to improve sustainability and for technology developers and distributors by providing implications of what the technology will need to do and where novel technology can have the largest impact.

Chapters 3 and 4 add insights into farm-level effects of SFT, focusing particularly on the S&B change the technologies can generate and how this, in turn, can affect farms' GHG emissions efficiency. Specifying the effects of SFT and how it affects farms' environmental efficiency is highly relevant for farmers and policymakers, and the methodological and conceptual contributions in these chapters enable future researchers to further expand their knowledge on the farm-level effects of SFT.

While the respective chapters highlight the individual studies' limitations, recommendations for future research, and policy implications, we want to dedicate the remainder of this introductory chapter to providing some general insights. First, we discuss some limitations of the studies and outlooks for future research. Second, and finally, we provide policy recommendations.

1.3.1 *Limitations and outlook*

We identify two main limitations of this dissertation which future research needs to address.

The first limitation relates to our choice of efficiency analysis as the main empirical method, which is a relative approach. Thus, we do not consider absolute environmental damage and social welfare levels. By assessing efficiency, we provide insights into, on the one hand, potential paths of development (Chapter 2) and, on the other hand, realised paths of development generated by technology adoption (Chapter 3). Nevertheless, none of the studies in this dissertation considers absolute levels of environmental and social indicators. While efficiency analysis offers the benefits of being easily quantified (Ait Sidhoum et al. 2022) sustainability is more difficult to define, especially on a sub-global level (Dearing et al. 2014). Some previous research has integrated efficiency measures with sustainability targets, for example, Martinsson and Hansson (2021), but more research is needed in this area.

To reach targets for sustainable development, it is important to assess the performance in all dimensions where decisions regarding sustainable development are made (Lemke and Bastini 2020). Thus, coupling the results from the efficiency analysis in Chapters 2 and 3 with sustainability targets and thresholds would provide valuable insights into the need for agricultural production to change to become sustainable. For example, the results could be coupled with the progress towards reaching the CAP 2023-27 targets or the related Sustainable Development Goals as defined in the Paris Agreement. Integrating efficiency scores with sustainability boundaries at regional and national levels would provide valuable insights into whether efficiency improvements will be sufficient to reach sustainability at different levels of aggregation or whether other changes in the food value chain will be required. Linking the efficiency scores to sustainability could offer insights in line with recent research efforts aspiring to provide pathways towards increased sustainability in EU agriculture (Müller et al. 2024)

The second limitation of the compiled research in this dissertation is the sole focus on agricultural production and the focus on farm-level when assessing the effects of SFT, thereby omitting potential market feedback effects. Throughout this chapter, we have discussed the need for, and the ability of, smart farming to improve agricultural sustainability. Nevertheless, even though farms are an integral part of the food system, other actors and stakeholders must be considered when discussing a sustainable transformation of the agricultural sector. Previous research has indicated that smart farming will affect social dynamics (Rose et al. 2021) and consumer behaviour (Regan 2019). To fully understand the role of smart farming in a sustainable transformation of agriculture, the findings in this dissertation should be considered in a broader context extending beyond agricultural production. Future research could, for example, extend the concept of smart farming-induced structural and behavioural change to the consumer side and integrate it into a systems perspective.

1.3.2 *Implications for policy*

We are entering the fourth agricultural revolution, where smart farming is playing an increasingly important role. This dissertation investigates the status quo of EU agricultural production and explores the potential of SFT to generate farm-level change in Europe.

Specifically, following the two objectives defined for this thesis, we can provide at least two policy recommendations.

The first objective of the thesis is to assess how well EU regions balance environmental and social efficiency in agricultural production and thereby outline paths for sustainable development. Based on the results from Chapter 2, we derive the first policy recommendation:

Policy recommendation 1: To ensure sustainable agricultural development, policymakers must focus on overcoming the trade-off between environmental and social efficiency.

In Chapter 2, our empirical insights indicate a trade-off between environmental and social efficiency, emphasising the importance of policy addressing both dimensions simultaneously to overcome this trade-off. SFT could be the way to achieve this, due to the technology's potential to improve both environmental and social conditions (Walter et al. 2017; Finger et al. 2019) but studies have also pointed to the potential risk of such SFT on the social dimension of sustainability (Rose et al. 2021; Eastwood et al. 2019). Therefore, ensuring that SFT is implemented and used in a way that jointly improves environmental and social conditions is crucial.

In Chapter 3, we evaluate the effects of AMS on farm-level GHG emissions efficiency. As AMS is mainly adopted to improve farmers' social welfare, the effects we identify on environmental efficiency further strengthen our case of the dual focus on environmental and social effects and emphasise this in the context of SFT. Furthermore, in Chapter 4, we provide more details on the mechanisms of smart farming that induce structural and behavioural change. This leads to the second policy recommendation:

Policy recommendation 2: For smart farming to successfully overcome the trade-off between environmental and social efficiency, smart farming-induced structural and behavioural changes, such as farm expansion, increased intensification, and specialisation, must be considered.

The S&B changes associated with smart farming need to be managed so that they contribute to emphasising the sustainability of aggregate adoption of SFT rather than cancelling out or adversely affecting farm- and regional sustainability. Chapters 3 and 4 present the concept of smart farming-induced structural and behavioural change, which can support policymakers and future research in assessing the effects of technology adoption in the relevant empirical contexts.

In summary, this thesis provides tools in the form of methodological procedures, empirical insights, and a conceptualisation to increase the knowledge regarding the effects of Smart Farming Technology and the Environmental and Social Efficiency of European agriculture.

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Chapter 1: Overview of the thesis

Chapter 2
Evaluating efficiency in the environmental and the social dimension of EU agricultural production

Abstract. Agricultural production must provide agricultural output as well as social welfare while at the same time mitigating environmental damage. It must avoid inefficiencies which waste resources or represent forgone opportunities to produce social welfare. In this study, we assess how efficiently EU regions turn their economic value of agricultural production into social benefits while at the same time minimising environmental damage. We evaluate interrelated scores of environmental and social efficiencies using meta-frontiers and data envelopment analysis, allowing us to inspect the trade-offs between environmentally and socially efficient production. Additionally, we consider the heterogeneity in performance between different groups of regions. We find indications that many regions can improve their relative efficiency in the environmental and social dimensions by learning from more efficient regions. However, we also find a strong trade-off between environmental and social efficiency, indicating that a systems redesign might be required to achieve a socially and environmentally efficient EU agricultural production.

Keywords: Data Envelopment Analysis (DEA), Metafrontier, NUTS2 regions, eco-efficiency, social efficiency

2.1 Introduction

Agricultural production faces the challenge of balancing economic and social aspects while at the same time limiting environmental damage. In the EU, attempts to mitigate agriculture's environmental impact recently led to farmer protests across Europe in 2023-2024. This event highlights the importance of agricultural policies promoting synergies between environmental regulation and farmer interests (Finger et al. 2024). The need for balancing social and environmental dimensions is also reflected in the recent policy debate (Strohschneider et al. 2024). However, despite this focus, we lack appropriate tools to jointly assess the current status of EU regions regarding their social and environmental performance. Additionally, we lack empirical insights as to what extent regions succeed in providing high levels of social and environmental outcomes jointly or if there is an inherent trade-off in current production systems. Identifying the existing trade-offs is crucial as it can indicate where a redesign of existing production systems, such as leveraging novel technologies (Finger 2023), might be needed to resolve these trade-offs.

In this paper, we use efficiency analysis to jointly assess the environmental and social performance of EU regions at the NUTS2 level. We aim to empirically answer how well EU regions balance environmental efficiency (EE) and social efficiency (SE) in agricultural production. Additionally, we address the question of to what extent heterogeneity exists in that balance among different groups of regions. Answering these questions allows us to provide insights into possible strategies for improving environmental and social sustainability.

Efficiency evaluations provide insights into how society can support a high standard of living with a high environmental quality (Huppes and Ishikawa 2005). From a policy perspective, efficiency is relevant as policies to improve efficiency are more likely to be accepted in society than policies restricting production (Beltrán-Esteve et al. 2017; Kuosmanen and Kortelainen 2005). The concept of eco-efficiency allows for investigating how environmental damage can be decreased for a given production level (Ait Sidhoum et al. 2022). Recent contributions have extended the eco-efficiency approach to consider social aspects both at the firm level (Ait Sidhoum et al. 2020; Chambers and Serra 2018; Figge and Hahn 2004) as well as the country level (Boussemart et al. 2020). However, the literature jointly assessing efficiency in the environmental and social dimensions is scarce.

We assess efficiency using meta-frontier Data Envelopment Analysis (DEA). The meta-frontier approach (O’Donnell et al. 2008) involves grouping regions into smaller, more homogenous groups. Previous studies using DEA to assess eco-efficiency have largely focussed on the farm level (see e.g. Bonfiglio et al. (2017), Gómez-Limón et al. (2012), Stetter and Sauer (2022), Martinsson and Hansson (2021), and Ait Sidhoum et al. (2020)) and on country level (Vlontzos et al. 2014; Beltrán-Esteve et al. 2014; Beltrán-Esteve et al. 2019). Recent contributions have provided regional assessments of agricultural production, including Manevska-Tasevska et al. (2021) assessing changes in technical efficiency in Swedish regions, Lin and Fei (2015) assessing differences in CO_2 performance in Chinese provinces and Tekiner-Mogulkoc (2022) assessing changes in agricultural productivity in Turkish regions. Following existing studies pioneered by Charnes et al. (1989) and Martić and Savić (2001), we apply DEA at the regional level. Considering a regional perspective enables using other data sources, such as emissions data (Boussemart et al. 2020; Peiró-Palomino and Picazo-Tadeo 2019; Camarero et al. 2013; Lin and Fei 2015), which is rarely accessible at a farm level. Additionally, to reach policy goals, it is important to assess efficiency on the levels of aggregation where decisions regarding sustainable development are made (Lemke and Bastini 2020).

Our study is the first to contribute an EU-wide regional efficiency assessment combining SE and EE. Based on the results, we can identify potential paths for sustainable development. Particularly, we can gain insights into whether there is potential for improving relative efficiency by learning from better-performing regions or whether there is a need for a system redesign to enable higher combined EE and SE. Identifying a need for system redesign is particularly relevant concerning smart farming and digital technology as these come with the promise to decrease environmental pressures (Walter et al. 2017; Storm et al. 2024). Specifically, smart farming decreases environmental damage by increasing efficiency, substituting away from harmful inputs, and redesigning the production system (Finger 2023). However, the technology will also have social impacts (Rose et al. 2021). An additional contribution of the paper is that we base the selection of the indicators to measure environmental and social outcomes on the recently developed *Agri Sustainability Compass*

(ASC) (European Commission 2024b). The ASC contains key indicators for sustainability in EU agriculture that are crucial for policy assessment. Using the same indicators in our assessment increases the policy relevancy of our results.

The remainder of this paper is structured as follows: In Section 2, we provide our conceptual framework. Section 3 outlines the indicators included in the analysis derived from the ASC. Section 4 explains our methods. As DEA is a data-driven method, we consider it beneficial to first present the indicators, followed by outlining the details of the methods, as some methodological considerations (e.g., how to specify the assurance ranges) will require knowledge of the included indicators. Section 5 presents and discusses the results. In section 6, we conclude.

2.2 Conceptual framework

We conceptualise efficiency as a necessary condition for sustainability, where inefficient regions are unsustainable as they can mitigate environmental damage or increase social welfare by increasing their efficiency. However, efficiency is not a sufficient condition for sustainability, as it merely considers relative levels of damage and benefits. Sustainability, however, is absolute and conceptualised by e.g. Rockström et al. (2009) and Steffen et al. (2015) as the planetary boundaries and Raworth (2012) as the Safe and Just Operating Space. Nevertheless, neither of these concepts provides guidance on achieving sustainable development (Biermann 2012) and defining environmental boundaries at a lower scale of operation is complex (Dearing et al. 2014). To this end, eco-efficiency can indicate how current operations are making the most of the available resources to produce output and show whether mitigation can be achieved by improving efficiency (Caiado et al. 2017).

Our approach contributes novel insights into how well regions balance EE and SE. From this, we aim to derive conclusions about potential pathways for improvements. We illustrate our conceptual approach in Figure 2.1.

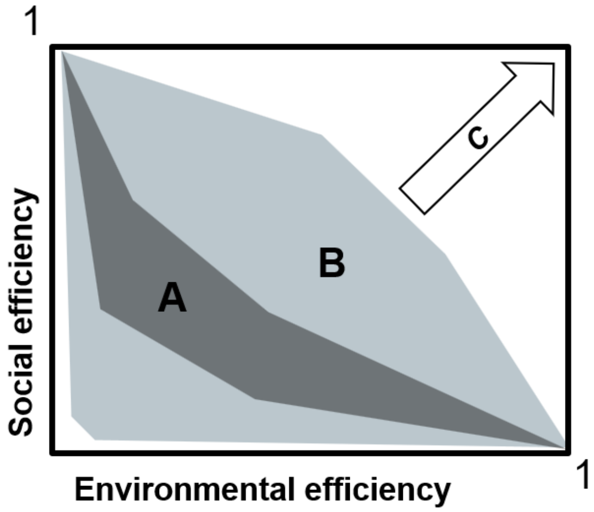

Figure 2.1: Illustration of the conceptual approach
Note: Own illustration

Assume we have assessed regions' relative SE and EE performance, with ranges between 0 (least efficient) to 1 (most efficient). As shown in Figure 2.1, we can plot EE along the x-axis and SE on the y-axis. The highest performance in both dimensions would be achieved in the top right corner. The shaded areas represent two examples of how the population of regions could potentially be distributed, illustrating different pathways for improvement. Distribution "A" shows a scenario with a strong trade-off between SE and EE and low heterogeneity in deviations from this trade-off. In this scenario, no region achieves high SE and EE jointly. This would imply little potential for improving joint SE and EE within the current production systems, indicating a need for system redesign. Distribution "B", in contrast, illustrates an example of high heterogeneity in the trade-off between SE and EE, where some regions achieve high SE and EE jointly. This implies a larger potential for units performing poorly in the EE and SE dimensions to learn from more efficient units. Hence, the width of the distributions A and B indicate the potential to improve efficiency by learning from other regions in the sample or using technology already used by other regions. Arrow C shows how much even the best-performing units in the sample would need to develop beyond what is observed with the current practices, thus indicating additional needs for system changes.

2.3 Deriving indicators from the Agri sustainability compass

The ASC builds on the data in the Agrifood Data Portal and the indicators are selected to represent key challenges in EU agriculture and the progress in these challenges over time (European Commission 2024b). Most of the indicators in the ASC are also part of the CAP indicators, which help assess the performance of CAP 2023-27 and EU member states' strategic plans of how to reach the CAP objectives. Figure 2.2 shows the ASC, outlining the indicators included in our analysis in red.

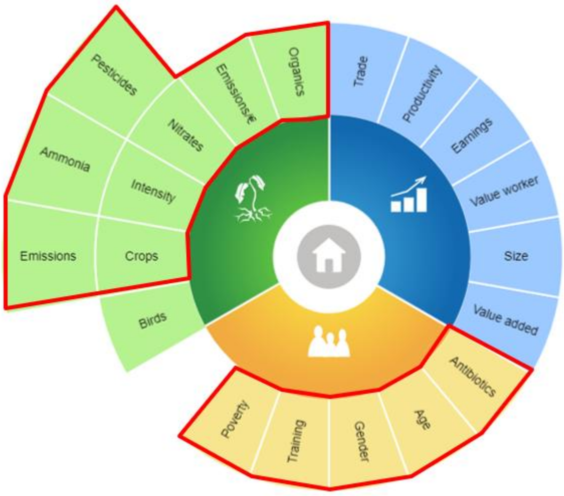

Figure 2.2: Illustration of the indicators included from the Agri. Sustainability Compass (European Commission 2024a).
Note: The highlighting of the indicators included is our own.

To follow the ASC, we use national indicators where regional data is unavailable. The indicators measured on a country level are indicated in Table 2.1. To benchmark the environmental and social performance towards production, we consider net value-added per UAA, defined as total output minus intermediate consumption and fixed capital consumption per UAA. Thus, the efficiency scores reflect a region's ability to minimise environmental damage and maximise social welfare given the net value added per UAA.

In our analysis, we consider 147 NUTS2 regions of 18[1] EU countries observed in 2020. Some regions are omitted due to a lack of data. Most significantly, there is missing data on economic accounts, mainly for Italy and Poland, that must be dropped. In other cases, missing data can be imputed. The handling of missing data is shown in Appendix 3. Further, to obtain a more homogenous sample, we omit regions based on two criteria: if the region is geographically outside of Europe and if the region produces less than 200 million EUR of agricultural output in 2020. Table 2.1 displays descriptive statistics for our dataset.

Table 2.1: Descriptive statistics

Indicator	**Min**	**Mean**	**Max**	**SD**
N = 147				
Net value-added (thousands of EUR / UAA)	0.10	0.94	6.63	0.10
Environmental indicators				
GHG (tonnes / UAA)	0.66	3.04	13.23	2.27
Share of conventional farms (% UAA)	0.62	0.92	0.99	0.07
Inverse Shannon diversity	0.011	0.49	1.44	0.21
Ammonia (kg / ha) (**Country-level)**	7.50	23.64	58.50	13.08
Pesticide (Harmonised risk indicator 1) (**Country-level)**	36.00	65.73	137.00	17.48
Nitrate (% of groundwater with high nitrate concentrations, >50mg/l) (**Country-level)**	0.90	16.22	26.70	7.52
Social indicators				
Female farmers (% of total)	0.02	0.14	0.41	0.09
Young farmers (<35 / >65)	0.07	0.86	7.21	1.01
Share of fully educated farmers (% of total)	0.01	0.35	0.92	0.24
Net value added / AWU (thousands of EUR)	0.12	2.04	8.94	1.50
Antibiotics (inverse of g/animal) (**Country-level)**	1.00 *	39.61	73.28	19.26

Note: *Manually imputed to avoid zero-values. UAA: Utilised Agricultural Area. AWU: Annual Working Unit.

2.3.1 *Environmental indicators*

We formulate six indicators from the nine in the ASC, excluding the bird's index due to a substantial lack of data and variations in methodology between countries. Instead, we consider biodiversity indirectly captured through crop diversity and other measures such as intensity,

[1] Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, the Netherlands, Portugal, Rumania, Slovakia, Spain, Sweden

nitrates, and pesticides. Furthermore, we only include one GHG-emission indicator, as the efficiency scores are already measured in relative terms. Additionally, we capture intensity indirectly through the eco-efficiency scores by relating farms' environmental indicators to their economic performance. The more intensively a farm uses inputs generating GHG, ammonia, pesticide and nitrate relative to the value it produces, the lower the EE. This section provides further information on the environmental indicators we include in our analysis.

Crop diversity

Crop diversity is crucial for improving soil quality and enhancing properties such as pH, organic carbon content, and water retention (Feng et al. 2020). The ASC defines crop diversity as the proportion of farms growing at least three different crops, but regional data is unavailable. Instead, we use Eurostat data to assess the utilized agricultural area (UAA) for each crop. To quantify the benefits of crop diversification, we apply the Shannon index, similar to Gómez-Limón et al. (2012) and Sipilainen and Huhtala (2013). We focus on the inverse of this index, subtracting the maximum value from the value assigned to each region. This method yields a metric where a higher score indicates lower crop diversity. The region with the highest Shannon index receives a score of zero, which we replace with the second lowest value to meet the positive value requirement of DEA.

GHG emissions

EU agricultural production is responsible for about 13% of total GHG emissions, where the main source of GHG emissions arising in agriculture are from enteric fermentation and soils (EEA, 2023). By formulating our indicator as total GHG emissions per UAA, we ensure alignment with the value indicator towards which we benchmark performance. We use data from the European Database for Global Atmospheric Research (EDGAR) and include GHG emissions from soil, manure and enteric fermentation. EDGAR provides indicators of sector-specific GHG-emissions using data from international statistics and scientific methods to estimate emissions on a country- and NUTS2 level (Crippa et al. 2021).

Organic farming

There are EU targets to increase the share of organically farmed UAA to up to 25% by 2030 (European Commission 2021). To reach this target, the CAP 2023-27 provides financial support for organic farming through rural development commitments and eco-schemes (European Commission 2022). In the ASC, the indicator for organic farming is defined as the share of the area farmed under organic farming. Data is available on a NUTS2 level through Eurostat. To formulate an indicator of environmental damage generated from a lack of organic farming, we consider the indicator as the share of conventionally farmed areas relative to the total UAA in an area. Thus, the higher the share of conventional farms, the larger the environmental damage.

Ammonia, Nitrates and Pesticides

Three indicators are not available on a NUTS2 level. Thus, we include these on a country level. These indicators are Ammonia emissions, Nitrates and a Harmonised pesticide risk indicator. The ASC includes the amount of total ammonia emissions from agriculture. To be consistent with our EE framework, we consider ammonia emissions per UAA using data from Eurostat. The ASC nitrate indicator is formulated as an index calculated by taking the average nitrogen per litre groundwater from 2000-2002. In our assessment, we want one value to reflect the state in 2020 and thus deviate from the ASC formulation to achieve this. We consider levels of nitrates in groundwater reported at the end of the Nitrates Directive Reporting period 7 (2016-2019), where nitrates are defined in 4 different classes (from high to low concentrations). We use % of high concentrations (>= 50ml/l) as the indicator. Finally, to account for pesticides, we use the harmonised risk indicator for pesticides provided by Eurostat, which is the same indicator included in the ASC.

2.3.2 *Socio-economic indicators*

By benchmarking the social indicators towards net value added per UAA, we consider that regions with higher value tend to have higher social welfare and that regions with higher social welfare are often more productive agriculturally. Specifically, we assume that increased net value added per UAA is associated with improvements in generational renewal, gender balance, farmer education, reduced antibiotic usage, and higher income per Agricultural Workforce Unit (AWU).

Farmer characteristics: Training, gender and age

In the CAP 2023-27, targets are formulated to increase training among farmers, improve generational renewal and increase gender equality among farm managers (European Commission 2022). The EU CAP 2023-27 directs funds to support young farmers and to improve the gender balance in farming (European Commission 2022). Data on these indicators are available on a regional level in the Eurostat database. We consider the share of female farm managers, the share of farmers with full agricultural education and the ratio of young farmers (<35) to farmers over 65 in our SE assessment. (Zagata and Sutherland 2015) previously used the age-ratio indicator to capture the issue of an ageing farming population.

Antibiotic usage

Antibiotic usage can lead to resistance and, thereby, a lack of health treatment options in humans and animals (European Commission 2024b). Besides affecting human health, antibiotic usage is related to animal welfare, where high animal welfare is associated with low antibiotic usage (Nunan 2022). The EU farm-to-fork strategy specifies the target to decrease the usage of antibiotics by 50% in 2030 compared to 2018 (European Commission, 2020). We formulate an indicator where lower usage of antibiotics indicates higher social welfare. We use the same data as the ASC on a country level provided by the European Medicines Agency (EMA), considering grams of antibiotics (except tablets) per livestock unit. To obtain an indicator where a higher value indicates higher welfare, we subtract the value for each country from the maximum value in the sample. To avoid zero values, we add one to the country with the highest antibiotic usage per LU (Poland) to account for the fact that this country delivers low welfare from mitigating antibiotic usage per animal.

Poverty: Income per annual working unit (AWU)

Poverty is a societal issue especially prevalent in rural areas, and low income from farming poses a high risk of poverty and social exclusion (Augère-Granier 2017). The ASC displays statistics over the percentage of the population living at risk of poverty, showing that poverty has decreased over time but that there still is a gap between poverty in rural areas and the full society. However, rural poverty is not solely attributable to agriculture but other societal structures. Thus, to account for agricultural production's contribution to mitigating poverty, we consider the net value added per annual working unit (AWU) employed in agriculture using data from Eurostat on a NUTS2 level. To ensure a fair comparison between countries, we adjust the income to the purchasing power in each country using purchasing power parity (PPP[2]).

2.4 Method

To assess EE and SE, we use DEA to evaluate two separate but interrelated efficiency models - one to assess environmental efficiency (EE) and one to assess social efficiency (SE). The EE model is input-oriented, whereas the SE model is output-oriented. To represent the relation between environmental pressures and value, we can use the formulation by Kuosmanen and Kortelainen (2005) to formulate the damage-generating technology set as *T(z) = {(Z, y); Z can produce y}* assuming n = 1, 2, …, N regions and where Z is a vector of environmental damage and y is the output. Defining environmental damage as inputs used in the production of conventional output is common in the literature (Kuosmanen and Kortelainen 2005; Gómez-Limón et al 2012; Martinsson et al. 2023). Similarly, we formulate a welfare-generating technology set as *T(s) = {(y, S); y can produce S}* where S is the social welfare generated through the production of y, the net value added per UAA. T(s) reflects that the agricultural

[2] We use the comparative price levels within the EU 2020 = 100. The comparative price levels are the ratio between PPP and the market exchange rate for each country. If the value is higher than 100 the country is expensive, if the value is lower than 100 the country is cheap. For most EU-countries, the PPP shows how many Euros one need in that country to maintain the purchasing power of one Euro in the EU on average. Nevertheless, some countries in the EU have not adapted the Euro as their national currency. For these countries, we first adjust the PPP to be expressed in Euro by multiplying the PPP with the exchange rate of the domestic currency in 2020.

sector provides social welfare on a regional level through the production of agricultural goods. The regions providing the highest social welfare relative to the level of net value added per UAA are operating with the highest SE. Previous literature has included social welfare indicators as outputs in a DEA framework (Puggioni and Stefanou 2019; Chambers and Serra 2018). Ait Sidhoum et al. (2020) include social indicators both on the input and output sides.

To ensure comparability between EE and SE, we use interdependency constraints (Boussemart et al. 2020; Dakpo and Lansink 2019; Kapelko et al. 2021) by benchmarking both environmental and social performance towards value added per UAA, denoted y in the technology sets.

We represent DEA in a ratio-form (Coelli et al. 2005; Kuosmanen and Kortelainen 2005). The weights are denoted w and u for the EE and SE models respectively assuming m = 1,…, M different environmental pressures and k = 1,…, K different social welfare indicators:

$$
\begin{aligned}
&\max_{w} EE_n = \frac{V_n}{w_1 z_{n1} + \cdots + w_{\mathrm{M}} z_{nM}} \\
&\text{s.t.} \\
&\frac{V_1}{w_1 z_{11} + \cdots + w_{\mathrm{M}} z_{1M}} \leq 1 \\
&\ldots \\
&\frac{V_N}{w_1 z_{N1} + \cdots + w_{\mathrm{M}} z_{NM}} \leq 1 \\
&w_1, \ldots, w_{\mathrm{M}} \geq 0 \qquad \text{n = 1, …, M}
\end{aligned}
\tag{2.1}
$$

$$
\begin{aligned}
&\max_{u} SE_n = \frac{u_1 s_{n1} + \cdots + u_{\mathrm{K}} s_{1K}}{V_n} \\
&\text{s.t.} \\
&\frac{u_1 s_{11} + \cdots + u_{\mathrm{K}} s_{1K}}{V_1} \leq 1 \\
&\ldots \\
&\frac{u_1 s_{N1} + \cdots + u_{\mathrm{K}} s_{NK}}{V_N} \leq 1 \\
&u_1, \ldots, u_{\mathrm{K}} \geq 0 \qquad \text{k = 1, …, K}
\end{aligned}
\tag{2.2}
$$

V_n is the net value added per UAA for region *n* and $z_{n\mathrm{m}}$ and $s_{n\mathrm{k}}$are the environmental damage *k* and the social welfare m for region *n*. Equations 2.1 and 2.2 optimise the efficiency by finding weights which maximise the eco-efficiency of unit *n* considering *M* different environmental pressures (Equation 2.1) and *K* different social welfare indicators (Equation 2.2). We conduct the analysis in R.

Additionally, we consider metafrontiers and weight restrictions. First, we use metafrontiers to split the full sample of regions into smaller but more homogenous subsamples. Second, we consider weight restrictions in the form of assurance ranges[3] to prevent some indicators from being assigned unreasonably high or low weights. The following subsections elaborate on the model additions.

Finally, we address the issue of outliers. We use super efficiency for outlier detection (Banker and Chang 2006), enabling us to include the same weight restrictions as applied in the analysis.[4] We consider units with an efficiency score higher than the third quartile added to 1.5 times the interquartile range (Q3-Q1) as outliers (Öttl et al. 2023). We categorize extreme observations into two groups: outliers and "special cases." Outliers are regions with super efficiency that fall outside a specified range in all groupings. We identified 11 outliers (1 in EE and 10 in SE), which are excluded from further analysis. "Special cases" are regions considered outliers in some groupings but not others, likely due to unique conditions or exceptional management strategies. Their performance is relevant but not directly comparable to other regions in the dimensions where they are classified as outliers. We omit these special cases from analysis in one dimension and then assess their efficiency in the other dimension.

3 What we in this paper refer to as “Assurance ranges” are in previous studies called “Assurance regions”. We use the term ranges here so as not to confuse it with NUTS2 regions.
4 Previous research points to that super efficiency is a useful method for outlier detection, but that it might not provide consistent ranking of units when assessing efficiency (Banker, Chang, and Zheng 2017; Banker and Chang 2006). Thus, we use super efficiency to detect outliers, but consider traditional DEA bounded between 0 and 1 when assessing the efficiency scores.

2.4.1 *Metafrontiers to increase sample heterogeneity*

DEA requires that the evaluated units perform similar activities and use similar inputs in similar production environments (Dyson et al. 2001). We use metafrontiers to create more homogenous groups of regions with similar exogenous conditions (O'Donnell et al. 2008). The metafrontier methodology involves splitting the full sample into subsets of more homogenous units (O'Donnell et al. 2008). A meta-frontier is estimated considering all units in the sample, enveloping the group frontiers (O'Donnell et al. 2008). The group frontiers enable us to better capture inefficiency arising from management and policy rather than exogenous conditions and how the metafrontier envelops the group frontiers. Figure 2.3 illustrates meta- and group frontiers.

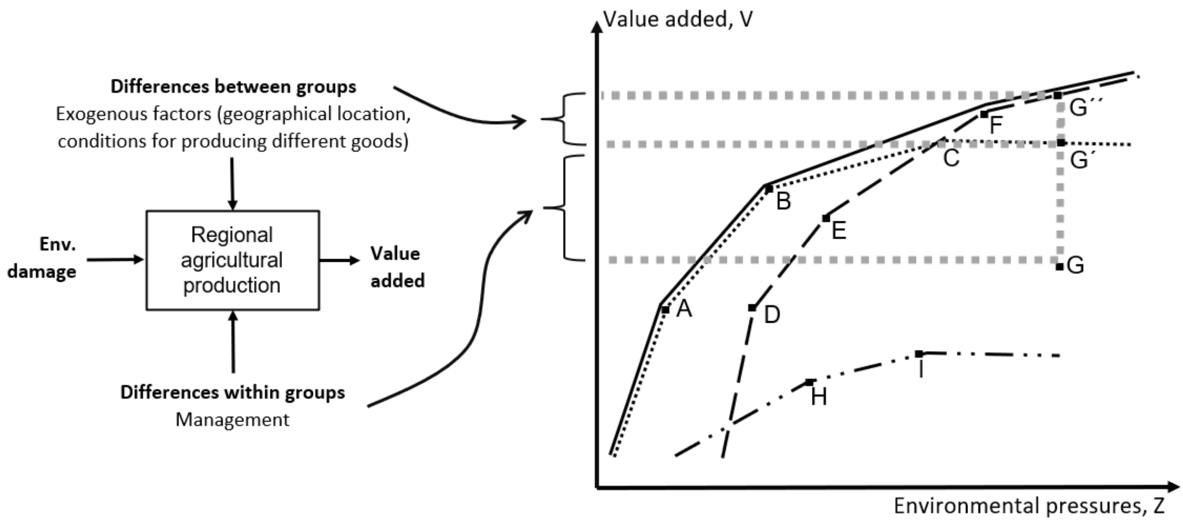

Figure 2.3: Illustration of the metafrontier
Note: the illustration is based on Bianchi et al. (2020) and Beltrán-Esteve et al. (2014). The meta-frontier, illustrated as the solid line, envelops the group frontiers. G is inefficient and belongs to the same group as A, B and C.

We face several options of grouping regions. For example, Bianchi et al. (2020) grouped regions based on population density. Halkos et al. (2015) and Czyżewski and Kryszak (2023) grouped regions based on the country in which they are located. Farm-level evaluations have grouped farms based on different modes of production, such as mountain and traditional plain olive farms (Beltrán-Esteve et al. 2014) or conventional and organic farming (Beltrán-Esteve et al. 2017; Aldanondo-Ochoa et al. 2014). Ideally, we would split our regions into sufficiently large groups where the regions face the same conditions for producing efficiently. In such a grouping, inefficiency would only result from differences in, not exogenous differences. However, such a grouping rarely exists. Instead, we analyse three groupings based on main specialization, population density, and biogeographical zone. Table 2.2 presents an overview of these groups and their observations.

Table 2.2: Overview of grouping

	Criteria	**n**
Specialisation	More than 50% of total agricultural value is derived from livestock.	46
	More than 50% of the value derived from crop production is attributable to arable crops.	60
	More than 50% of the value derived from crop production is attributable to high-value crops.	41
Population*	Rural	64
	Intermediate	57
	Urban	23
Climate**	Continental	65
	Atlantic	42
	Mediterranean	26

Note: *Typology from Bianchi et al. (2020); **Biogeographical zones from EEA

2.4.2 *Weight restrictions*

Efficiency is determined by optimising the weight parameters w and u in the EE and SE assessments, respectively (Equations 2.1 and 2.2). Determining weights within the model is often considered a strength and a weakness of DEA (Kuosmanen and Kortelainen 2005; Theodoridis and Ragkos 2015; Thompson et al. 1990). The drawback is that some indicators can get weighted unreasonably high, while others receive weights close to zero. We want to avoid that some regions can obtain high efficiency by solely focusing on one environmental or social aspect while ignoring the other dimensions. To prevent this, we specify a lower and a higher boundary, an assurance range, which each weight can take on, relative to the weight of a benchmark indicator (Podinovski and Thanassoulis 2007).

When restricting weights in DEA, the indicators should be defined in similar units (Sarrico and Dyson 2004). We follow (Soteriades et al. 2020) and divide each indicator by its standard deviation. To ensure that this standardisation results in weights on the same scale assigned to the pressures and social welfare indicators, we inspect that no weights stand out in size when using standardized variables before applying the weight restrictions.

We specify the assurance ranges to be between 0.1 and 2 for both EE and SE. This means that no pressure (welfare indicator) can receive a weight less than 0.1 or more than 2 times the environmental pressure (social welfare indicator) we specify as the benchmark. We consider the indicator with the highest and most non-zero weights, without any weight restrictions, as the benchmark indicator. For EE, this is GHG/UAA; for SE, this is income per AWU. A more detailed description of the procedure to set assurance ranges together with a robustness check is available in Appendix 2.

2.5 Results and discussion

In this section, we present and discuss the results. First, we discuss the outliers and the special cases, followed by the meta-efficiency and how the different groups compare in their efficiency performance. Finally, we discuss the within-group heterogeneity.

2.5.1 *Outliers and special cases*

Before assessing efficiency, we test the sample for outliers and 'special cases' (Table 2.3). The last column shows the number of regions without special cases and outliers. We identify 11 outliers. We also consider a region as an outlier if it is excluded from the biogeographical grouping (as is the case for regions in Boreal, Pannonian and Alpine areas) and detected as an outlier in the two other groupings.

Table 2.3 Outliers and special cases

Group	Special cases in EE	Special cases in SE	Incl. units
Livestock	3 (NL12, NL31, ES11)	4 (**SK03***, **FRI2**, **AT32***, **FRC2**)	43
Arable Crops	4 (BE31, FRE1, SE22, HR02)	5 (**SK04***, FI1C, **SE12***, **FRF3**, **BG41**, BG34)	56
High-value Crops	1 (**NL33**)	5 (**HR03**, FRK2, FRM0, RO22, ES43)	36
Urban	1 (**NL33**)	3 (CZ02, FR10, EL30)	20
Intermediate	3 (PT15, FRL0, NL34)	4 (**FI1C***, **SE12***, **BG41,** SE23)	50
Rural	6 (EL65, EL61, EL52, EL63, EL53, ES11)	8 (**SK04***, **SK03***, **HR03**, **FRI2**, **AT32***, **FRF3**, **FRC2**, BE34)	57
Continental	7 (DEB3, SE22, FRF1, BE33, FRJ1, DEA1, HR02)	4 (**FRI2**, **FRF3**, **BG41**, **FRC2**)	59
Atlantic	5 (**NL33**, NL32, FRL0, NL42, NL23)	1 (FRJ2)	37
Mediterranean	0	2 (**HR03**, ES43)	25
Total			147

Note: * These regions were identified as outliers when grouped on specialisation and population but were not included in the grouping on biogeographical conditions. The underlined regions are the outliers.

The only outlier in EE is NL33, and the outliers in SE are SK03, SK04, FRI2, AT32, FRC2, FRF3, BG41, HR03, FI1C and SE12. NL33 (South of Holland) has a very high agricultural value per UAA in our dataset, which is more than double compared to the regions with the second highest value for this indicator. This is likely what causes NL33 to come out as an outlier.

The outliers in SE are all among the regions with the lowest value per UAA. Thus, these regions benefit because their social sustainability indicators are related to a very low value per UAA. Additionally, AT32, BG41, and HR03 have a high share of female farmers, and FRC2, AT32, and FRF3 have among the youngest populations farmers. SK03, SK04, FI1C, SE12 and AT32 are omitted from the grouping of biogeographical zones as they belong to zones with only a small number of other observations and are indicated as outliers in the two other subsets. In Appendix 3, we provide Figures to illustrate these statements.

2.5.2 *Metafrontier efficiency*

In the meta-frontier, displayed in Figure 2.4, efficiency is calculated under the assumption of equal operating environments in all regions in the sample (Bianchi et al. 2020). We observe a substantial trade-off between regions with high EE and SE. This result shows that under the assumption of equal operating environments across the sample of EU NUTS2 regions, no region is achieving high efficiency in both EE and SE.

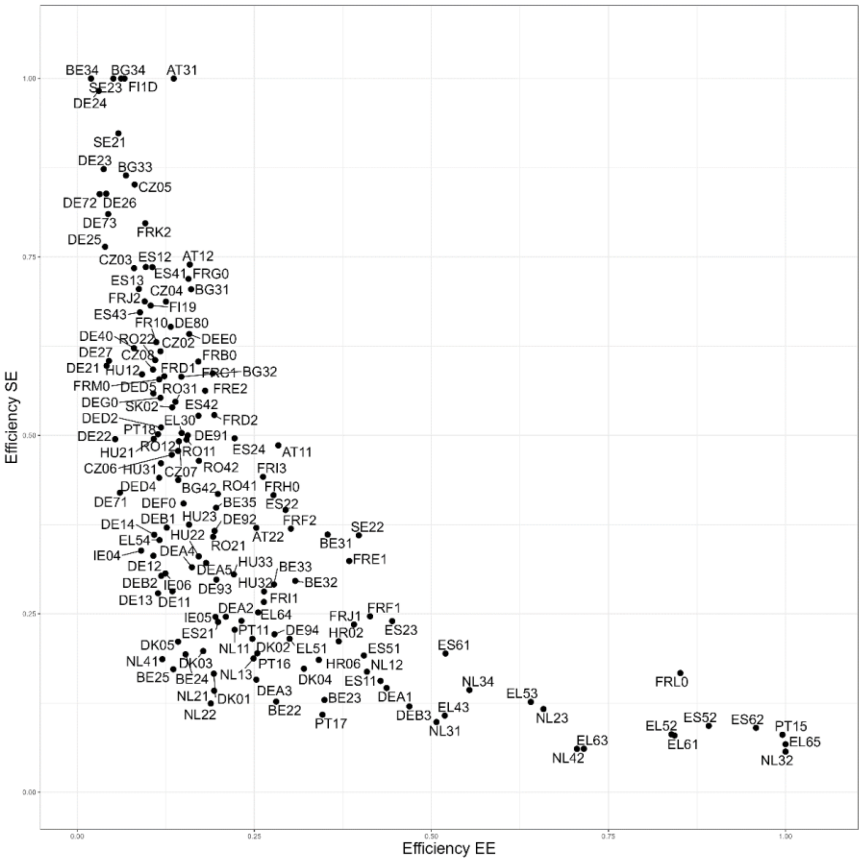

Figure 2.4: Distribution of the efficiency scores in the full sample
Note: EE on the X-axis and SE on the Y-axis

2.5.1 *Group* efficiency

The group efficiency adheres to the assumptions in DEA of comparable units and allows us to evaluate how more homogenous subsets of EU regions balance EE and SE. By comparing group performance to the overall sample, we identify strengths and weaknesses, providing insights for improving sustainability. Before analysing results, Figure 2.5 illustrates how differences between meta-efficiency and group efficiency can be interpreted, with arrows indicating performance shifts. Figure 2.5 serves as a foundation for analysing the results in Figure 2.6.

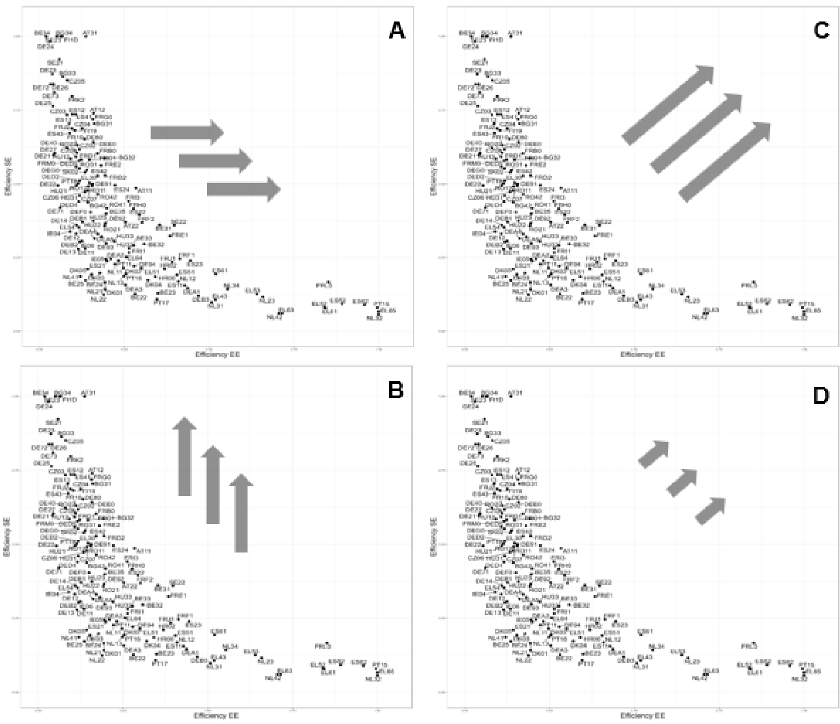

Figure 2.5: Illustration of the interpretation of different shifts compared to the meta efficiency
Note: A and B illustrate the direction of the shift, while C and D illustrate the magnitude of the shift.
A: Such a group would constitute the most socially efficient regions in the full sample.
B: Such a group would constitute the most environmentally efficient regions in the full sample.
C: Such a group faces relatively less beneficial exogenous conditions (there is a large gap between the group- and the meta-frontier, as illustrated with the distance G´G´´ in Figure 2.3).
D: Such a group faces relatively more beneficial exogenous conditions (there is a small gap between the group- and the meta-frontier, as illustrated with the distance G´G´´ in Figure 2.3).

Figure 2.6 illustrates the efficiency scores resulting from the grouping (blue) and the meta-efficiency scores in Figure 2.4 (light grey). We highlight the regions included in each group in black. By comparing the meta efficiency (the black dots) to the group efficiency (in blue), we illustrate how each region improves its relative performance compared to a smaller group of homogenous regions rather than the entire sample. The grey area in Figure 2.6 displays the special case regions assessed separately and only in one dimension.

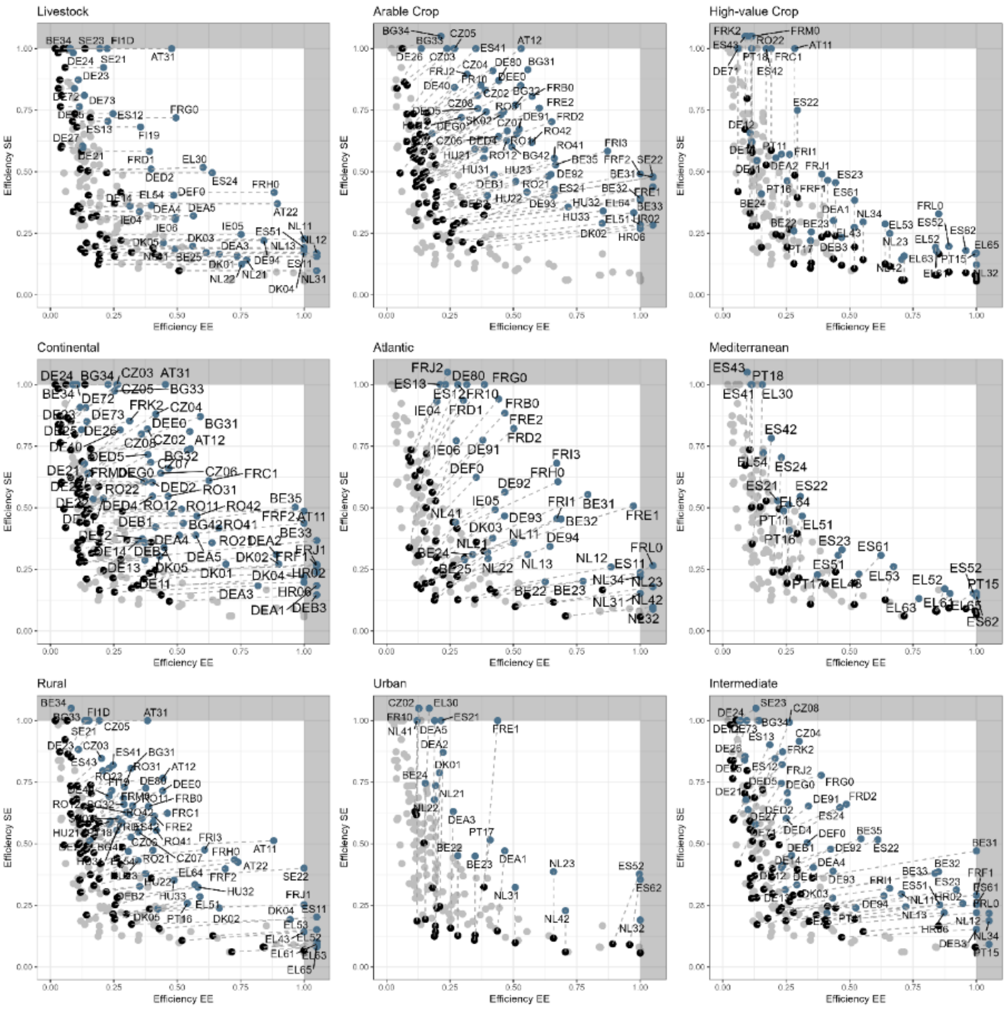

Figure 2.6: Metafficiency scores compared to the different groupings.
Note: The dotted lines illustrate the difference between the meta frontier (black dots) and the group frontier performance (blue dots). The full lines indicate NUTS2 IDs where the observations are too close for the name to be listed next to them for clarity.

Our research aim is to answer how well EU regions balance EE and SE in agricultural production. Figure 2.6 shows that the relation between EE and SE varies, but the trade-off persists in all groups. In the following sections, we discuss the differences between group performance and meta-efficiency displayed in Figure 2.6, followed by an analysis of the within-group efficiency.

2.5.2 *Differences between groups*

In Figure 2.6, the livestock group shift horizontally, indicating that these regions dominate the SE frontier but that no livestock region is on the EE frontier. This implies that given the grouping based on specialisation, there is a difference in the ability of livestock regions and crop regions to produce efficiently; the livestock regions have better capacity in the SE dimension, and the crop regions, particularly the high-value crops, have better capacity in the EE dimension. Thus, livestock production could mitigate damage for a given value when compared to regions specialising in crops, where novel technology could be a solution. Alternatively, there needs to be a shift towards less emissions-intensive production in these regions. Based on specialisation, we can also see a vertical shift in the regions specialising in high-value crop production, indicating that this subset contains the regions on the EE frontier in the full sample but does not contain any regions with full SE in the full sample. Thus, this group of regions need to be targeted with strategies to improve social welfare for the given production level.

When grouping based on biogeographical regions, the difference in performance between groups is not as distinct as when grouping based on specialisation. The Continental and Atlantic regions improve their performance in both dimensions when compared within the respective group. Many Mediterranean regions shift vertically, indicating part of the EE but not of the SE frontier in the full sample analysis. In the groping based on population density, Rural and Intermediate regions shift more horizontally while urban regions shift vertically. In this respect, the urban region displays similarities with the Mediterranean group of regions in providing better conditions for eco-efficient production.

Summarising, there are differences in the joint EE and SE performance between groups of regions indicating different conditions for efficient production. We can conclude that overall, livestock regions could adopt more environmentally sustainable practices, e.g., implementing novel technology to mitigate the environmental impact. On the other hand, regions with the main share of crops need to implement practices or policies that can improve social welfare. We also identify the potential to adapt practices to increase SE in the Mediterranean and urban regions. Overall, these findings provide guidance for interventions targeting system shifts in different regions to overcome the contextual hindrances for environmentally and socially efficient production.

2.5.3 *Within-group efficiency*

We gain insights into the potential for relative efficiency improvements by considering the distribution of efficiency scores within the groups. This corresponds to the example distributions A and B in Figure 2.1. Here, we study the potential for efficiency improvements within the group. Figure 2.7 shows that the heterogeneity in trade-off between EE and SE is higher for the arable crop regions and the continental and Atlantic regions. The lowest heterogeneity in trade-offs is found in Mediterranean regions. On the one hand, this finding implies that in regions specialising in arable crops, the Continental and Atlantic regions might have the largest potential to increase efficiency within the existing production system. On the other hand, the Mediterranean regions show little potential for improving relative efficiency within existing systems, indicating the need for system redesign.

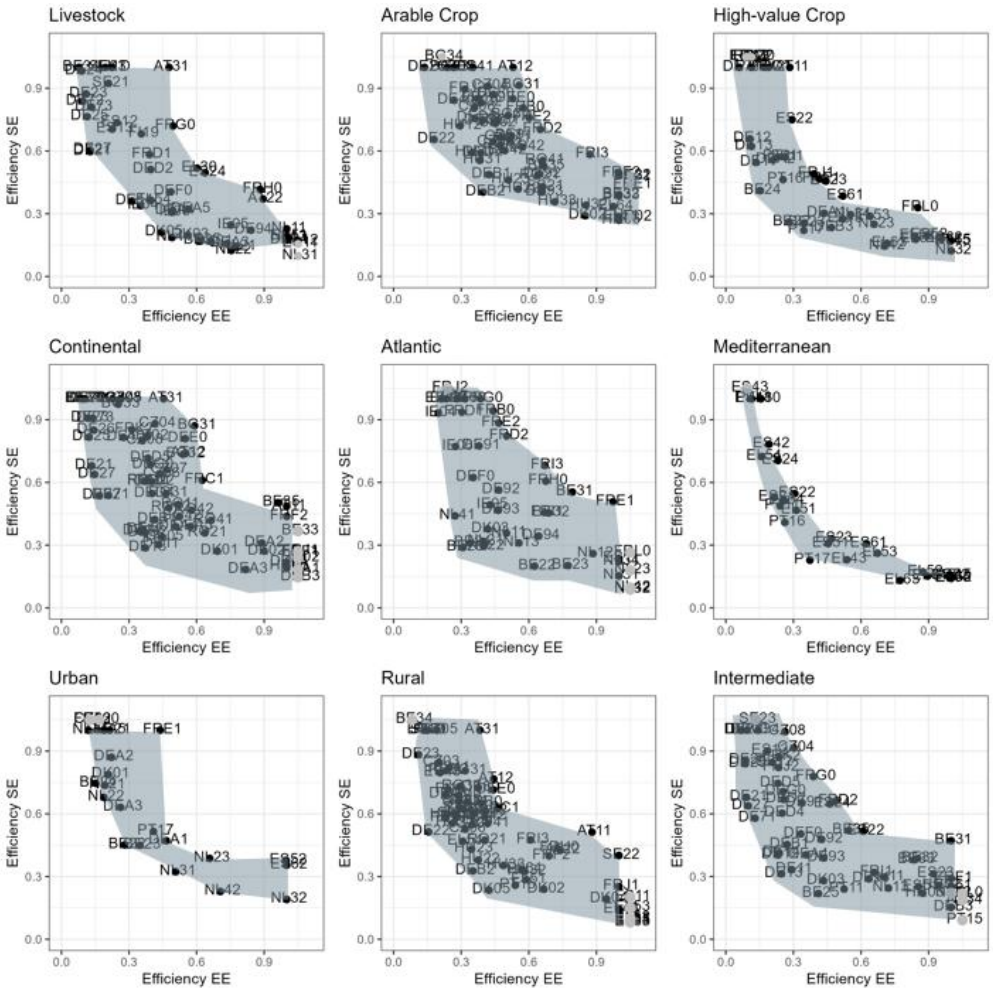

Figure 2.7: Within-group heterogeneity

Note: The grey area is manually marked to improve the visualisation of the potential for improving relative efficiency in the EE and SE dimensions.

The negative correlation between EE and SE is highest among the Mediterranean, high-value crops, and urban regions. Thus, these groups perform poorly in balancing the two objectives of EE and SE, indicating a need for system redesigning to overcome this negative correlation. Based on Figure 2.7, the trade-off appears to be the least prevalent for the Arable, Continental and Atlantic regions. In these groups, some regions achieve efficiencies above 0.5 in the EE and SE dimensions combined. In contrast, no region is observed with joint EE and SE efficiency above 0.5 in the remaining groups.

2.6 Conclusion

This study uses DEA to assess the regional environmental and social efficiency of EU NUTS2 agricultural production. This is the first EU-wide assessment of agricultural production's environmental and social efficiency. We formulate a procedure to jointly assess EE and SE and use the ASC to select indicators. The aim of this study is to provide insights into the joint performance in the EE and SE dimensions in EU regions and thereby identify potential pathways to improve environmental and social sustainability.

A limitation of the used method is that we do not consider absolute environmental damage and social welfare - Efficiency analysis is a relative measure. We show how the sustainability of production can be increased through efficiency improvements. However, as we do not include absolute values, we cannot derive insights into when production can be considered sustainable. Further, our results are influenced by the data availability as we, for some indicators, resort to country-level data. The country-level indicators might benefit some regions and disadvantage others. For example, regions specialising in high-value crops might benefit from the pesticide index being measured at the country rather than the regional level. Nevertheless, we argue that including some indicators on the country level is still better than omitting them completely from the analysis.

We find a trade-off between EE and SE, which persists in all groupings. We conceptualise efficiency as a necessary condition for sustainability. Thus, given our findings of a persistent negative relation between EE and SE, no region can be considered sustainable as no region is operating efficiently in both dimensions. This indicates a need for a transformation of agricultural production to balance efficiency in both the environmental and the social dimensions. To this end, novel technology and novel agricultural production strategies can present ways forward towards mitigating environmental damage by substituting harmful inputs while improving social conditions by, e.g., making the agricultural sector more attractive for a younger and more well-educated generation.

By comparing the group performance to the full sample, we show that performance varies between the groups. For some groups, particularly the Continental, Atlantic, and regions specialising in arable crops, we identify large heterogeneity in the trade-offs between SE and EE. This indicates a potential for increasing efficiency within existing production systems. Thus, policies can be targeted to increase the relative performance of regions lagging behind, considering the high-performing regions in the groups as examples of successful strategies. More concretely, policies can ensure better utilisation of technology and production systems already in place by e.g., supporting information exchange between regions facing similar conditions. However, there is no one-fits-all solution, and the individual conditions of each region need to be considered before providing more specific guidance on how each region should act to improve their relative efficiency.

Future research could further investigate the drivers of efficiency to provide more targeted policy recommendations. Further, future research could couple these findings with absolute environmental damage and social welfare levels by, e.g., computing regional social and environmental boundaries.

Acknowledgement

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2.8 Appendix 1: data processing

The analysis includes 147 NUTS2 regions. Some regions have incomplete data that can be imputed. Table 2.4 provide details to the imputed values.

Table 2.4: Imputed data

Indicator with missing values	Method of deriving or imputing the data	Regions where the value was imputed (total number in parenthesis)
UAA dedicated to different crops (used for the Shannon index).	We subtract the other usages for arable land from the total UAA to derive the missing data.	BG31, BG32, BG33, BG34, BG42, DK01, DK05, ES11, ES21, ES22, ES23, ES62, BE33, IE06, NL31, BE34, RO12, BE31, ES13, PT15, EL63, EL30, IE04, FRM0 (24)
Farmers under 25 (used when computing the farmer age ratio.)	We subtract the other age-categories from the total number of farmers to derive the missing data.	BE31, NL23 (2)

Total agricultural output, output of livestock products, and output of crop products are used as inclusion criteria when categorising regions based on specialisation.	We impute this indicator by using the values of 2021, where 2020 is missing.	FI19, FI1D (2)
Net value added is used as the economic indicator in EE and SE.	We impute this indicator by using the values of 2021, where 2020 is missing.	BE22, BE23, BE24, BE25, BE31, BE32, BE33, BE34, BE35, FI19, FI1D (11)

2.9 Appendix 2: robustness check

Weights in DEA are typically distinguished between relative and absolute (Podinovski and Thanassoulis 2007). We use relative (homogenous) weight restrictions, enabling including subjective weights without introducing bias in the efficiency scores (Podinovski and Thanassoulis 2007). Furthermore, relative weight restrictions can be separated between linked and unlinked. We use unlinked weight restrictions, commonly referred to as Assurance ranges of type I (AR1) (Podinovski 2015; Thompson et al. 1990; Cooper et al. 2011). We use AR1 weight restrictions formulated as:

$$L_i \le \frac{w_i}{w_1} \le H_i$$

$$l_r \le \frac{u_r}{u_1} \le h_r$$

L_i (l_r) and H_i (h_r) represent the lower respectively higher boundary for weight of environmental pressure *i (*social welfare indicator *r)* relative to the weight of environmental pressure (social welfare indicator) 1. Figure 2.8 and Figure 2.9 presents the robustness check results for varying benchmark indicators. We consider the other indicators at the regional level as potential benchmarking indicators.

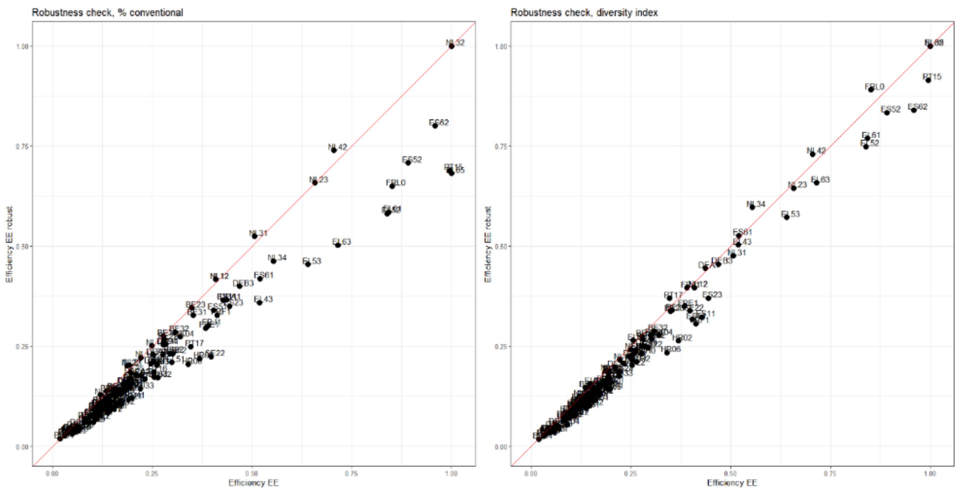

Figure 2.8: Robustness check, EE

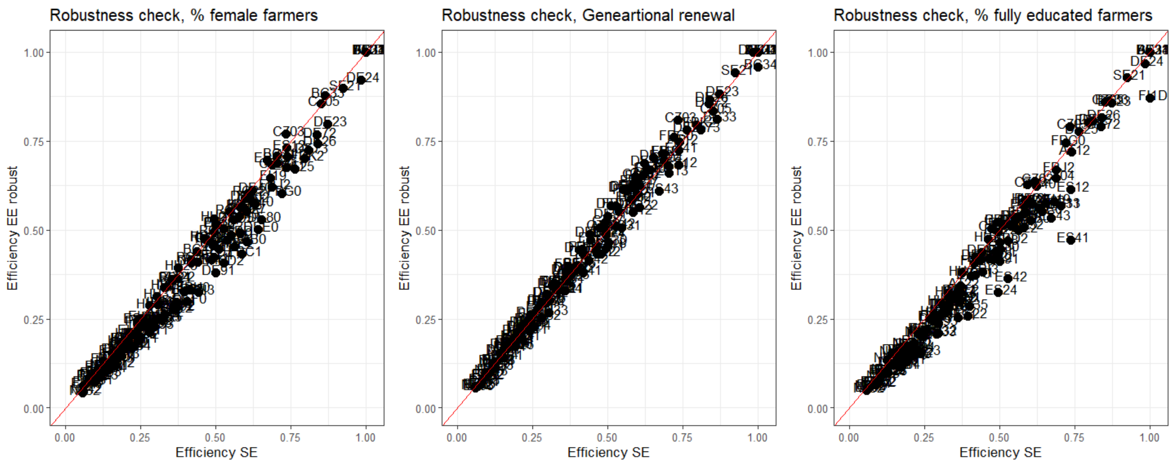

Figure 2.9: Robustness check, SE

Finally, we consider the efficiency with and without including weight restrictions. As seen in Figure 2.10, efficiency scores are higher for some regions when weights are allowed to vary freely. These regions are putting high emphasis on one environmental pressure or social welfare indicator, and thus when restricted to include strictly positive weights for all indicators, the efficiency scores of these regions become lower.

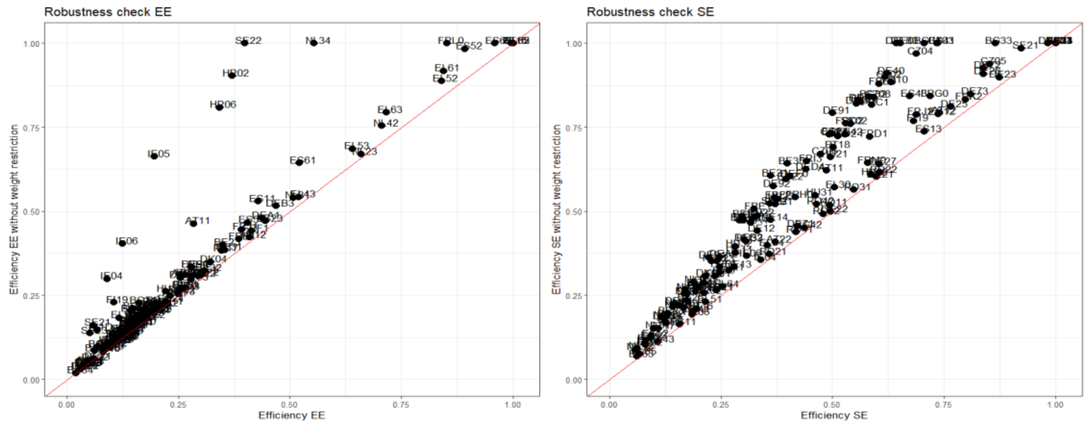

Figure 2.10: EE and SE with and without weight restrictions

Note**:** The left panel displays the EE and the right panel the SE. The y-axis displays the efficiency scores without using any weight restriction, and the x-axis displays the efficiency scores with the weight restrictions.

2.10 **Appendix 3: outliers**

In this Appendix, we provide Figures to back up our claims regarding why these regions come out as outliers as we discuss in Section 2.5. The outlier in EE is NL33. Figure 2.11. shows the value per UAA for NL33.

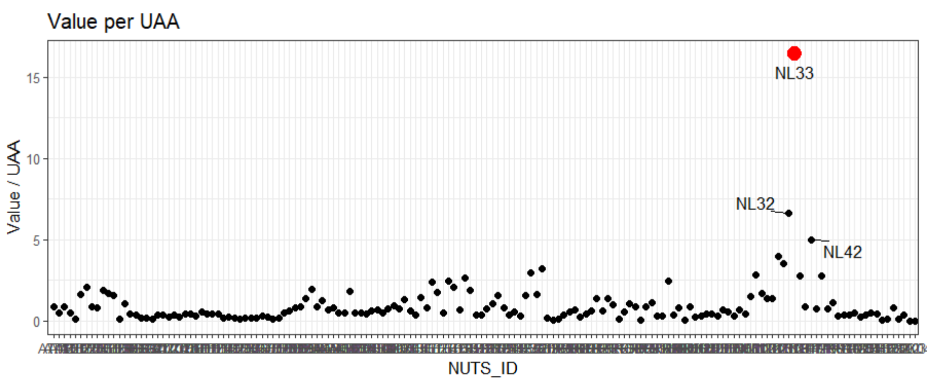

Figure 2.11: Outliers in value per UAA

The outliers in SE are AT32, BG41, FI1C, FRC2, FRF3, FRI2, HR03, SE12, SK03, SK04. These regions are all among the regions with the lowest value per UAA. Figure 2.12 illustrates this, limiting the y-axis to only range up until 2.5 million EUR per UAA to enable distinguishing the different regions with the lowest value per UAA.

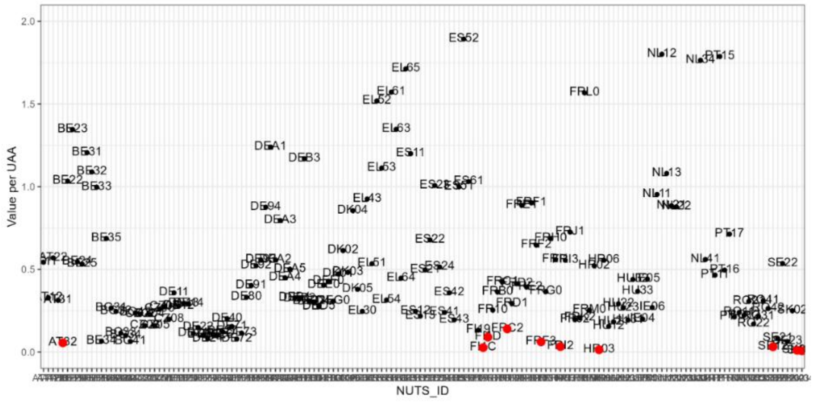

Figure 2.12: Outliers in the SE dimension, value per UAA

Figure 2.13 shows the share of female farmers, generational renewal, share of fully educated farmers and the inverse antibiotic usage divided by value per UAA. Income per UAA is not plotted, as this indicator does not exhibit unusually high scores among the outlier regions.

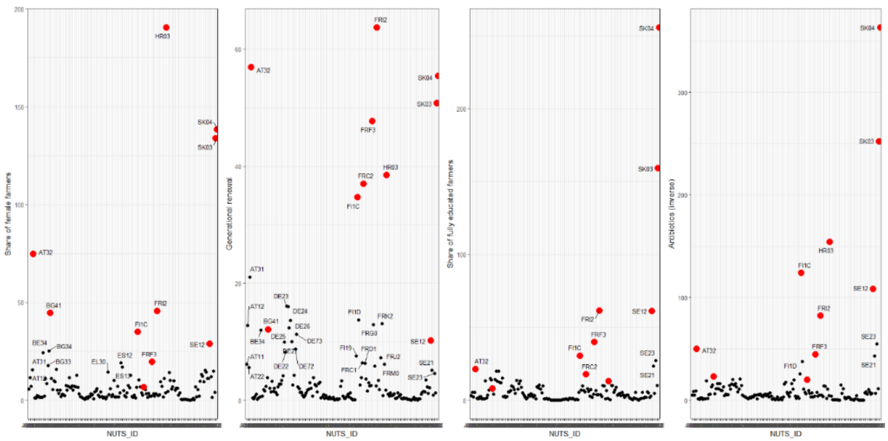

Figure 2.13: Outliers in SE dimension, social indicators

Chapter 3
Evaluating environmental effects of adopting automatic milking systems on Norwegian dairy farms[1]

Abstract: We present a novel procedure based on eco-efficiency for assessing farm-level effects of technology adoption while considering secondary effects. Secondary effects are defined as structural and behavioural adaptations to technology that may impact environmental, social or economic outcomes. We apply the procedure to automatic milking systems (AMS) in Norway and find that AMS induces secondary effects, most strongly by decreasing labour per cow and increasing herd sizes. For estimating effects of AMS we employ a novel causal machine learning approach. AMS induce heterogenous effects on eco-efficiency, negatively associated with herd expansion and labour per cow.

Keywords: eco-efficiency, automatic milking robots, Norway, agricultural innovations

3.1 Introduction

Technical improvements at the farm level are one crucial path to improved environmental sustainability (Messerli et al. 2019). However, new technologies may induce additional changes that positively or negatively affect environmental outcomes. Overlooking these effects increases the risk that novel technologies lead to maladaptation (Pörtner et al. 2022). We refer to these changes as 'secondary effects', defined as structural and behavioural adaptations to novel technology, which may impact environmental, social or economic outcomes. It is crucial

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to consider secondary effects when assessing how (novel) technology affects farm sustainability. Awareness of secondary effects enables steering technology adoption and usage through regulatory changes or technological advancements to promote sustainable development. Yet, secondary effects are often overlooked when assessing farm-level effects of novel technology in terms of economic or environmental impacts. Previous literature has indicated secondary effects of, for example, smart farming technologies on the likely responsiveness to greenhouse gas (GHG) taxes (Schieffer and Dillon, 2015), the social impacts of GHG mitigating policy (Harrison et al. 2021) or as rebound effects where efficiency improvements can lead to increased resource usage (Herring and Roy, 2007; Sears et al. 2018; Paul et al. 2019). Smart farming technology is predicted to improve the sustainability of agriculture (Balafoutis et al. 2017; Duckett et al. 2018; Finger et al. 2019). Nevertheless, as the extensive usage of most smart farming technologies and robotics still lays in the future, empirical evaluations are scarce (Lieder and Schröter-Schlaack, 2021), and the inclusion of secondary effects is rare.

As European agriculture accounts for approximately one-tenth of global GHG emissions (FAO, 2020), the technological development must contribute to lowering this environmental impact. One type to robotic technology that is already widely adopted by farmers are automatic milking systems (AMS) which provide an interesting study case for secondary effects. In the livestock sector, accounting for a large share of agricultural GHG emissions, there is considerable potential for mitigating emissions by reducing the emission per unit of product (Mbow et al. 2019). In dairy farming, one way to reduce emissions per unit of product is to increase the milk yield per cow (Zehetmeier et al. 2012), which can be achieved by adopting more efficient technology, such as AMS. One of the countries with the highest implementation of AMS is Norway. In 2018, cows milked with AMS produced 47 per cent of the milk (Vik et al. 2019). In 2020, this had increased to 57 per cent (Mikalsen et al. 2021). Norwegian farmers adopt AMS to increase their work-time flexibility and thus quality of life, and to reduce farm labour requirements (Hansen, 2015; Stræte, Vik and Hansen, 2017; Vik et al. 2019). However, previous studies have also indicated that AMS adoption in Norway is coupled with structural changes on farms, specifically farm expansion (Vik et al. 2019; Rønningen et al. 2021). AMS has also been found to be associated with changes in feeding patterns towards more high-energy feed (Bijl et al. 2007; Oudshoorn et al. 2012; Schewe and Stuart, 2015) and less grazing allowing for cows to be milked more frequently (Oudshoorn et al. 2012; Gołas et al. 2020; Lessire et al. 2020). Furthermore, using AMS is associated with increased energy consumption (Steeneveld et al. 2012). Consequently, AMS can generate secondary effects as it is coupled with several farm-level changes. The implications of those changes for farms' environmental performance, particularly GHG emissions, remain an open question. To this background, the question arises of how AMS relate to farms' structural development and environmental performance.

In this paper, we provide novel insights on the effects of AMS adoption on farm-level environmental performance, specifically focusing on the effects of AMS on GHG emissions efficiency. GHG emissions efficiency refers to an eco-efficiency measure focusing specifically on GHG emissions as the environmental outcome (Stetter, Wimmer and Sauer, 2022). Eco-efficiency is expressed as a ratio between value-added and indicators for GHG emissions. Integrating economic and environmental factors into one efficiency measure is crucial to managing trade-offs between environmental objectives and production (Huppes and Ishikawa, 2005). Using data envelopment analysis (DEA), scores are generated describing farms' ability to produce output while inducing minimal environmental damage (Kuosmanen and Kortelainen, 2012). We aim to assess what structural and behavioural factors can be identified as secondary effects of AMS adoption and how this affect farms' GHG emissions efficiency. Our aim is formulated as two research questions:

1) What structural and behavioural factors can be identified as secondary effects of AMS adoption?
2) Does AMS adoption generate changes in farms' GHG emissions efficiency, which can be associated with the structural and behavioural changes?

We contribute to the literature evaluating the secondary effects of AMS through our empirical results. The procedure we provide in this paper can also be applied in other settings when evaluating the secondary effects of novel technology. Using our novel approach, we combine results on how AMS generate secondary effects with results on how AMS induces changes in GHG emissions efficiency. Linking AMS adoption to eco-efficiency is already a novel contribution. This allows to understand the secondary effects of AMS adoption in the form of structural and behavioural changes and in terms of farms' environmental performance. By attributing the effect of AMS on GHG emissions efficiency to the identified secondary effects, insights for policy and extension can be provided on what aspects to target to achieve sustainable development of farms when adopting AMS.

We find that AMS adoption is associated with increased herd sizes, increased share of feed concentrates and increased milk yields per cow. Further, we find largely heterogenous effects of AMS adoption on GHG emissions efficiency with a negative effect on average. The effect of AMS adoption on GHG emissions efficiency highlights the importance of evaluating how new technology affects farms environmental outcomes.

The remainder of the paper is organised as follows: First, we present our novel procedure to evaluate secondary effects of novel technology and the methodologies we use. Second, we present the dataset we use to conduct the empirical evaluation. Third, we present the findings, and discuss the conclusions that can be drawn from using this approach in the context of Norway and AMS adoption. Finally, we provide some suggestions for future research.

3.2 Method

We employ a novel four-step procedure to identify structural and behavioural factors as secondary effects of AMS and to assess whether AMS adoption generates changes in farms' GHG emissions efficiency which can be associated with the structural and behavioural adaptations. An illustration of this procedure is provided in Figure 3.1.

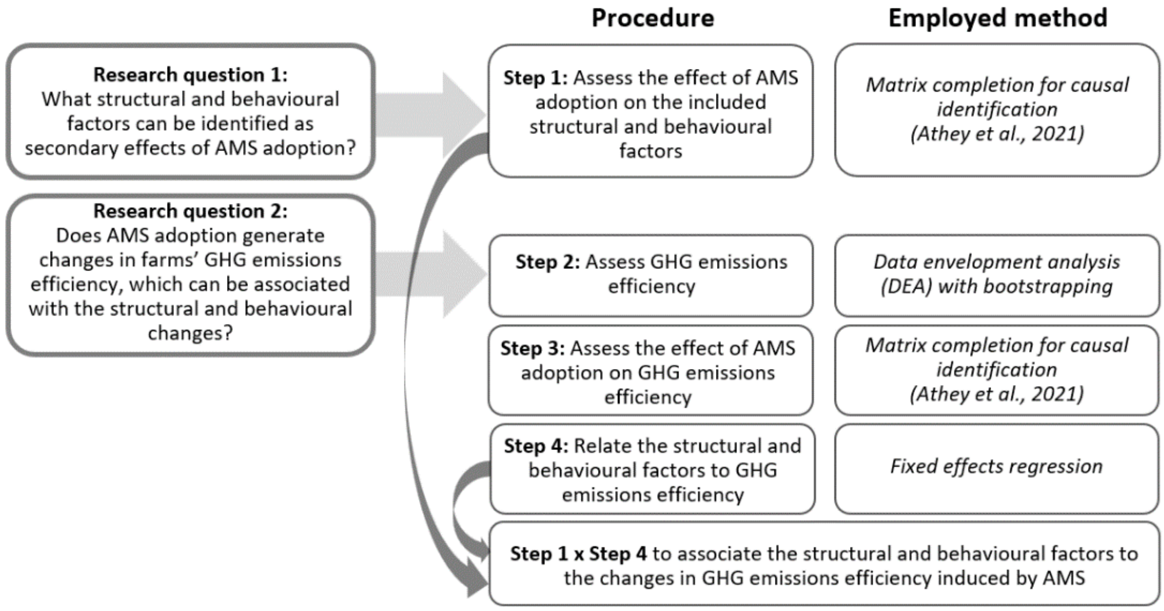

Figure 3.1: Summary of the four-step procedure applied in this paper
Note: The Figure describes what is done in each step and which method is employed

In steps one and three, we assess the effect of AMS adoption on structural and behavioural factors and on GHG emissions efficiency, respectively. We identify six factors as important in terms of AMS adoption and GHG emissions efficiency based on previous research. These factors are labour per cow, number of cows, share of feed concentrates, arable land per milk output, milk per cow and off-farm income. To assess GHG emissions efficiency we include value-added, energy consumption, fertiliser consumption and enteric fermentation. We present these variables and motivate their inclusion in Section 3.3. We obtain the effect of AMS adoption on each of the factors by calculating their counterfactual development if the farms had not adopted AMS by using a matrix completion approach by Athey et al. (2021). From this counterfactual, we can calculate an average treatment effect for the treated (ATT). The advantage of the matrix completion approach is that it basically performs a matching based on the pre-treatment trend, for example matching adopting farms that grow in herd size prior to adoption to non-adopting farms with similar growth in herd size. Additionally, it allows for controlling of individual time-invariant unobserved factors as well as time individual-invariant factors, similar as a fixed effects (FE) regression. Nevertheless, it is important to underline the possibility of reverse causality between the factors and AMS adoption. For example, we cannot detangle if the motivation to increase herd size leads to adopting AMS or if the availability of AMS motivates a farm to increase herd size. Similarly, AMS adoption might increase value-added, which would affect farms' GHG emissions efficiency, but it might also be that changes in value-added make adoption affordable. Our approach cannot resolve this potential reversed causality, which is also conceptually difficult to detangle. However, by matching observations on pre-treatment development, we can compare farms on a similar development trajectory. Further, even if adopting AMS is part of an expansion or intensification strategy, if AMS allows the farmer to realise this strategy is already a secondary effect according to our definition. Nevertheless, we are careful in concluding directions of causality. Another aspect to consider is that the factors included as potential secondary effects likely interact. We do not account for these interactions when assessing the effects of AMS adoption as we want to obtain estimates of the changes in each factor independently. However, in the OLS regression (step four), the interaction between the factors is controlled for to enable explaining the changes in GHG emissions efficiency.

For our second question, regarding how AMS adoption affects GHG emissions efficiency and whether we can associate this to the secondary effects identified in step one, we employ steps two to four. In step two, we assess farm-level GHG emissions efficiency using the methodology developed by Kuosmanen and Kortelainen (2005). Previous evaluations of efficiency in livestock farming focusing explicitly on GHG emission include the works of Dakpo et al. (2017) and Stetter et al. (2022). In the fourth step, we determine which variables correlate with

GHG emissions efficiency using linear OLS regression. Finally, we seek to identify how the factors we identify as secondary effects can be associated with the relation between AMS adoption and GHG emissions efficiency. We multiply the effect of AMS adoption on each factor as assessed in step one with the marginal effects obtained in the regression in step three. This indicates how structural and behavioural change can explain the changes in GHG emissions efficiency generated by AMS adoption. We dedicate the rest of this section to outlining the details of the methods applied in each step of our procedure.

3.2.1 *Steps one and three: assessing the impact of automatic milking systems*

In steps one and three, we evaluate the effects of AMS on the structural and behavioural factors and GHG emissions efficiency. In these steps, we require a method to deal with unbalanced panel data and staggered adoption. For this, we rely on a novel machine-learning approach in line with an increasing stream of literature in recent economic research that has also turned to machine learning for causal questions (Storm et al. 2019). Specifically, we employ a matrix completion approach for causal panel data models (Athey et al. 2021) that allows estimating a treatment effect in cases of staggered adoption and an unbalanced panel dataset. This approach can be seen as nesting a two-way fixed effect approach with synthetic control approaches (Abadie and Gardeazabal, 2003). The two-way FE allow to control for time-invariant as well as unit-invariant unobservables. The synthetic control approach constructs a synthetic counterfactual by matching on pre-treatment trends over time. Specifically, the approach considers treatment effect estimation as a missing data problem, where we lack the counterfactual outcomes that need to be predicted in order to compute treatment effects. In the matrix completion approach, the missing counterfactual observations are predicted by learning a low-rank representation of the observed non-treated outcomes using nuclear norm regularisation (Athey et al. 2021). Based on this low-rank representation, the counterfactual observations can be predicted. As the approach nests the FE and the synthetic control approach, it allows to combine both and determine their relative weighting in a data-driven way. Previously, researchers needed to decide a priori which of the two approaches to use.

The matrix completion method allows for including time- and farm-specific covariates, which are utilised in this paper. Including time- and farm-specific covariates adds to the FE already included in the model as it allows to account for the interaction between farm and time fixed factors. For example, being located in a remote region (a farm-fixed covariate) while diesel prices rise (a time-fixed covariate) might play a role in the effect of AMS on GHG emissions efficiency and is considered by adding the covariates. The included farm characteristics are a binary indicator for adoption, the farmer's year of birth, the farm's location and the year of AMS adoption (set to zero for non-adopters). Furthermore, we include 370 agricultural input and output prices (The Budget Committee for Agriculture, 2022) as time-specific variables, such as prices of various crops and vegetables, livestock and livestock products (such as milk) and inputs like fertiliser and subsidies. One advantage of the approach is that it uses regularisation to avoid overfitting, allowing to include a larger number of control variables.

Having derived counterfactual outcomes for adopting farms if they did not adopt AMS, we estimate the average effect of treatment for the treated (ATT) as: $\tau = \sum_{i,t:\, W_{it}=1}[Y_{it}(1) - Y_{it}(0)] \,/\, \sum_{i,t} W_{it}$ if a farm has adopted and $W_{it} = 0$ otherwise. $Y_{it}(1)$ is the observed outcome for the observations with AMS, and for $Y_{it}(0)$ we estimate their counterfactual outcome as $Y_{\bar{it}}(0)$. Finally, we calculate the difference between the realised outcome and the counterfactual for each observation to gain insights on the distributions of the effects.

To increase transparency of the results and to provide an understanding of how this method compares to more commonly used econometric procedures, we conduct a two-period propensity score weighted difference-in-difference (PS-DID) regression and a FE regression in Appendix 1.

3.2.2 *Step two: assessing GHG emissions efficiency*

We assess GHG emissions efficiency, a measure of eco-efficiency only considering indicators for GHG emissions. Throughout this section, we use the term 'eco-efficiency' when describing the procedure, as this is the most commonly used terminology. Eco-efficiency considers farms' ability to minimise the environmental damage caused at 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). Thus, it is a relative measure where eco-efficiency is achieved when production compensates the environmental harm it generates with sufficient value-added. What is considered sufficient value-added is determined by the structure of the sample, with the most eco-efficient farms having the highest ratio of economic value to environmental damage. Thus, if observations are added to a sample, the eco-efficiency of an individual unit can change if the efficiency frontier is affected. Although this paper focuses on GHG emissions, Kuosmanen and Kortelainen's (2005) approach has the potential to simultaneously examine multiple environmental factors. Another term for eco-efficiency is sustainable intensification (Firbank et al. 2013; Gadanakis et al. 2015; Smith et al. 2017). The most common application of eco-efficiency in agriculture is at the farm-level (Zhou et al. 2018), which is the focus of this paper. The definition of an eco-efficiency only focusing on GHG emissions as 'GHG emissions efficiency' was initially made by Stetter et al. (2022).

We use DEA (Charnes et al. 1978) to assess eco-efficiency, followed by bootstrapping of the efficiency scores to reduce sample bias (Simar and Wilson, 2000). DEA is a deterministic approach that evaluates each unit towards an efficiency frontier constructed from the most efficient units in the sample. Following the approach by Kuosmanen and Kortelainen (2005), our analysis rests on the assumption of a pollution-generating technology set which states that 'value-added v can be generated with environmental damage z'. We consider that this pollution-generating technology set can improve over time, such that more value-added can be generated with less environmental damage, by assuming irreversible technical change. The assumption of irreversible technical change is based on the rationale that the technology available in each year consists of the technology in previous years and new technology developed in the year under evaluation (Lansink et al. 2002). This assumption implies that observations are only compared to other observations with at least as good technology as themselves. Thus, observations of farms in earlier years can have the opportunity to achieve higher efficiency, despite not having access to as advanced technology as the observations made in later years. Practically, this is implemented by including all observations in the current year and all previous years in the comparison group when computing the eco-efficiency (Lansink et al. 2002). Apart from implementing the assumption of irreversible technical change, the same methodology as in previous papers using cross-sectional observations can be applied (Gómez-Limón et al. 2012; Martinsson and Hansson, 2021; Pérez Urdiales et al. 2016).

Following the notation used by Kuosmanen and Kortelainen (2005), we express the eco-efficiency for farm n as $EE_n = V_n / D(Z_n)$, where V_n denotes the value-added and $D(Z_n)$ is a damage function of the environmental pressures Z of farm n. The function D of the M environmental pressures for farm n can be approximated linearly as $D(Z_n) = w_1 z_1 + w_2 z_2 \ldots + w_M z_M$, where there are z_M environmental pressures, each with its own weight w_m. Weights are determined using DEA to produce the highest eco-efficiency score possible for each observation. The inverse of the maximisation problem is calculated to obtain linearity:

$$\begin{aligned}
&\min_w EE_n^{-1} = w_1 \frac{z_{n1}}{V_n} + \cdots + w_M \frac{z_{nM}}{V_n} \\
&s.t. \\
&w_1 \frac{z_{11}}{V_1} + \cdots + w_M \frac{z_{1M}}{V_1} \geq 1 \\
&\ldots \qquad (3.1) \\
&w_1 \frac{z_{N1}}{V_N} + \cdots + w_M \frac{z_{NM}}{V_N} \geq 1
\end{aligned}$$

We evaluate (1) for each year subsetting the data such that the observations are compared to observations made in the same year or in previous years. That is, when evaluating farms observed in 2013 (our earliest year of observation), we only compare these to other observations made in 2013. Evaluating farms in 2014, we include observations from 2013 and 2014, and so on. Eco-efficiency is measured against a frontier estimated from the sample, where the addition or omission of observations may alter the frontier and, consequently, the farms' estimated efficiencies. Eco-efficiency is a further development of assessing technical efficiency. Thus, this paper's eco-efficiency formulation corresponds to an input-oriented Farrell (1957) efficiency model, with environmental pressures as inputs and value-added as the only output (Bonfiglio et al. 2017). Furthermore, the method utilised in this paper is based on a radial assumption, which can be a limitation in a short run perspective if not all variables can be varied at the same rate. Nevertheless, with a longer time frame, this assumption becomes more feasible.

Using bootstrapping, pseudo samples are generated from which efficiency estimators are derived. From this, Monte Carlo realisations of the estimated efficiency can approximate the bias. The final step is calculating bias-corrected efficiency scores by subtracting the bias from the estimated efficiency. The bootstrapping is done as a Shephard input distance function (Simar and Wilson, 1998; Bogetoft and Otto, 2022). Following Simar and Wilson (1998), we set the number of bootstraps in this application to 1,000. Furthermore, DEA is sensitive to outliers in the data, and it is common to drop observations identified as outliers (see e.g. Latruffe and Desjeux (2016); Weltin and Hüttel (2019)). Applying the procedure by Wilson based on log-ratios, we identify seven observations as outliers. By inspecting the data, we cannot find anything atypical about these observations identified as outliers that would indicate mistakes in the data recording. Thus, we chose to keep all observations.[2] The eco-efficiency scores are generated using the R software, and the package Benchmarking (Bogetoft and Otto, 2011) which draws heavily on the FEAR package (Wilson, 2008).

V and Z values in equation (3.1) must be positive to obtain a finite solution. This is known as the DEA's positivity property (Bowlin, 1998). Thus, we replace values of Z that are zero or less with a small arbitrary number (Bowlin, 1998). Farms with negative V values are omitted from the analysis because they would generate eco-efficiency scores close to zero. Thus, we remove one farm with negative value-added. Meanwhile, energy and fertilisers both exhibit negative values for environmental pressures. This indicates that nothing was consumed of that

[2] We run the analysis without the outliers and find only minor changes in the results which do not change any of the conclusions drawn in this paper.

indicator that year, which encourages the replacement of a small number to enable computation of the farm's eco-efficiency for that year.[3]

3.2.3 *Step four: assessing the association between GHG emissions efficiency and the structural and behavioural factors*

We use a FE regression to assess the drivers of the GHG emissions efficiency. This constitutes the fourth step in our procedure (see Figure 3.1) and allows us to establish a connection between the changes in secondary effects and those in GHG emissions efficiency. A set of factors with hypothesised relationship to AMS adoption and GHG emissions efficiency are included in a linear regression as

$$GHG\ emissions\ efficiency_i = \alpha_i + \gamma_t + \sum_{n=1}^{N} \beta_n (factor_n)_{it} + \varepsilon_{it} \tag{3.2}$$

where α and γ are farm- and year-FE, respectively. The result from this step shows the marginal effect of each factor on GHG emissions efficiency. We use the results to link the GHG emissions efficiency to the factors included as potential secondary effects of AMS. A FE approach allows us to control for unobserved farm- and time-invariant heterogeneity, which is beneficial as we want to use the result of Equation 3.2 to assess how farms' GHG emissions efficiency changes through potential changes in the factors. However, it comes at the cost that only within-variation can be exploited for identification, producing less precise estimates. An alternative to including FE would be to pool the observations in a cross-sectional regression. This would increase the estimation efficiency and enable using all data rather than only the within-variation, but would not provide estimates on within changes on farms.

Theoretically, linear regression can be used to explain DEA efficiency scores (Hoff, 2007; McDonald, 2009). DEA scores are bounded between 0 and 1. However, by applying a bootstrapping procedure, few farms are evaluated as fully efficient (obtaining a score of 1) and

[3] 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. We conduct the analysis also dropping these observations finding that this does not change the eco-efficiency results significantly.

thus fewer corner solutions are realised, which further supports the usage of OLS. As argued and further explained by Hoff (2007) and McDonald (2009), DEA scores are best described as fractional data generated from a normalisation process rather than censored data for which a Tobit model would be appropriate. However, using OLS in the second stage has also drawn criticism due to the efficiency scores' serial relationship (Simar and Wilson, 2007). The method proposed by Simar and Wilson (2007) tends to generate similar results as linear OLS regression when explaining eco-efficiency (Latruffe et al. 2008). Banker and Natarajan (2008) demonstrated that two-stage DEA provides a consistent estimator when data are generated by a monotone increasing and concave production function, further supporting the use of OLS regression in the second stage. OLS regression also has the advantage of being widely used and recognised by many, which offers an advantage in transparency and understandability, as also pointed out by McDonald (2009). Nevertheless, as Tobit regression has also been pointed out as a feasible method for this purpose (Hoff, 2007), we conduct a Tobit regression as a robustness check to the OLS. The Tobit is displayed in Appendix 2, and the results are close to what we obtain with the OLS.

3.3 Data and descriptive statistics

We focus on conventional dairy farms using the Norwegian account results in agriculture and forestry, comparable to the EU's Farm Accountancy Data Network, between 2013 and 2019. The dataset includes information on AMS usage, providing a unique opportunity to study AMS usage at the farm level. The dataset is an unbalanced panel. We filter the data such that farms adopting AMS are all observed for at least one year before adoption, allowing the time of adoption to be determined. Thus, our analysis includes 273 farms that did not adopt AMS and 47 that adopted AMS between 2014 and 2019, adding up to 1,594 observations. Table 3.1 presents some descriptive statistics for each variable used in the analysis splitting the data between farms adopting AMS before and after adoption and non-adopters. Table 3.1 distinguishes between structural and behavioural factors and the variables used to calculate

GHG emissions efficiency. We deflate value-added and off-farm income to 2015's consumer price index (Totalkalkylen, NIBIO).

We can obtain some first indications of the effects of AMS by testing whether there are differences in means between the farms before compared to after adopting AMS. We test for differences in means using a two-sample t- test after concluding normality using QQ plots. We do not find strong evidence to reject the null hypothesis of equal means for energy consumption, fertiliser usage and off-farm income. For the other variables, the null hypothesis can be rejected. This indicates changes after AMS is adopted and motivates further investigation.

Table 3.1: Variable description and descriptive statistics

	Adopters, before AMS (n=138)		**Adopters, after AMS (n=136)**			**Non-adopters (n=1320)**	
	Mean	Sd	Mean	Sd	P-values of two-sample t-test	Mean	Sd
Structural and behavioural factors							
Labour per cow *(hours per head)*	137.19	42.837	102.62	32.764	0.000***	182.6	66.303
Milk per cow *(100 litre output per head)*	68.43	9.49	74.31	9.97	0.000***	67.22	8.79
Off-farm income *(100 nkr per total net income)*	197.39	427.70	121.46	260.31	0.118	79.78	161.56
Number of cows *(heads)*	29.32	11.556	38.12	11.480	0.000***	21.21	9.359
Feed concentrates *(feed units, share of total feed concentrates and roughage)*	0.417	0.086	0.474	0.098	0.000***	0.4205	0.082
Arable land per milk output *(m^2 per litre milk output)*	0.30	0.99	0.08	0.43	0.017**	0.38	1.46

Eco-efficiency							
Value-added *(1000 nkr)*	792.80	380.38	951.10	385.10	0.000***	638.25	316.38
Energy *(100 litre diesel)*	68.20	39.71	71.56	40.902	0.280	45.19	29.27
Fertilisers *(100 kg)*	221.96	126.93	244.30	131.43	0.150	168.90	105.47
Enteric fermentation *(CH_4)*	3415.3	1656.99	4067.80	1591.42	0.000***	2322.20	1476.66

Note: T-tests are conducted comparing farms before and after AMS adoption. '***' and '**' indicate significance at the 1% and 5% level respectively.

Table 3.1 shows that farms that adopting AMS are different in the considered parameters than those that do not adopt. For example, farms observed before adoption already have higher energy usage, lower labour per cow and are slightly larger in the number of cows. Further, there are likely other aspects of farms which we do not consider here that determine whether farms adopt AMS or not. In this paper, we do not study the determinants of adoption, but recognising that farms adopting AMS are different from farms not adopting AMS is important for interpreting our results as effects of AMS among the farms that adopt.

3.3.1 *Operationalisation of GHG emissions efficiency*

In Norway, GHG emissions from livestock production are primarily caused by field emissions, forage production and intrinsic animal emissions (Oort van and Andrew, 2016). This is measured from enteric fermentation, manure management, feed production and energy consumption. The indicators selected for this efficiency evaluation reflect this to the extent possible, given the available data. Energy expenditures and fertiliser expenditures are divided by the price of diesel and mineral fertiliser, respectively, for each year obtained from NIBIO (Totalkalkylen, NIBIO) and are thus expressed as quantities. Enteric fermentation is calculated using IPCC methods (Eggleston et al. 2006) using values adapted to the Norwegian context from the national inventory report (NIR) from 2021 (Bjønness, 2021). Details on the calculation of the emission factors are provided in Appendix 3.

Despite being a major contributor to farms' GHG emissions, we do not consider manure management. Arguably, manure management systems do not differ significantly regarding GHG emissions (Soteriades et al. 2019). However, IPCC methods for calculating GHG emission coefficients vary based on manure management. The lack of knowledge regarding the manure management system employed is a deficiency, and incorporating this information into the Norwegian account results dataset would allow for a more accurate evaluation. In 2018, three of four farms used a blade spreader for manure application, indicating limited variation between farms (Kolle and Oguz-Alper, 2020).

Finally, we use value-added as the economic indicator in our GHG emission efficiency formulation. Value-added is formulated as the total value of production from agriculture, including subsidies and minus intermediate consumption. Intermediate consumption includes purchased animals, feed, seeds, fertilisers, machinery maintenance, fuel and hired labour. The animals included are all animals purchased to a farm in a year, including cattle such as calves which are bread on the farm for meat or milk production. Thus, it does not include the value of the permanent livestock. Value-added measures the remuneration to own labour, capital and land.

3.3.2 *Operationalisation of structural and behavioural factors*

This section provides definitions of the variables and a discussion about their potential relation to AMS adoption and GHG emissions efficiency. We include the structural and behavioural factors based on the hypothesis that they are secondary effects of AMS adoption. Figure 3.2 illustrates the relationship between the factors and AMS adoption and GHG emissions efficiency, respectively.

Figure 3.2: Illustration of the potential effects of AMS adoption on the structural and behavioural factors and their relation to GHG emissions efficiency

Note: '+' indicates a positive association, '-' indicates a negative association and '-/+' indicates that previous findings are contradictive or that no previous assessments have been made. The arrows going from AMS adoption to the factors illustrate that we assess a causal effect between these (matrix completion), while the arrows reaching between the factors to GHG emissions efficiency illustrate that we are assessing a correlation (OLS regression). In the remainder of this chapter, we provide motivation for inclusion of each of the factors.

Herd size

Adopting AMS can be part of an expansion strategy and sometimes an unintended consequence where farmers expand to utilise the machine and recoup their investment fully (Vik et al. 2019). Previous eco-efficiency evaluations have shown a positive relation with the number of cows (Soteriades et al. 2020; Martinsson and Hansson, 2021). On the one hand, the number of cows enables farms to generate higher value-added by increasing the size of production, but, on the other hand, more cows also generate higher (total) enteric fermentation and higher energy costs as the size of production is larger. Associating herd size to GHG emission efficiency provides indications of whether it is best to have more small farms or fewer larger ones from a GHG emissions efficiency perspective. How herd size relates to GHG emissions efficiency depends on, for example, how well the farmer can manage the herd and on contextual constraints to produce as efficiently as possible and generating high value-added while keeping the GHG emissions to a minimum. It is important to emphasise that herd size and eco-efficiency are not correlated by construction, as both farms with large and small herds have opportunities to produce eco-efficiently.

Labour per cow

A primary motive among Norwegian farmers for investing in AMS is reducing labour and increasing work-time flexibility (Stræte et al. 2017). The indicator labour per cow captures the total labour per cow, including both hired and family labour. Previous eco-efficiency assessments have studied the relation to hired labour, finding that hired labour is negatively associated with eco-efficiency (Bonfiglio et al. 2017; Martinsson and Hansson, 2021). We hypothesise that higher family labour per cow can be negatively related to GHG emissions efficiency, as the farmer can spend less time on farm management when more physical work is required in the production. Thus, we hypothesise that our indicator of labour per cow shows a negative association to GHG emission efficiency.

Milk per cow and share of feed concentrates

Milk per cow and the share of feed concentrates are included as secondary effects as they can change with AMS adoption, as AMS allows for increased milking frequencies (Oudshoorn et al. 2012). The variables are related as the cows need to consume more feed concentrates if milking intervals are to be increased, which reduces grazing (Lessire et al. 2020) but increases milk yield per cow. There are conflicting findings on whether farms with AMS import more high-energy feed (Oudshoorn et al. 2012). Both factors reflect managerial decisions on the level of intensity and potentially affect GHG emissions efficiency: Milk per cow enables farmers to generate more agricultural value relative to the number of cows, and the share of feed concentrates fed to the cows affects their enteric fermentation.

Off-farm income and arable land

The share of income derived from non-farm sources and the farmland used for grain and cash crop production relative to milk output are measures of specialisation, which might change when the farmer invests in AMS. Many Norwegian farmers seek income elsewhere because their farms are typically small and produce little economic value (Oort van and Andrew, 2016). Off- farm income reflects the farmers' focus on farming relative to other income-generating activities, and the farmland used for grain and cash crops reflects the degree of farm specialisation. We hypothesise that investing in AMS will increase the farmers' dairy-focus and thus decrease off-farm income and arable production relative to milk. Specialisation has been found to be negatively related to environmental performance on a sector-level considering the milk yield relative to beef output on dairy farms (Soteriades et al. 2019). Thus, we hypothesise that arable land per milk output can have a positive association to GHG emissions efficiency. Farmers engaged in off-farm activities have higher labour opportunity costs, which could create an incentive for managing the farm more efficiently. To our knowledge, specialisation in terms of off-farm income and share of arable production has not been related to eco-efficiency previously.

3.4 Results and discussion

In this section, we present the results of our four-step procedure. First, we answer the question of what structural and behavioural factors can be attributed as secondary effects of AMS adoption. Second, we answer whether AMS adoption generates changes in farms' GHG emissions efficiency, which can be associated with structural and behavioural changes. In the analysis, we use the standardised form of the structural and behavioural variables obtained by subtracting the mean and dividing by the standard deviation. As the variables are expressed in different units, using their standardised version enables an easier comparison of the effects. We explain the interpretation of the standardised variables in the following sections. 33.9 per cent of our data is imputed to obtain counterfactual outcomes using matrix completion, comparable to 25 per cent missing entries in the example provided by Athey et al. (2021) to illustrate their method.

3.4.1 *Identifying structural and behavioural factors as secondary effects of AMS*

From the matrix completion procedure, we obtain ATT estimates for each factor. As we use the variables' standardised form, the effects express average changes in standard deviations with AMS adoption. The standard deviations for each factor are displayed in Table 1. For example, the number of cows is increased by 0.76 standard deviations on average when AMS is adopted, corresponding to 8.7 cows (0.76*11.5). Beside ATT effects, we also compute the effect of AMS for each observation as the difference between the observed and the predicted outcome. Results indicate a substantial heterogeneity in the estimated effects around the ATT effects (Figure 3.3).

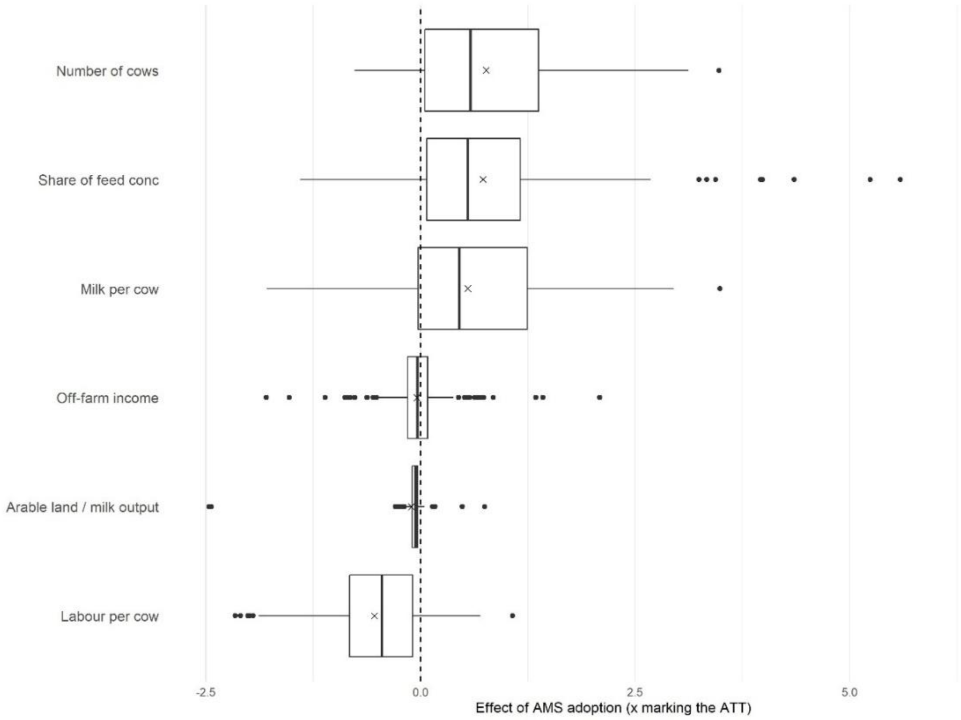

Figure 3.3: Result of matrix completion for each structural and behavioural factor.[a] The dotted line marks zero and 'x' marks the ATT for each factor (the exact values of the ATTs are displayed in Table 3).

Note: The results are estimated with separate models of matrix completion for each factor. Root mean squared error: Off-farm income: 0.37; Nr of cows: 0.28; Milk/cow: 0.61; Labour/cow: 0.47; Feed conc./tot feed: 0.47; Arable land/milk output: 0.22. The variables are standardised.
[a]Two outlying observations of the effect on off-farm income is omitted in the table to enable a better display of the results. The omitted observations are −4.89 and 8.4

Earlier studies already documented that farms with AMS have larger herd sizes than farms without (Rønningen, Magnus Fuglestad and Burton, 2021). We can add to these findings that differences between farms with and without AMS are not only due to baseline differences but that adopting AMS is associated with an enlargement of the herd. Vik et al. (2019) previously found that farms with AMS expand through a qualitative study, and our results support this finding. Moreover, we find that the adoption of AMS positively correlates with increased milk production per cow, as expected, given that AMS adoption offers the potential to increase milking frequency (Oudshoorn et al. 2012). Further, the share of feed concentrates in the diet is rising. The ATT is negative for labour per cow and arable land per milk output. This indicates a higher intensification and specialisation in dairy production compared to crops. At the same time, the negative ATT of areal production seems to be driven by some negative outlier observations. Off-farm income displays a small negative ATT highly centred around zero. Considering the effect for each observation indicates that for most factors, the direction of the effect is clear, while the magnitude of the effect is heterogeneous. Our findings indicate that farms develop in similar directions in the structural and behavioural variables after AMS adoption.

Nevertheless, interpreting the effects as causal should be done with caution. We do not account for potential interrelation between the change in these variables, as we estimate the effect in separate models. This must be considered when concluding, as the change in one variable from AMS adoption might be affected or driven by the change in another.

3.4.2 *Identifying the effect of AMS adoption on GHG emissions efficiency and the relation to the structural and behavioural factors*

We investigate how farms' GHG emissions efficiency is affected by AMS adoption and to what extent we can attribute this to structural and behavioural factors. We first present the results of the GHG emissions efficiency evaluation and how this is affected by AMS adoption. This is followed by the estimated association between the GHG emissions efficiency and the structural and behavioural factors, coming together in Table 3 to answer our question of how AMS affects GHG emissions efficiency and if this can be associated with the effects of AMS adoption observed in the structural and behavioural variables.

The average bias-corrected GHG emissions efficiency for the complete sample is 0.47, indicating room for improvement. Farms could reduce environmental pressures by 53 per cent while maintaining value-added to become fully efficient. Table 3.2 shows the results of the GHG emissions efficiency assessment for the entire sample and when separating adopters and non-adopters. Note that no observation is on the frontier, resulting from bootstrapping.

Table 3.2 GHG emissions efficiency scores: All observations, adopters observed before adoption, adopters observed after adoption and non-adopters

	Total ***(n=1,594)***	**Adopters, before AMS** ***(n=138)***	**Adopters, after AMS** ***(n=136)***	**Non-adopters** ***(n=1,320)***
Mean	0.47	0.43	0.40	0.48
Max	0.96	0.82	0.82	0.96
Min	0.006	0.07	0.03	0.006
Sd	0.17	0.17	0.17	0.17

Non-adopting farms have the highest mean efficiency, whereas the adopting farms after adoption have the lowest. We test the differences in means between the three groups in Table 3.2 using t-tests. We can reject the null hypothesis of equal means between AMS adopters and non-adopters before and after adoption. Comparing the adopters before AMS with the adopters after AMS using the same t-test yields a p-value of 0.2.

Figure 3.4 displays the effect of AMS on GHG emissions efficiency generated from the matrix completion. The root mean squared error (RMSE) is 0.17. The ATT of AMS adoption on GHG emissions efficiency is −0.015, indicating that the average effect of adopting AMS among the adopters is to decrease GHG emissions efficiency by 0.015. However, computing the effect of each observation, it is evident that there are large heterogeneities in the results. Figure 3.4 shows that the small average effect is not due to an absence of impact but rather to the large heterogeneity in responses.[4]

As the matrix completion procedure does not consider dynamic effects (Athey et al. 2021), Figure 3.4 does not display differences in the effects given time since AMS adoption.

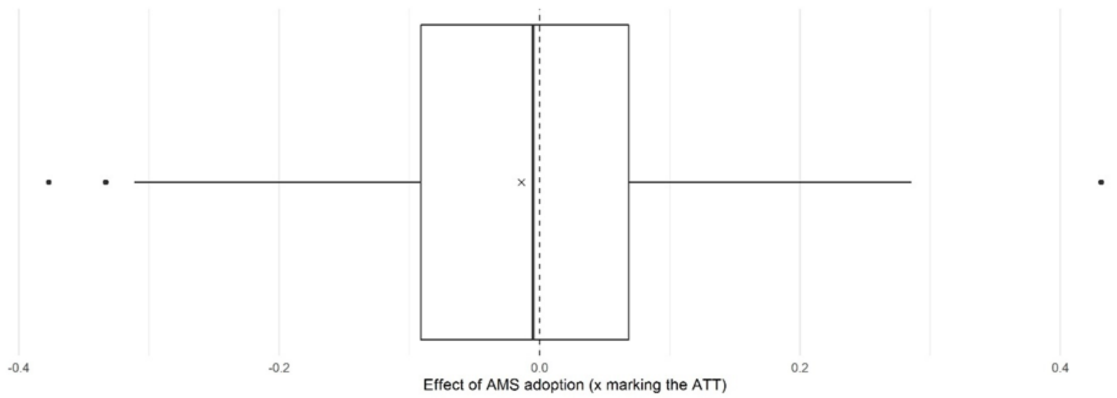

Figure 3.4: Result of matrix completion for GHG emissions efficiency.
Note: The dotted line marks zero and the x marks the ATT= −0.015. Root mean squared error: 0.17.

Finally, we aim to attribute the effects of AMS adoption on GHG emissions efficiency to the structural and behavioural factors to provide insights into the mechanisms behind the changes in GHG emissions efficiency. Correlating the changes in GHG emissions efficiency to the structural and behavioural factors can provide explanations for the large heterogeneity between farms, and potentially contradictory effects can explain the small average effect.

[4] Contrasting the results to the PS-DID and the fixed effects regression (Appendix 1), the PS-DID yield estimates of a somewhat stronger effect (−0.06 using full matching) while the fixed effects provide very similar results as the matrix completion (−0.011).

We obtain the contributing power of each factor to the association between GHG emissions efficiency and AMS by multiplying the relationship between each factor and GHG emissions efficiency (step three) by the change in each factor associated with AMS (step one). Still, we use the standardised forms of structural and behavioural factors. For the number of cows, this would indicate that when increasing the number of cows by one standard deviation (11.5, Table 1), GHG emissions efficiency is expected to change by −0.02. Thus, the increase in herd size induced by AMS (0.77 standard deviations) contributes to a decrease in GHG emissions efficiency by 0.77 * (−0.02) = −0.015. We conduct this procedure for each factor listed in Table 3.3

Table 3.3: The contribution of each factor to the effect of AMS adoption on GHG emissions efficiency

Factor	**Change induced by AMS (ATT, step 1)**		**Correlation between the factors and GHG emissions efficiency (step 3)**		**Contributing power to the relation between AMS adoption and GHG emissions efficiency**
Cows	0.77	×	-0.02	=	-0.015
Feed concentrates	0.73	×	-0.01	=	-0.007
Milk per cow	0.55	×	0.02	=	0.011
Off-farm income	-0.02	×	-0.00	=	0
Areal production per milk output	-0.11	×	0.00	=	0
Labour per cow	-0.54	×	-0.04	=	0.022
			Total effect		0.011

Note: The result is obtained by multiplying the effect of AMS on each factor (step one) with the result from the FE linear regression (step three). The second column contains the estimates of the FE OLS regression (step 3). The total effect is obtained by summarising the right-side column.

The total effect displayed in Table 3 is obtained by summing up the contributing power of all factors. This total effect of 0.011 is smaller in absolute terms than the estimated effect of AMS on GHG emissions efficiency in step 3, which we estimate to be −0.015. Thus, other processes may be at work which are not reflected by the structural and behavioural variables we include in the model. Nevertheless, our procedure demonstrates the relative importance of the factors as secondary effects affecting farms' environmental performance. In Table 3.3, the structural and behavioural factors show contradicting relations to GHG emissions efficiency, which can explain the small average effect of AMS adoption on GHG emissions efficiency.

The second column displays the result from the linear regression outlined in Equation 3.2. We generate the results using a two-way FE regression. Despite the contributing power of each factor being relatively small, they are not irrelevant. Small decreases in farm-level GHG emissions efficiency can substantially increase total emissions. However, as displayed in the regression plot in Figure 3.5, the confidence intervals are large, indicating that more data would be required to increase the precision of the result. For example, access to a balanced panel data of the farms between 2013 and 2019, or a panel data covering a longer period of time, could help narrowing the confidence intervals. Not being able to reject the null hypothesis that there is no relationship between changes in a factor and changes in the GHG emissions efficiency calls for further investigation.

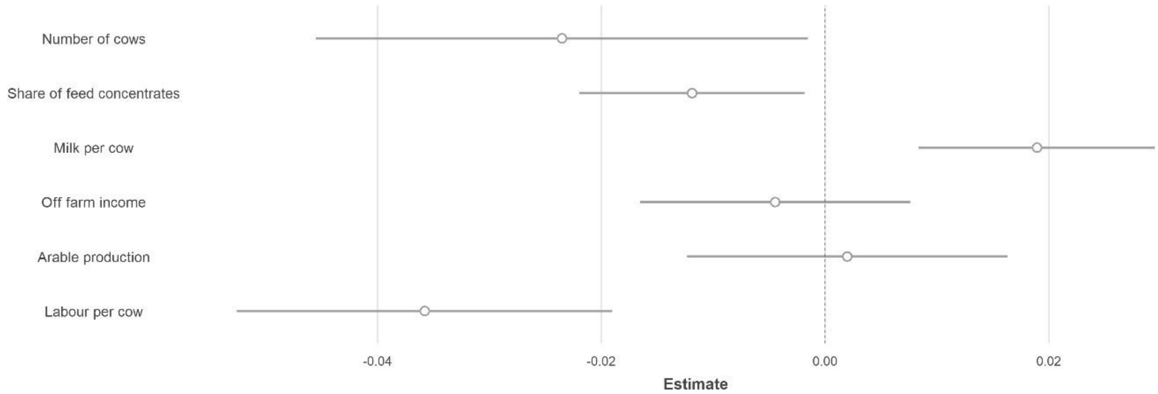

Figure 3.5: Coefficient plot of the FE regression
Note: 95 per cent confidence intervals

Decreasing the labour per cow is associated with higher GHG emissions efficiency and constitutes the largest contribution to the effect of AMS adoption on GHG emissions efficiency. The negative association between labour per cow and GHG emissions efficiency is consistent with prior findings (Bonfiglio et al. 2017; Martinsson and Hansson, 2021). The strong association between labour per cow and changes in GHG emission efficiency generated by AMS comes both from a relatively large effect of adopting AMS, but also from a large estimated association with GHG emissions efficiency. Thus, decreasing the labour per cow on a farm due to AMS contributes positively to farms' GHG emissions efficiency. Whereas the previous findings of a negative relation between labour per cow and eco-efficiency has focused on a cross-sectional setting, our findings indicate that it is not only the case that farms with more labour per cow also have lower eco-efficiency, but that there is also an association between these variables when considering changes within farms.

The number of cows also displays a large contribution to the changes in GHG emissions efficiency, mainly through the effect generated by adopting AMS. The result of a negative association between number of cows and GHG emission efficiency contradicts previous findings such as Martinsson and Hansson (2021). One reason for the negative association with GHG emissions efficiency could be that increasing the number of cows increases enteric fermentation. Another reason could be that diesel consumption is higher on larger Norwegian farms (van Oort and Andrew, 2016), possibly due to long distances between the farm centre and the most distant fields. Nevertheless, further research is required to investigate why larger farms are less GHG emissions efficient. Extension services, farmers and researchers need to find ways to achieve herd expansion combined with higher GHG emissions efficiency.

The contradicting effect of labour per cow and herd sizes illustrates that the small estimated effect of AMS adoption on GHG emissions efficiency (Figure 3.4) is not due to a lack of processes, but rather that the adoption of AMS is associated with several processes that have contradicting effects on GHG emissions efficiency.

Milk yield per cow and the share of feed concentrates have contradicting effects and are nearly cancelled out, as seen in Table 3.3. The changes in these variables are likely a result of increased milking frequency, which is enabled by AMS adoption (Oudshoorn et al. 2012).

Previous research has identified milk yield per cow to be positively associated with eco-efficiency (Soteriades et al. 2020), which the findings of this study support. Achieving the maximum milk yield with the smallest proportion of feed concentrates can support increasing GHG emissions efficiency. Thus, we must identify ways to increase milk yield without increasing feed concentrates to affect GHG emissions efficiency positively.

Off-farm income and areal production per milk output have little influence on the association between GHG emissions efficiency and AMS adoption, as they are estimated to have very low correlation to GHG emissions efficiency and change little with the adoption of AMS.

To sum up, the most GHG-emissions-efficient farms in the sample have lower labour per cow, smaller herds, higher milk yield and a lower proportion of feed concentrates in the dairy cow feed ratio. These results indicate a challenge for the Norwegian dairy industry in maintaining GHG emissions efficiency as demand for dairy products increases and mechanisation drive farms to expand in size (Vik et al. 2019). Understanding the importance of different structural and behavioural factors that could drive the overall change in GHG emissions efficiency provides valuable insight into the significance of various underlying processes triggered by the adoption of novel technology. Based on this, future research efforts and extension services can be more precisely targeted. Investigating the correlation between the GHG emissions efficiency and the structural and behavioural changes, we do not find any indications that the included variables can explain the considerable heterogeneity in farms' GHG emissions efficiency responses to AMS adoption.

3.5 Conclusion

We present a novel analytical approach for evaluating farm-level effects of new technology adoption, including secondary effects. We use matrix completion and DEA to assess the impact of adopting AMS on structural and behavioural factors and farm GHG emission efficiency. To our knowledge, this paper is the first to empirically demonstrate the presence of secondary effects and use eco-efficiency evaluation to assess the effects of new farm technology. This procedure can be used in future research to evaluate other technologies.

We identify that AMS adoption generates secondary effects in our sample of Norwegian dairy farms. After AMS adoption, farms increase herd sizes, the share of feed concentrates in the cows' diet and milk yield per cow while decreasing labour per cow. The average effect of AMS adoption on GHG emission efficiency is small (-0.015) but with significant heterogeneities across observations. The negative and heterogenous relationship between AMS adoption and GHG emissions efficiency is a novel finding that highlights the importance of evaluating farm-level effects of novel technology, including the possibility of secondary effects, as they can have unexpected effects on GHG emissions efficiency. For agriculture to develop towards increased environmental sustainability while ensuring economic viability, novel technology must contribute to improved farm-level eco-efficiency.

By providing a link between AMS adoption and structural and behavioural factors, our study enables more precise steering of the development of farms to achieve desired policy targets given AMS adoption. Furthermore, linking structural and behavioural factors to GHG emissions efficiency allows for deriving insights into which processes to target for eco-efficient AMS implementation. We recommend providing extension services to enable farms to expand while maintaining or increasing their GHG emissions efficiency and increasing milk yield per cow without increasing the share of feed concentrates. Further, it is interesting to note the considerable heterogeneity in the effects of AMS adoption on GHG emissions efficiency, which calls for further research to determine what drives farms to increase or decrease their efficiency after adopting AMS in particular and novel technology in general. Future research should also invest in understanding the mechanisms behind the secondary effects of novel technology to enable forecasting the development of farms as more autonomous technology is developed and made available to farmers. For example, expanding the procedure to consider interrelations between the variables as AMS is adopted would be a helpful extension adding further understanding to the effects of AMS adoption. Further research should also expand the approach by Kuosmanen and Kortelainen (2005) to implement more realistic assumptions of non-radial changes of variables in the very short run.

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3.7 Appendix A: PS DID and fixed effects regression

We apply PS-DID and FE regression to estimate how AMS adoption affects GHG emissions efficiency. Comparing the more unconventional machine learning approach to classic econometric methods improves the transparency and understanding of the results. The main differences are that the econometric methods provide statistical significance and confidence intervals, which the matrix completion currently lacks, and that the matrix completion can make use of the full dataset and utilise the variations there, while the econometric methods are more limited in this respect. We apply the econometric methods to assess the effect of AMS adoption on GHG emissions efficiency to illustrate the differences between the methods. In this appendix, we briefly outline the PS-DID and FE regression. Both methods produce similar results as the matrix completion approach, showing that our results are robust across different methodologies.

PS DID. As AMS adoption is not randomly distributed, we use propensity scores to control for factors which impact the adoption decision. Including propensity scores help to realise the parallel trends assumption, which is a prerequisite for a DID regression. The variables used for calculating the propensity scores are displayed in Table 3.4.

Table 3.4: Descriptive statistics of covariates used for the propensity score calculation

	Adopters (n=47)		**Non-adopters (n=273)**	
Covariates for propensity score matching	Mean	Sd	Mean	Sd
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
Off-farm income *(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
Areal 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
Fertilisers *(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

Further, DID requires treated and control groups to be observed in two periods: one period before adoption and one after. Thus, we subset the dataset to only keep observations the first and the last time they are observed. The average treatment effect of adoption can be determined by comparing the outcomes of adopters and non-adopters (Khandker, Koolwal and Samad, 2009). The DID regression can be expressed as $\triangle EE_i = \alpha + \beta_1(adoption_i) + e_i$. Adoption is a binary indicator of whether the farm is an adopter or not. PS are included as weights in the regression.

To test the robustness of the PS and the sensitivity of their specification to the result, we consider two versions of the DID using PS calculated through two different methods: Full matching and inverse probability weights (IPW). We use the Matchit package in R (Stuart et al. 2011) to obtain propensity scores and conduct the full matching. We calculate the IPW weights as $IPW_i = \frac{Adoption_i}{P(X)_i} + \frac{1-Adoption_i}{1-P(X)_i}$. $P(X)_i$ is the propensity score and $Adoption_i$ is, as before, a binary indicator of whether farm i is an adopter or not. The matching satisfies the condition of common support as depicted in Figure 3.6.

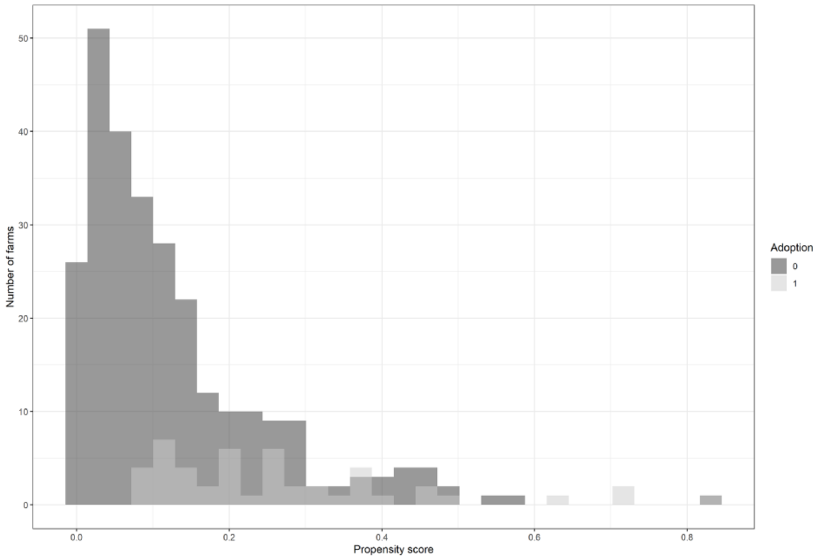

Figure 3.6: Distribution of the propensity scores for adopters and non-adopters separately.
Note: Adoption = 0 are non-adopters and adoption = 1 are adopters, indicated by light and dark grey, respectively.

Recent methodological contributions have suggested ways to expand the method to allow for staggered adoption by e.g. formulating different groups of adopters adopting in different times

(Callaway and Sant'Anna, 2021). However, this comes with the issue that it requires sufficiently large groups of adopters in the different years. In our application, this would result in small subsets of farms adopting in each year.

FE regression. The other alternative we consider to assess the impact of an intervention is to use a two-way FE regression, including a dummy variable for the change in adoption status. The dependent variable is GHG emissions efficiency, and the explanatory variables are years since adoption, with one dummy for each year relative to adoption. We can create dummy variables of whether farms are in the years before adoption, as the actual adoption is preceded by a decision to adopt which can generate adaptive changes already before the AMS is implemented on the farm. However, the estimates do not reflect any counterfactual outcomes, but only consider how AMS affects the adopting farms. We include dummies for up to four years before adoption and four years after adoption, with an omitted reference period of five years before adoption. The regression can be written as $EE_{it} = \alpha_i + \varphi_t + \beta_1(yr\_since\_adopt_{it}) + \sum_{n=-4}^{4} \beta_n dummy\_yr\_since\_adop_{it} + e_{it}$. Farm and year-fixed effects are included, denoted by α and φ in the FE regression equation. This method only considers variation among farms whose adoption status changes, i.e. farms that adopt AMS; non-adopting farms are excluded. The results of the PS DID and FE regression are displayed in Figure A2.

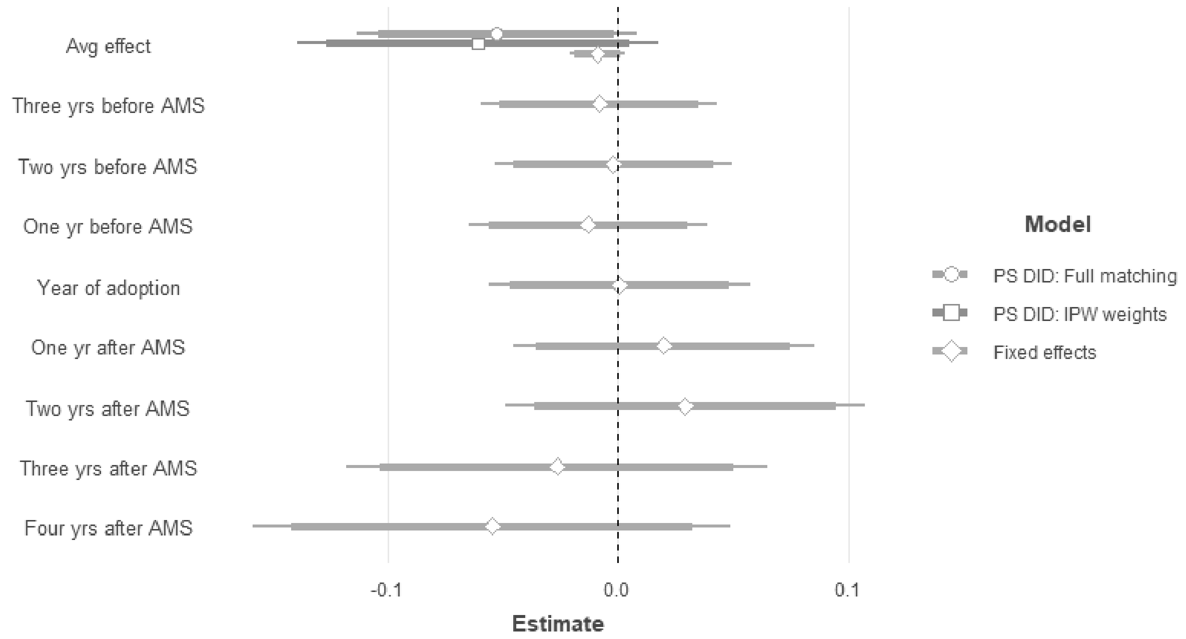

Figure 3.7: The effect of AMS adoption on GHG emissions efficiency estimated using PS-DID with full matching, IPW weights and the fixed effects regression, respectively.

Note: The average effect is the result from the PS DID and fixed effects regression. All effects over time since adoption are generated using the fixed effects. The average effects are: −0.052 (full matching), −0.06 (IPW weights) and −0.11 (fixed effects). 90 per cent and 95 per cent confidence intervals

3.8 Appendix B: Second stage DEA using Tobit regression

A commonly used alternative to OLS regression in DEA efficiency assessments is Tobit (Hoff, 2007; McDonald, 2009). As Tobit has been identified as a feasible alternative to OLS, we apply it as a robustness check to our OLS estimation used in the paper. While McDonald (2009) reached the conclusion to not use Tobit in the second stage DEA, Hoff (2007) identified Tobit as sufficient in representing second stage DEA assessments. Tobit regression is best used with censored data or where corner solutions are present, which is the case with DEA efficiency scores ranging between 0 and 1 (Hoff, 2007). The results from the Tobit regression are displayed alongside the results from the fixed effects OLS regression and shown in

Table 3.5.

Table 3.5: The result from the Tobit and the OLS regression.

	Tobit	FE OLS
Cows	-0.04***	-0.02
	(0.0049)	(0.016)
Feed concentrates	-0.01***	-0.01**
	(0.0037)	(0.005)
Milk per cow	0.02***	0.02***
	(0.0037)	(0.005)
Off-farm income	-0.02***	-0.00
	(0.0034)	(0.007)
Areal production per milk output	-0.01***	0.00
	(0.0034)	(0.003)
Labour per cow	-0.01*	-0.04***
	(0.0048)	(0.011)

Note: Clustered standard errors in parenthesis. '***' 1% significance, '**' 5% significance, '*' 10% significance.

3.9 Appendix C: Emissions factors calculation

To calculate methane emissions from enteric fermentation, we use equations provided by the IPCC (Eggleston et al. 2006) adapted to the Norwegian context in the NIR (Bjønness, 2021). We use the following equation to calculate enteric fermentation:

$$Enteric\ fermentation = EF_i \times N_i$$

where EF_i denotes emissions factors for animal category i, and N_i is the number of individuals in that category. To calculate enteric fermentation, we use the variables number of cows (including heifers and bulls), litre milk yield (including milk sold, milk consumed on the farm and waste), feed concentrates and roughage expressed in feed units from the Norwegian account results dataset. Emissions factors are calculated using the IPCC equation:

$$EF = \frac{GE * Y_m * 365}{55.65 mj/kgCH_4}$$

Where GE is gross energy intake and Y_m is the methane conversion rate and depend on the climatic conditions and geographical area considered. To enable calculating these factors in the Norwegian context, we use estimates from the Norwegian national inventory report (NIR)

(Bjønness et al. 2021) which provides equations for calculating the GE and Y_m for dairy cattle, and provide estimations of the emissions factors for other livestock. Following the Norwegian NIR, we use the following equations to calculate GE, and Y_m:

$$\mathrm{GE} = 137.9 + 0.0249 \times \mathrm{Milk305} + 0.2806 \times \mathrm{Concentrate\_proportion}$$

$$\mathrm{Ym} = 7.38 - 0.00003 \text{ x } \mathrm{Milk305} - 0.01758 \text{ x } \mathrm{Concentrate\_proportion}$$

$\mathrm{Milk305}$ is the energy corrected milk yield during the 305 days long lactation period. Due to data availability, we use the total yearly milk yield without correcting for energy content. In our calculation of enteric fermentation, we also include heifers and bulls, by multiplying the number of individuals in each category with emissions factors calculated using gross feed intake and methane conversion rate calculated for the Norwegian context from the NIR report (Bjønness et al. 2021). Thus, in total there are five categories of livestock included when we calculate a farms' enteric fermentation; dairy cows, heifer >1 year, heifers <1 year, bulls >1 year and bulls <1 year.

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Chapter 4
Conceptualization of how adopting novel technology induces structural and behavioural changes on farms[1]

Abstract: Predicting the effects of adopting novel technology, particularly smart farming, is challenging as farmers often modify their behaviour and farm structures once a new technology is adopted. Nevertheless, by considering features of novel smart farming technology and relying on economic theory, we derive incentives for structural and behavioural changes that adoption can trigger. This paper presents a conceptual framework describing processes linked to features of smart farming technology that can incentivise farm-level structural and behavioural change. Specifically, we focus on rebound effects, economies of size (EoSi) and scope (EoSc), and risk-balancing. To provide examples of how the conceptual framework applies, we conduct a literature review of previous research studying farm-level effects of smart farming.

Keywords: agricultural technology, structural change, rebound effects, conceptual framework

4.1 Introduction

Digital innovation is transforming the agricultural industry (Klerkx and Rose 2020). The European Union's Common Agricultural Policy for 2023–27 reflects a desire to promote digital

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and smart farming technology to modernise agriculture through innovation and knowledge (European Commission, 2019). One of the outcomes sought by increasing the use of digital technology is enhancing resource use efficiency and halting biodiversity loss (European Commission, 2019). However, whether increasing the adoption of digital and smart farming technology will provide these desired outcomes of increased sustainability is uncertain (Klerkx et al. 2019). The effects crucially depend on which farms adopt the technologies at what point in time, how the technology is used, and what **structural and behavioural (S&B)** adaptations follow after adoption.

In this paper, we use economic theory and insights from previous literature to conceptualise smart farming-induced S&B change. Thereby, we contribute insights on important farm-level mechanisms and outcomes generated as farmers adopt and use smart farming technology. The induced S&B effects can alter sustainability outcomes and the development of the agricultural sector by, for example, driving changes in farm size and specialization of farms. Understanding induced S&B change is especially important for smart farming technology, which, although not yet widely implemented, is expected to transform the agricultural sector (Klerkx and Rose 2020; Daum 2021). Nevertheless, the determinants and drivers of S&B incentives generated by smart farming technology are poorly understood.

This study contributes to understanding smart farming-induced S&B change. Specifically, we aim to provide insights into how novel smart technology motivates farm-level S&B changes and what outcomes this can yield. To achieve this, we formulate two objectives:

1. To construct a theoretically derived conceptual framework which describes and conceptualize mechanisms that can create incentives for S&B change.
2. To provide examples of how the framework applies through a literature review of farm-level effects of smart farming.

We apply the theoretically derived framework which we formulate in this paper to smart farming in livestock and crop production. Findings from the literature review are analysed separately for the two specializations due to differences in smart farming technology used in livestock farming compared with crop production. Constructing the conceptual framework and conducting the literature review are not two isolated processes. By first developing the conceptual framework, we use it to formulate the keywords for the literature review. Further, when conducting the literature review, we allow for updating the conceptual framework with new insights, gained throughout the process of reviewing the literature. The literature review further reveals how previous studies have approached smart farming-induced S&B change and contributes to highlighting the contribution of our conceptual framework.

Previous literature has primarily investigated the determinants of adopting smart farming and digital technology (Tey and Brindal 2012; Gallardo and Sauer 2018; Michels et al. 2020; Shang et al. 2021; Khanna et al. 2022; Gabriel and Gandorfer 2022; Khanna et al. 2024). Adoption studies provide valuable insights into the effects of technology, as technology will only have an impact if adopted. Research has also studied the direct effects of incorporating robotics into agriculture, showing that agricultural robotics can have positive effects by increasing resource use efficiency, reducing labour requirements and lowering production costs (Walter et al. 2017; Duckett et al. 2018; Finger et al. 2019; Martin et al. 2022; Storm et al. 2024). S&B change of smart farming has also been studied previously. For example, a farmer might need to adjust field structures to enable a field-robotic technology to operate efficiently (Sparrow and Howard 2021), reorganize farm labour to utilize the autonomous features of an automatic milking system (AMS) (Martin et al. 2022), expand farm sizes to fully benefit from the AMS (Vik et al. 2019) or be motivated to reinvest savings in production costs from the adoption of smart farming and intercropping technologies (Paul et al. 2019). However, the literature studying smart farming induced S&B change is scarce and the mechanisms behind farmers adapting and changing their production decisions in response to smart farming technology are poorly understood and conceptualized.

Previous concepts for studying the effects of smart farming technology include activity theory, which considers the interaction between actors (Lioutas et al. 2019; Rijswijk et al. 2021) and responsible research and innovation, which highlights ethical and social considerations (Rose and Chilvers 2018; Regan 2019). Nevertheless, no conceptual framework exists to study farm-level S&B adaptations to novel smart farming technology. As a result, smart farming-induced S&B change is often overlooked. We gather inspiration for our conceptual framework in previous similar contributions, such as Paul et al.'s (2019) conceptual framework of rebound effects in land and soil management, Shang et al.'s (2021) framework integrating empirical evidence with agent-based models and Finger et al.'s (2019) review of how precision farming can be transformed to benefits for the agricultural sector. Nevertheless, none of these previous contributions includes smart farming-induced S&B change. Instead, most studies on smart farming focus on potential impacts using experimental data or model predictions, giving little attention to the observed effects (Finger et al. 2019). In a review by Lowenberg-DeBoer et al. (2020) on the economics of field crop robotics, the authors conclude that the literature on this topic is scarce and that more research needs to investigate the potential of crop robotics to change the optimal scale and size of farms.

The effects of novel technology are difficult to capture, and the exact effects can be as diverse as the number of farms. In particular, the effects of novel smart farming technology, which are still not widely adopted, are impossible to predict fully. Nevertheless, the effects of technology can be better understood by determining how specific technology characteristics create incentives for S&B change through various mechanisms. The mechanisms are derived from economic theory to develop a conceptual framework that can be used to support hypothesis formulation about changes that will arise on farms after smart farming technology is adopted. This framework is important for three reasons: it informs empirical research, provides information for modelling and informs policymakers in their efforts to promote sustainable development through smart farming. Specifically, we assume that induced S&B change that can arise from changes in economies of size (EoSi) and scope (EoSc) and changes in risk and rebound effects arising from increasing resource use efficiency are considered. In Section 3, we thoroughly explain each concept and how we hypothesize that smart farming technology can generate S&B change through the respective concepts.

The rest of the paper is structured as follows. In Section 4.2 we provide the basis of the framework by defining the types of effects we focus on and specifying the definition of smart farming technology. Section 4.3 provides the theoretical foundations by discussing EoSi and EoSc, rebound effects and risk and how they can trigger S&B change. The first objective is to derive a conceptual framework describing mechanisms that create incentives for S&B by considering the theoretical foundations in the context of smart farming technology. Section 4.4 presents the literature review, keywords, and inclusion criteria. In Section 4.5 we present the results. Finally, Section 4.6 concludes.

4.2 Structural and behavioural change induced by smart farming technology

In our study, we want to increase the understanding of how the adoption of smart farming can incentivize farm-level S&B changes. Thus, we do not focus on the farmers' intentions with adopting the technology but instead aim to understand how attributes of technology can create incentives for S&B change, disregarding if the farmer was targeting these changes before the adoption of the technology or not. There is already a vast amount of literature on farmers' intention to adopt smart and precision farming technology (Tey and Brindal, 2012; Pathak et al. 2019). However, we attempt to disentangle which mechanisms can incentivize S&B change given the specific characteristics of novel smart farming technology.

As an example of incentivized S&B change, consider adopting an AMS. Farmers' intention for adoption could be expansion and to enable shifting to a more modern and flexible lifestyle (Vik et al. 2019). Disregarding the initial incentives, the characteristics of AMS can incentivize farm expansion for example to fully exploit the machine capacity or motivate farmers to increase production to finance the investment (Vik et al. 2019). We aim to provide a theory-based framework that allows to evaluate how certain technology characteristics induce S&B change.

We do not put any evaluation in whether the induced changes are desirable or not, or whether they occur in the short or long term. The focus is on the features of novel smart farming technology and what farm-level mechanisms are potentially triggered by adopting and using the technology on the farm.

Smart farming is a broad term used to define the transformation of the agricultural sector jointly including aspects of technology, the diversity of agricultural production systems and the interaction between different institutions such as markets and policies (Walter et al. 2017). Nevertheless, the term "smart farming technology" is not uniquely defined in the literature. One type of technology with an important role in the smart farming transition is precision agriculture (PA). Which is defined as "…*a management strategy that gathers, processes and analyses temporal, spatial and individual plant and animal data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production."* (The international society of precision agriculture (ISPA)). However, robotic and fully automated systems are also increasingly being developed and adopted to farms, thus also playing a crucial role in the transition towards smart farming (Moysiadis et al. 2021). with the addition that this study also focuses on autonomous technology. Thus, we classify a technology as smart farming if it has at least one of the following features: gathers and provide information, enables for or conducts variable rate application (VRA) or is a fully automated system.

4.3 Theoretical foundations of induced structural and behavioural change

This section presents a conceptual framework of smart farming-induced S&B change. Specifically, the contribution presented in this section consists of describing and connecting important economic mechanisms and outcomes triggered by smart farming technology. It conceptualizes the relation between features of smart farming, mechanisms of smart farming-induced S&B change and the outcomes this yields.

The conceptual framework rests on the assumption that traits of smart farming can induce S&B change through the economic concepts of EoSi, EoSc, rebound effects and risk. The economic concepts which we include in our conceptualization do not encompass all potential effects of novel technology, but they provide an important starting point for explaining S&B change processes after adopting smart farming technology. While there is previous literature on how novel agricultural technology can generate rebound effects (Paul et al. 2019) and change EoSi (Lowenberg-DeBoer et al. 2022), EoSc and risk are less frequently studied than drivers of S&B changes generated by adopting new technology.

We gather inspiration for formulating the conceptual framework from Lange et al. (2021) conceptualization of rebound effects, which considers separate rebound mechanisms and rebound outcomes in energy savings. Similarly, this study disaggregates induced S&B change effects into mechanisms and outcomes. The connection between technology features, mechanisms and outcomes is the basic premise of the framework presented in this study and is illustrated in Figure 4.1. Specifically, the study conceptualizes a link between features of smart farming technology, which triggers mechanisms that motivate the change. The outcomes are then the results of the farmer acting on the mechanisms, giving rise to S&B changes. In opposite to Lange et al. (2021), who focuses exclusively on the rebound effect, this paper considers a broader range of mechanisms and focuses to the specific features of smart farming technology.

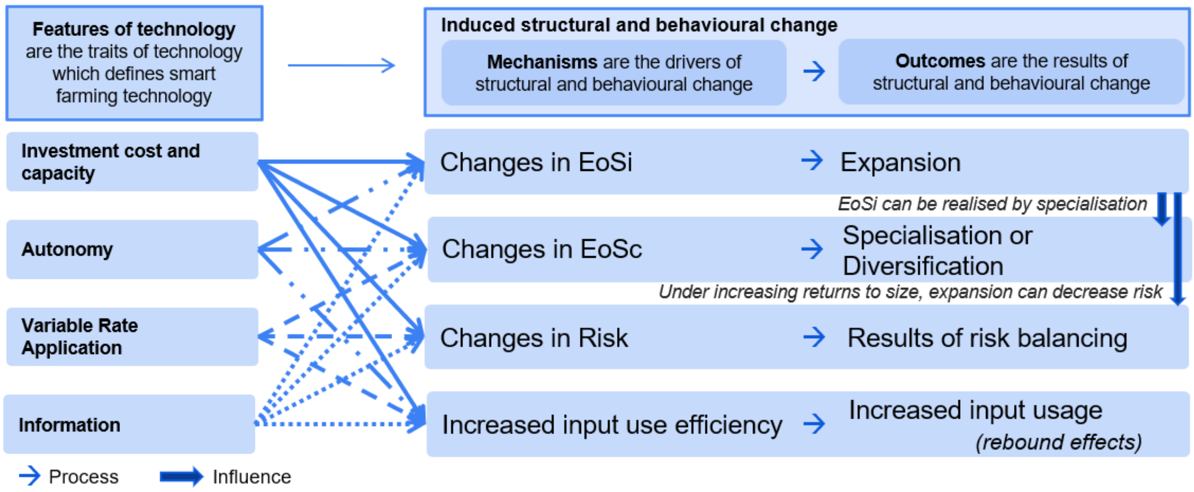

Figure 4.1: Theoretically derived conceptual framework of induced structural and behavioural (S&B) change.

Note: The arrows going from the features of technology to the effects are illustrating which features can trigger which effects given the economic theory. The different style of arrows is made to increase readability.

We focus on four mechanisms. As depicted in Figure 4.1, we consider that S&B change will be induced if a novel technology changes the cost-minimizing size of the farm (changes EoSi), changes the cost-minimizing scope (EoSc), increases or decreases risk and uncertainty (changes risk), or increases input use efficiency (enabling re-investments giving rise to rebound effects). These mechanisms change the status quo on the farm, and the outcomes will be structural or behavioural changes following the economic concepts listed. Notably, there are overlaps between the effects we discuss in this paper. Particularly, EoSi and rebound effects overlap in the respect that input use efficiency at certain scales of production can be used to measure EoSi, while increasing input use efficiency is also an indicator for rebound effects. The key differences between each of the concepts are, however, the mechanisms through which the features of technology generate the outcomes distinct for the different economic theories and will be elaborated on in the following sections. In the remainder of this section, we review the economic theories and explain the relation between the features and induced S&B change, as illustrated with the arrows in Figure 4.1.

4.3.1 *Economies of size and scope as incentives for structural and behavioural change*

Technological development has encouraged expansion towards larger and more specialized farms (Bowman and Zilberman, 2013). EoSi is an important driver of farm expansion as technological development progresses (Schimmelpfennig, 2016; Key, 2019). Nevertheless, these conclusions are commonly drawn at the sector level and not attributed to farm-level adoption of new technology, which can incentivize farmers to expand using EoSi. While the current development of farms is towards becoming larger and more specialized under the economic rationale to pursue EoSi and increase technical efficiency rather than focusing on diversification (de Roest et al. 2018), smart farming technology can also enable both increased and new forms of diversification of production (Walter et al. 2017) and enable preserving smaller farm sizes by removing the pressure to expand (Lowenberg-DeBoer et al. 2021). However, technological lock-ins could also contribute to increasingly specialized farming systems, as identified for crop production (Magrini et al. 2016; Meynard et al. 2018).

To this background, we consider changes in EoSi [2] and EoSc necessary to study on a farm level as potential mechanisms of S&B change. EoSi is present when costs per output can be decreased by increasing the size of production in any cost-minimizing way and EoSc is present when costs per output are minimized when inputs are used to produce several different goods. EoSc can arise from product-specific EoSi (Panzar and Willig, 1981). In the following, EoSi and EoSc are described from the perspective of how these theories can provide motivations for S&B effects of smart farming technology.

Economies of size (EoSi)

EoSi specifies a scenario where average costs, i.e., costs per output, can be minimized by increasing production quantity. Average costs consist of fixed and operational (variable) costs and are commonly illustrated as an L- or U-shaped curve, where costs for low levels of

[2] This also covers the notion of economies of scale, when scaling up all inputs by a factor leads to increases in output with more than that factor. See (Duffy, 2009) for a clear outline of the concepts' differences.

production is high due to high fixed costs and decrease with size enlargement (Chavas, 2008; Duffy, 2009; Lowenberg-DeBoer et al. 2021). At very large farm sizes, average costs can increase, indicating diseconomies of size (Alvarez and Arias, 2003).

A recent stream of studies how crop robotics can change farms' average cost and EoSi using a linear programming optimization model developed by Lowenberg-DeBoer et al. (2021). With such a model it can be shown how the usage of crop robotics changes the average production cost and that this largely depends on the required supervision time. A high degree of autonomy without the need for human supervision can decrease the advantage of larger farms and make smaller farms more economically feasible (Lowenberg-DeBoer et al. 2022). However, even with high supervision requirements, the same model shows that crop robotics are found to decrease average costs (Maritan et al. 2023). A high requirement for human supervision makes the EoSi for larger farms more noticeable than for smaller farms and the implication of "bigger is better" is increased when crop robotics need more supervision (Lowenberg-DeBoer et al. 2022).

The introduction of novel technology is one important tool to enable farms to expand to previously unfeasible sizes (Hermans et al. 2017), where otherwise further expansion would be limited due to managerial confinements which would cause the farm to run into decreasing returns to size (Alvarez and Arias, 2003). Such large-scale operations are referred to as Megafarms and are particularly prevalent in Eastern Europe, South America and China (Hermans et al. 2017). EoSi can enable megafarms, as the large farm size enables spreading fixed costs over a larger quantity, increasing the attractiveness of the farm for managers and technical staff and enabling full utilization of facilities and farm infrastructures (Chaddad and Valentinov, 2017). Furthermore, megafarms have the means and capacity to invest in modern information and communication technology, which enables them to continue to grow (Chaddad and Valentinov, 2017). Megafarms also benefit from EoSi as geographical and product diversification expansion can decrease price and production risk (Chaddad and Valentinov, 2017).

Given EoSi and previous studies on how novel technology can change average costs and thus change EoSi, we identify four ways smart farming technology can shift average costs to induce S&B change. First, suppose the technology has a high investment cost, this can generate EoSi by shifting the average cost curve to the right, driving farms to expand to minimize production costs (Duffy, 2009; Weersink, 2018). Second, whether the technology requires high or low supervision time has implications for the slope of the average cost curve, where high supervision time will create a negative slope persisting until large farm sizes. In contrast, low supervision time will also enable small farms to minimise average costs (Lowenberg-DeBoer et al. 2022). Third, suppose the novel smart farming technology can provide higher managerial capacity. In that case, it can allow farms to grow more before encountering diseconomies of size, or even grow without encountering diseconomies of size as in the case of megafarms with several operators (Chaddad and Valentinov, 2017; Hermans et al. 2017). Finally, the indivisibility and investment costs of the technology can create thresholds for further expansion. Indivisibility refers to the extent to which technology employment can gradually increase (Rasmussen, 2012). In contrast, high indivisibility means that the usage of the technology cannot be gradually increased but rather stepwise. Figure 4.2 illustrates these three potential effects of smart farming technology.

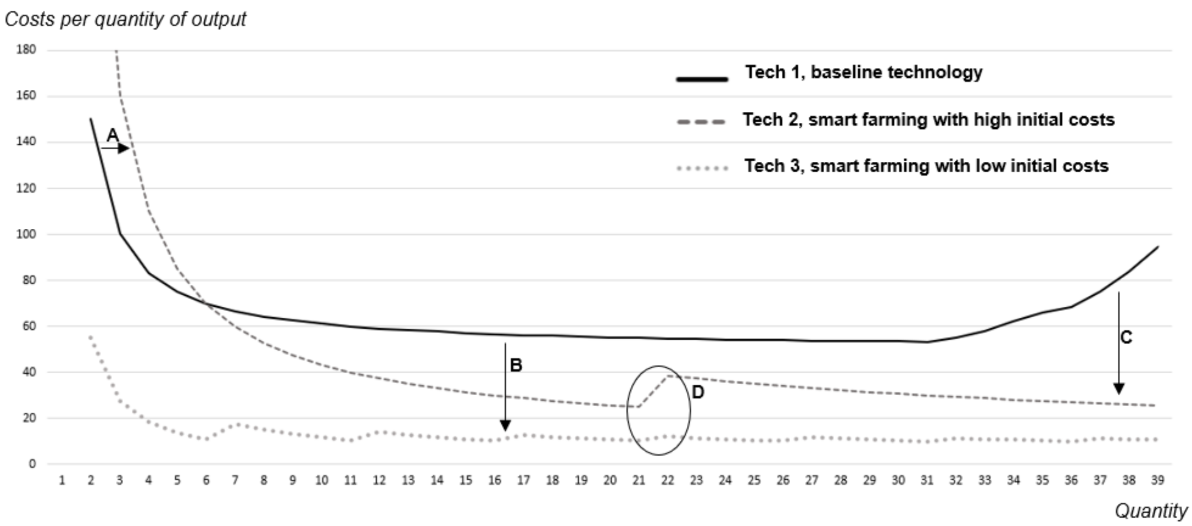

Figure 4.2: Illustration of Economies of Size (EoSi) for different features of the technology.

Note: The three curves illustrate three different hypothetical technologies and show how average costs might change as novel technology is adopted. Fig 2 is simulated by the authors using arbitrary numbers to illustrate potential shifts in the average cost curve for smart farming technology. A-D represent the four potential effects from changing EoSi as discussed in the section before the figure. A: Higher investment cost. B: Changing slope of the average cost curve. C: Decreasing diseconomies of size for large farm sizes. D: Investment cost and indivisibility, creating potential hurdles for further expansion.

For illustration, Figure 4.2 shows two types of smart farming technology: one with high indivisibility, high investment costs and high supervision requirements (technology 2) and one with low investment costs, high divisibility and low supervision requirements (technology 3). Relating to technology features, EoSi can be affected by high investment costs and the indivisibility of a technology, which can shift the average cost curve down and to the right (A in Figure 4.2), creating hurdles for further expansion (D). The degree of autonomy of technology can change the slope of the cost curve, where high supervision time will create a negative slope and low supervision time will flatten out the slope, making smaller farm sizes more feasible (B). Finally, information gathering and provision and VRA can alleviate the managerial limitations at large farm sizes, enabling farms to continue to grow without running into decreasing returns to size (C).

Economies of scope (EoSc)

We follow the definition of EoSc as sharable inputs (Panzar and Willig, 1981). Sharable, or complementary, inputs provide arguments for diversification because such inputs can be used to produce several goods simultaneously (Bowman and Zilberman, 2013). Analogously, the absence or decrease of sharable inputs motivates specialization. (Panzar and Willig, 1981) categorized sharable inputs as 1) elements of productive capacity (such as electricity), 2) indivisible equipment usable for producing more than one good and 3) human capital or other inputs that inevitably offer coproducts (the typical example being sheep offering mutton and wool). Similarly, (Lansink, 2008) exemplifies sharable inputs such as labour, farm structures and machinery. In addition, knowledge is a sharable input that provides arguments for diversification, as diversified systems are often more complex to manage than specialized ones

(Chavas and Barham, 2007). Both Lansink (2008) and Chavas and Barham (2007) build their formulations of sharable inputs on Panzar and Willig (1981).

Smart farming technology can generate both increasing and decreasing EoSc, depending on whether it increases or decreases the usage of sharable inputs. While EoSc is barely studied in the context of the effects of technology, Takeshima et al. (2020) provide an example by studying mechanization on Nigerian farms identifying that diversified systems are likely to be preserved where mechanization is more versatile and can be applied to different crops (Takeshima et al. 2020), i.e. when technology is sharable. On the one hand, if technology has high indivisibility, replaces labour and provides knowledge for a specific production process, this motivates expanding production of the good where the improved technology is applicable while decreasing the production of other goods. On the other hand, smart farming can enable more diversified production by increasing sharable inputs. Considering the features of smart farming technology, both increasing and decreasing EoSc can be generated through all technology features, depending on the possibility of applying the features to several production processes. Figure 4.1 illustrates that all technology features can affect EoSc, as long as the feature increases or decreases sharable inputs.

4.3.2 *Rebound mechanisms as drivers of induced structural and behavioural change*

Rebound effect is a broad term initially developed to explain the difference between potential and actual energy savings (Sorrell, 2007). However, the exact definition vary (Peters et al. 2012; Lange et al. 2021). Rebound effects can arise when an efficiency improvement lowers production costs, resulting in savings on the farm. These savings can be re-invested into expanding production, changing production processes, or be allocated elsewhere Paul et al. 2019). A common distinction of rebound effects is between income and substitution effects. Income effects define a situation where cost savings can be re-invested and substitution effects define substituting processes towards using more of the process of which efficiency was increased (Sorrell, 2007; Paul et al. 2019). However, all rebound effects occur through adaptive responses to an efficiency increase that offset part or all of the resource savings achieved by the efficiency improvement (Sorrell, 2007; Paul et al., 2019; Lange et al., 2021).

Rebound effects are relevant to explain changes in farm structures after adopting novel technology. These effects have been intensively studied for technologies that improve water use efficiency (Albizua et al. 2019; Song et al. 2018; Wang et al. 2020) and land use efficiency (Meyfroidt et al., 2018; García et al., 2020). The 2019 IPCC report underscores the importance of considering rebound effects, particularly in the livestock sector, as reductions in emission intensities need to be coupled with appropriate governance to avoid rebound effects, offsetting mitigation efforts (Mbow et al. 2019).

Considering the features of smart farming, input use efficiency can be increased through the traits of capacity, autonomy, VRA and information, as these are all features that can increase input use efficiency. Whether the capacity of the technology will trigger rebound mechanisms depends on whether the farm is operating at the optimal size for the technology such that efficiency can be increased or if the farm first will undergo some structural change triggered by changed EoSi to realize efficiency gains. VRA increases the efficiency of inputs, commonly pesticides and fertilizers in crop production or livestock in animal husbandry, generating rebound effects that result in lower resource savings compared to a scenario without any induced S&B change. Using VRA can also increase the relative efficiency of using fertilizers or chemicals compared to mechanical methods and thus, through the rebound effect, motivate the farmer to increase the usage of these inputs, creating a larger environmental burden.

Information gathering and provision, and autonomy can increase labour efficiency. Autonomous technology replaces the need for some labour tasks, where cost savings can generate rebound effects in other inputs. Decreases in labour requirements can give rise to rebound effects, mainly as autonomous technology replaces more high-skilled jobs rather than just standardized tasks (Marinoudi et al., 2019), leading to considerable cost savings. The cost savings can be re-invested to change farm structures; however, the exact outcomes generated through rebound mechanisms are not inherent in the theory but rather vary depending on how the farmer chooses to reinvest the cost savings.

4.3.3 *Risk balancing as a driver of induced structural and behavioural change*

Farming is characterized by risk, and farmers' attitudes to risk shape their decisions for their farms (Just and Just, 2016). Risk and uncertainty also play an essential role in adopting new technology (Marra, Pannell, and Abadi Ghadim, 2003). A common assumption is that new technology is associated with higher risk than the old traditional technology, but findings imply that new technology can also help farmers decrease uncertainty (Barham et al., 2014). Furthermore, new technology on farms affects the risks the farmer faces (Kim and Chavas, 2003; Orea and Wall, 2012; Wauters et al., 2014). Smart farming can, for example, reduce risks through VRA (Lowenberg-DeBoer, 1999) or enable earlier detection of pests, thereby reducing risks of pest damage (Liu et al., 2017; Rojo-Gimeno et al., 2019). Farmers' responses to risk can be highly heterogeneous (Ramsey et al., 2019), making it challenging to describe general principles of how smart farming can generate S&B change through changes in risk.

We follow the risk balancing principle by Gabriel and Baker (1980) and focus on two broad types of risk: business and financial (Komarek et al. 2020). Risk-balancing behaviour has been identified empirically among European farmers (Gabriel and Baker, 1980; de Mey et al. 2014 & 2016). Business risks stem from the market and production, while financial risks involve how the farm is financed (Gabriel and Baker, 1980; Komarek et al. 2020). Farmers identify farm survival and profit maximization as two objectives to maximize subject to the constraint that risks should not exceed a certain level. Farmers' risk preferences, a key concept in agricultural economics, are reflected in the level of risk a farmer is willing to accept. The risk balancing is illustrated as the sum of business and financial risks constrained by a maximum acceptable level of risk, β. The risk constraint can be expressed as (Gabriel and Baker, 1980):

$$\frac{\sigma}{cx} + \frac{\sigma I}{cx(cx-I)} \leq \beta \tag{4.1}$$

The first operator denotes business risk as the net cash flow standard deviation (σ) over the net cash flow (cx). Variations in cash flow come from the market or the production process. In contrast, financial risk concerns how the farm is financed, denoted by the second operator in Equation 4.1, where risk is increased by fixed financial obligations such as the obligation to repay a debt (Gabriel and Baker, 1980; Komarek et al. 2020). I denotes the fixed debt servicing obligation. If σ is increased, both business and financial risks increase and the risk must be adjusted. For example, a farmer can make decisions about production, farm financing, investment decisions or a combination. However, when σ is decreased, there is slack in the risk constraint and the farmer can afford to make riskier decisions.

Considering risk balancing (Gabriel and Baker, 1980), we can consider two scenarios where a smart farming technology can affect behavioural adaptations by changing risk: when business risk decreases, leaving a slack in the risk constraint or when increases in financial risk result in higher risks than the level which is acceptable to the farmer. Recent findings indicate that production and financial risk are independent of each other, such that a farmer's attitude towards production risk is a poor predictor of farmers' attitude towards financial risk (Finger et al. 2023). This indicates that the different types of risks are handled separately by farmers, which could imply that adopting novel technology could generate S&B change if technology is adopted to address one of these risk domains, requiring later adaptation in the other.

We consider scenarios in which risks must decrease to comply with the risk constraint and when risk can be increased if there is a slack in the risk constraint. The following section discusses the technology features that trigger these changes in risk.

Slack in the risk constraint

From the risk constraint in Equation 4.1, slack can motivate farmers to adapt their behaviour to increase profits by increasing the SD of net cash flow or debt obligations. Debt can be increased by taking a loan to invest in new technology or to invest in farm structural change and increasing productivity and capacity (Uzea et al. 2014). Thus, when there is a slack in the risk constraint, a farmer can make investments that increase risks with the prospect of higher gains. However, investing in expansion can also decrease the total risks if the farm is characterized by increasing returns to size (Langemeier and Jones, 2000). Thus, if a farm is expanding to use increasing returns to size and maintain slack in the risk constraint or even decrease risks on farms, it might be motivated to expand or increase capacity even further to increase risks to meet the risk constraint.

A slack in the risk constraint can be generated by the smart farming feature of VRA, which can increase cash flow from increased efficiency, or from increasing information that decreases production risks. This is illustrated in Figure 4.1. Figure 4.1 also illustrates an influence between risk balancing and changes in EoSi as under increasing returns to size, farmers can opt to expand to decrease risks, incentivizing them to take riskier decisions by, e.g., expanding further or investing in additional technology, as risks are below the tolerated level.

When risks are too high

If technology increases risks and the left-hand side of Equation 4.1 is higher than β, a farmer is motivated to decrease risks to meet the constraints. This situation can arise if the technology is a high investment and the farmer must take a loan. Griffin et al. (2018) illustrate financial risks by asking, “Will this investment pay for itself quickly?”. As financial risks increase and if the novel technology does not decrease business risks, farmers may be motivated to decrease risks to meet the risk-balancing constraint.

A common way to manage increased financial risk is to keep more liquid assets (e.g. animals ready for slaughter or grain or forage directly convertible to cash) (Gabriel and Baker, 1980; Langemeier and Jones, 2000; Ullah et al. 2016). In contrast, illiquid assets are livestock and machinery (Harwood, 1999). Thus, farmers facing high financial risks are less likely to expand because they hesitate to invest in more land and machinery. Instead, farmers are motivated to increase liquidity to manage their debt. An exception to this hesitation to expand can be seen in cases where the farm is operating under increasing returns to size, where increasing production to utilize the technology fully decreases production risks (Langemeier and Jones, 2000). Thus, when a farmer takes on increased debts by investing in a technology, risk-balancing behaviour can provide an additional drive to utilize size effects as a way to lower risks. However, it could lead farmers to be more cautious with further investments on the farm.

Worth noting here is that there are other risks associated to smart farming often highlighted in the literature. Such risks are the potential marginalisation of farmers not adopting the technology, worries about data security and the risk of autonomous technology creating a disconnect between farmers and their crops and animals (Sparrow and Howard 2021). Furthermore, increasing the autonomy on farms can be associated with risks which we cannot yet imagine as full autonomy on farms is still in its early days (Shutske, 2023). These types of risks are outside the scope of this study, but nevertheless important to consider when visualizing the future of agriculture.

4.4 Empirical foundations: literature review

In this section, we review previous research on farm-level effects of smart farming with the aim of providing examples of how the conceptual framework applies. To reach this aim, we conduct a structured literature search of the Web of Science (WoS) and Scopus database, including peer-reviewed literature and conference contributions. We borrow elements from the systematic literature review by following the five steps of a systematic literature review (Khan et al. 2003; Okoli, 2015): framing the questions, identifying relevant work, assessing the quality of studies, summarizing the evidence and interpreting the findings. To identify relevant work, we use the keywords in Table 4.1. However, our approach deviates from a systematic review in how we screen the resulting studies for inclusion: Rather than mapping all literature on the subject, we follow the principles of a narrative literature review by organizing the findings thematically based on whether they contain smart farming induced S&B change and whether we can map the changes into the mechanisms covered in our framework. In this respect, we do not aim to provide an exhaustive overview of the entire literature on the topic of assessing the effects of smart farming technology but rather investigate whether we can identify studies providing examples of the conceptual framework presented in Figure 4.1.

Table 4.1:. Keywords for the literature search.

Group		**Search terms**	**Nr studies**
1 – specify context (joined by AND) *All papers should include some elements of agriculture, technology and structural change*	Agriculture (from Shang et al. 2020)	*TS = agricultur* OR farm* AND*	
	Identify the technology context (also from Shang et al. 2020 adding "robot")	*TS = technolog* OR innovation* OR robot* AND*	
	Identify the element of structural change	*TS = 'structural change' OR structural OR 'behavio$ral change'OR behavio$r OR intensif* OR expans* OR specialis* OR 'farm size' OR diversific* OR 'herd size'*	= 11 566
2 – specify induced structural and behavioural change (joined by OR) *All papers should also include an*	Economies of size and scope	*TS = 'economies of size' OR 'economies of scale' OR 'diseconomies of scale' OR 'diseconomies of size' OR 'economies of scope' OR 'diseconomies of scope' OR 'scale enlargement' OR expansion OR 'specialised farms' OR 'farm diversification' OR 'complementary inputs' OR 'sharable inputs'*	

element of EoS, risk or increasing input use efficiency.	Risk	*TS= ambiguity or hazard or uncertain* or risk* or variab* or volatil* or stabil* or vulnerab* or resilien* or robust* debt OR purchase*	
	Increasing the input use efficiency	*TS = 'rebound effect*' or Jevon* or 'labo$r use efficiency' OR work* OR labor OR labour OR job* OR task* OR employment**	
3 – specify smart farming	Smart farming (adapted from Shang et al. 2020)	*TS = precision OR digital OR 'smart farming' OR robot* OR autonomous OR automa* OR 'unmanned aerial vehicle*' OR drone OR 'cloud computing' OR 'site specific' OR 'variable rate' OR 'GPS' OR 'remote sensing' OR 'soil sampling' OR 'yield mapping' OR 'yield monitor*' OR 'autosteer' OR drip OR irrigation OR 'water saving'*	= 1660 (filtered for papers in English)

Note: * are used to broaden the search terms.

4.5 Results

In this section, we discuss the literature review results and draw connections between the literature and the conceptual framework in Figure 4.1. We searched the databases a final time on 08 January 2025. The literature search resulted in 10 546 papers. After excluding duplicates, papers based on meso topics (WoS) and subject area (Scopus),[3] 3 263 papers remained to screen for inclusion. This process is illustrated in Figure 4.3. Refining searches by topic follows Šarauskis et al. (2022). Next, we formulate a protocol for what qualifies a record to be included in the literature review (available in Appendix 1). When screening titles and abstracts, many papers are excluded as they focus on adoption determinants, contribute to developing technology or do not consider smart farming technology.

[3] Excluded meso-topics (WoS): Oceanography, meteorology and atmospheric sciences, Archaeology, Marine biology, Modern history, Soviet, Russian and East European history, space sciences.
Excluded subject areas (Scopus): Computer science, Engineering, Mathematics, Earth and Planetary Sciences, Physics and Astronomy, Biochemistry, Genetics and Molecular biology, Materials science, Medicine, Chemical engineering, Chemistry, Veterinary, Pharmacology, Toxicology and pharmaceutics, Immunology and microbiology, Neuroscience, Health professions, Nursing.

Notably, when considering the 196 articles for full-paper reads, few studies include the potential of smart farming to induce S&B change. As seen in Figure 4.3, most papers are excluded at this stage because they consider the future potential of a smart farming technology (25 studies on farm-level and 8 studies on a higher or lower level of aggregation), adoption determinants (20 studies) and effects of the technology without incorporating S&B change (18 studies). Finally, we identify any S&B change generated by smart farming technology in 34 papers. We identify the S&B mechanisms and outcomes in our conceptual framework (Figure 4.1) in 27 of these studies. The 7 papers indicating S&B change which are not included in our framework mention the absence of effects due to a lack of trust in the technology (Eckelkamp and Bewley, 2020), that the farmer seeks more education to enable efficient use of the technology (Busse et al. 2015; Barnes et al. 2019) or that, after having adopted information technology, farmers increase their commitment to climate change mitigation (Irawan et al. 2023; Mao et al. 2024). Two papers state that the adoption of smart farming technology generates S&B change but does not specify the mechanisms triggering the changes (Martinsson et al. 2023; W. Wang et al. 2024).

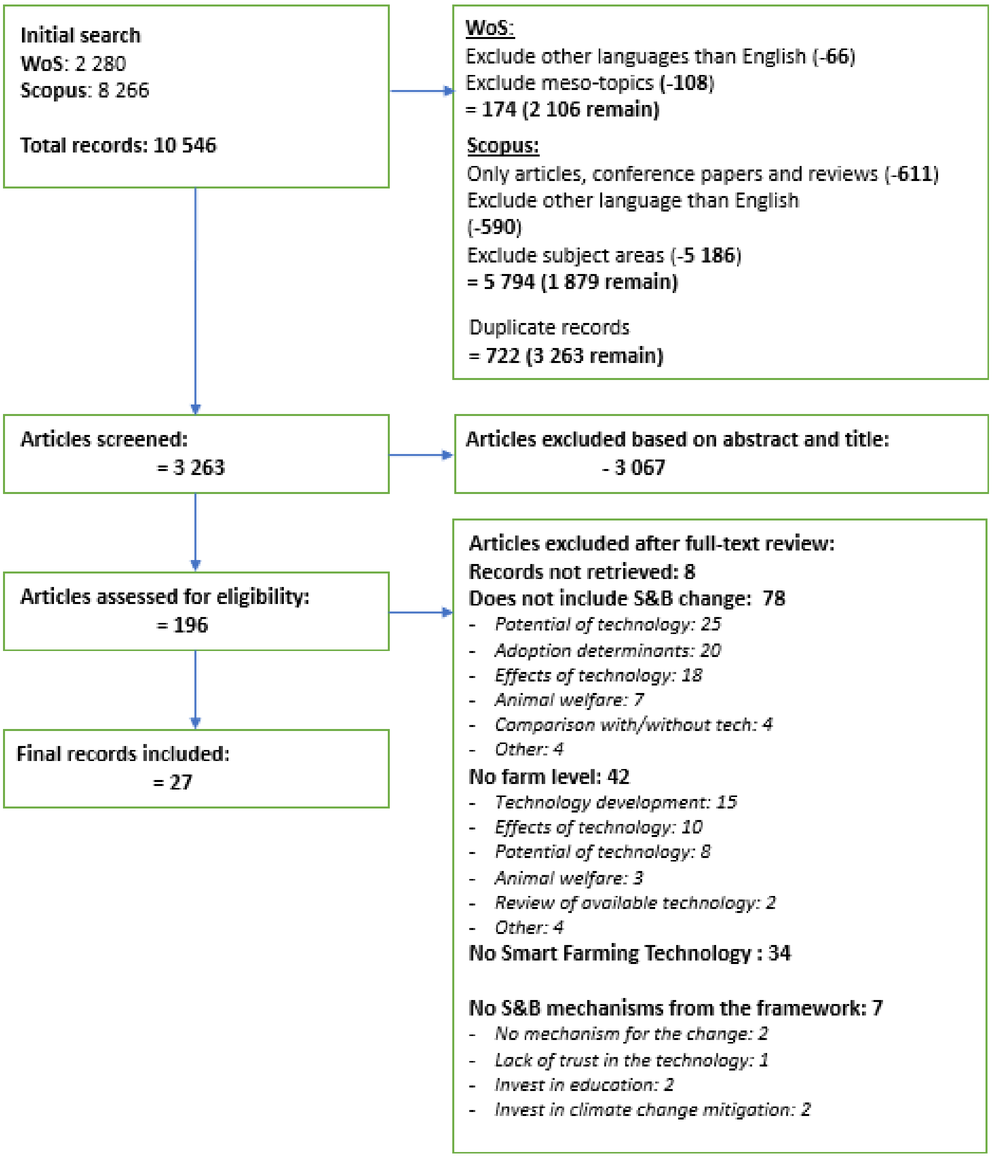

Figure 4.3: Structural and Behavioural (S&B) change in previous literature

We list the mechanisms and outcomes for each paper, then consider whether it fits as one of the processes identified from the theory. In most papers, the mechanisms are not mentioned explicitly but are deduced from the motivations for change described in the papers. Many of the included studies only briefly mention the mechanisms through which smart farming-induced S&B change occurs or refer to them indirectly. Our finding that few studies include the possibility for S&B change and that the few studies that do, in many cases, refer to such change indirectly highlights the need for more research on this topic. Future research on smart farming-induced S&B change can make use of the conceptual framework presented in Section 4.3. For transparency, the quotes from the papers where the induced S&B change is identified are displayed in Appendix 2.

Table 4.2 presents an overview of the results. We distinguish between livestock and arable production as the smart farming technology used in the specializations is significantly different, and thus, this is discussed separately in the following sections. Table 4.2 presents an overview of the results of labelling the EoSi, EoSc, rebound mechanisms, or risk of the 27 papers in which at least one process was detected. In the following, we further discuss the results from the literature review regarding induced S&B change for livestock and arable production.

Table 4.2: Induced structural and behavioural (S&B) change derived from the literature.

Reference	Technology	EoSi	EoSc	Rebound	Risk
Livestock production					
Tangorra et al. (2022)	AMS	X	X		
Rotz et al. (2003)	AMS	X			
Qi et al. (2022)	Automatic oestrus detection	X			
Schewe and Stuart (2015)	AMS	X			X
Steeneveld et al. (2015)	Sensor systems for livestock			X	
Castro et al. (2012)	AMS	X			
Jacobs and Siegford (2012)	AMS		X		
Rodenburg (2017)	AMS		X		
Hansen (2015)	AMS	X			
Vik et al. (2019)	AMS	X			
Hogan et al. (2023)	Automatic calf feeders	X			
Lyons et al, (2014)	AMS	X			
Martin et al. (2022)	AMS	X			
Keeper et al. (2017)	AMS		X		
Bach and Cabrera (2017)	AMS		X		
Lee et al. (2024)	AMS			X	
Arable production	Technology	EoSi	EoSc	Rebound	Risk
Schimmelpfennig (2019)	PA in rice production			X	
McFadden et al. (2022)	Yield and soil mapping			X	
Tenreiro et al. (2023)	VRA	X			
Monzon et al. (2018)	PA			X	X

Lieder and Schröter-Schlaack (2021)	Smart farming		X	X	
Paul et al. (2019)	Precision technology			X	
Lowenberg-DeBoer et al. (2022)	Fleet robotics	X			
Zhang and Mishra (2024)	Information technology			X	
MacPherson et al. (2025)	Digital tools		X		X
Lowenberg-DeBoer et al. (2021)	Autonomous equipment	X			
Smith (2024)	Digital tools			X	

Note: Abbreviations: AMS: Automatic milking system. VRA: variable rate application. PA: Precision agriculture. EoSi: Economies of size. EoSc: Economies of scope.

4.5.1 *Induced structural and behavioural change in livestock production*

Of the 27 included papers, 16 focus on livestock farming. Of these, 13 provide evaluations of AMS. The remaining articles focus on technologies to improve animal monitoring in dairy farming (Steeneveld et al. 2015), automatic oestrus detection (Qi et al. 2022) and smart calf feeders in cattle and dairy farming (Hogan et al. 2023). Automatic oestrus detection is a technology worn by the cow (Qi et al. 2022) and, thus, does not come with the same structural requirements as AMS. Sensor systems are a broader category of technology, which can both be stationary and coupled with an AMS or activity meters placed on the cows (Steeneveld et al. 2015). Thus, the sensor systems, including the automatic oestrus detection, differ from AMS in that these are information systems, without also being large machinery. The calf feeding systems studied by Hogan et al. (2023) are more similar to AMS in that they are large machinery.

We identify S&B change processes through all four mechanisms for smart farming in livestock production. Table 4.3 provides an overview. In Appendix 2, Table 4.5, we provide more detail on the effects derived from each paper.

Table 4.3: Induced structural and behavioural (S&B) change in livestock production

Reference	Technology trait	Effect	Mechanism	Outcome

Tangorra et al. (2022)	Capacity	EoSc	A certain farm structure is required	More farm structures for dairy production are built
	Autonomy	EoSi	Labour use efficiency can be improved for larger farm sizes	Expansion to increase efficiency
Rotz et al. (2003)	Capacity	EoSi	Potential to increase economic viability at full utilisation	Increased herd size
Qi et al. (2022)	Capacity	EoSi	No increased costs for herd expansion	Increased herd size
Schewe and Stuart (2015)	Investment cost	Risk balancing	Increased debt load	Increased intensity of production
		EoSi	Increased production to offset the investment	Increased herd size
Steeneveld et al. (2015)	Autonomy	Rebound effect	Increased labour use efficiency	No decrease in labour input
Castro et al. (2012)	Capacity	EoSi	Potential to increase economic viability	Increased herd size to full utilisation
Jacobs and Siegford (2012)	Autonomy	EoSc	Potential to increase efficiency	Increased labour usage in the milking process
Rodenburg (2017)	Capacity	EoSc	Potential to increase efficiency	Structural adaptations of the barn
Hansen (2015)	Capacity	EoSi	Need to adapt farm structures to the technology	Expansion and investment in new technology
Vik et al. (2019)	Investment cost	EoSi	Need to finance the investment	Increase production
		DisEoSc	Need to finance the investment	Increase specialisation in dairy
Hogan et al. (2023)	Capacity	EoSi	Potential to increase labour use efficiency	Increased herd size to full utilisation
Lyons et al. (2014)	Capacity	EoSi	Potential to increase economic viability	Increased herd size to full utilisation
Martin et al. (2022)	Investment cost	EoSi	Potential to increase economic viability	Increase production
	Capacity	DisEoSi	Potential to maintain economic viability	Maintain production
Keeper et al. (2017)	Capacity	DisEoSc	Potential to increase milking efficiency and reduced labour requirements	Adapt farm structures to the AMS (specialise in dairy)
Bach and Cabrera (2017)	VRA	DisEoSc	Need to optimise the technology	Adapt farm structures to dairy

Lee et al. (2024)	Autonomy	Rebound effect	Labour savings	Invest to improve productivity

We derive effects through EoSi from 11 of the 16 papers. EoSi arises after adopting AMS (Rotz et al. 2003; Castro et al. 2012; Vik et al. 2019; Tangorra et al. 2022; Martin et al. 2022; Lyons et al. 2014) but also after adopting livestock sensor systems (Steeneveld et al. 2015) and automatic calf feeding (Hogan et al. 2023). Automatic oestrous detection technology is also included in this process, as it increases managerial capacity and thus decreases diseconomies of size, enabling more efficient expansion and overcoming decreasing returns to size (Qi et al. 2022). Finally, Martin et al. (2022) state that farms adopting AMS will decrease profits if the herd size is expanded above what can be utilized in the AMS unit on the farm, which is classified as EoSi through technology indivisibility.

The papers identifying EoSc focus on AMS and relate to the technology's indivisibility and high structural requirements. As outlined in Section 3.1.2, we identify EoSc as sharable or complementary inputs that can produce several goods simultaneously (Bowman and Zilberman, 2013). When AMS is adopted, dairy production efficiency increases, increasing relative costs for producing other goods. There are two ways through which this is realized as induced S&B change. First, structural change and further investments optimize the usage of the AMS (Jacobs and Siegford 2012; Hansen 2015; Rodenburg 2017; Keeper et al. 2017; Bach and Cabrera 2017; Tangorra et al. 2022). Second, to adapt to the AMS, Martin et al. (2022) point out that farmers are motivated to adopt more complementary technology. This underpins a feedback effect, where an outcome can be the decision to adopt another technology, generating more S&B change.

The key to rebound effects is that efficiency increases generate cost savings that can be re-invested or used to substitute less efficient processes. One process was identified through which rebound effects can arise, driven by increasing labour use efficiency and where the cost savings can be re-invested in expanding or intensifying production (Steeneveld et al. 2015; Hogan et al. 2023; Lee et al. 2024).

Finally, we consider mechanisms of risk. One paper identified that the debt burden from investing in an expensive technology (in this case, AMS) drives intensification (Schewe and Stuart, 2015). Following risk balancing (Gabriel and Baker, 1980), farmers facing increased debt are unlikely to expand their farm structures. Still, they may be motivated to increase production to keep more liquid assets and repay the debt. This aligns with the behaviour derived from Schewe and Stuart (2015).

Concluding the findings on smart livestock farming, indications of induced S&B change were identified for all mechanisms specified a priori in the theoretical foundations. Smart livestock farming, mainly by AMS, can motivate expansion through EoSi and rebound mechanisms. Farms expand after adopting AMS because there is a prospect of lower costs and increased benefits if herds are larger and because AMS generates cost savings, which can be re-invested (rebound mechanism). Technology can also drive farmers to intensify production by increasing the milk yield per cow as feeding efficiency increases and as a strategy to cope with the increased debt. Identifying these effects alone is not novel; however, the novelty lies in identifying the different processes driving the development of farms through smart farming-induced S&B change. Thus, we add detail and improve the understanding of why livestock farms evolve the way they do after adopting a novel smart farming technology. That only one of the 16 records included in livestock farming considers debt burden as a driver of change indicates a gap in the research; it is more likely that this aspect was omitted by previous research rather than the effect is absent.

4.5.2 *Induced structural and behavioural change in arable production*

We identify 11 papers focusing on arable production, including studies on yield and soil mapping for maize production (McFadden et al. 2022), VRA of nitrogen fertilizer in wheat production (Tenreiro et al. 2023), PA for grain production (Monzon et al. 2018), different smart farming technologies in arable production (Lieder and Schröter-Schlaack, 2021), precision farming in rice production (Schimmelpfennig, 2019), fleet robotics in crop production (Lowenberg-DeBoer et al. 2021 & 2022) and information technology (Smith, 2024; MacPherson et al. 2025). Notably, all but two included technologies enable intra-field intervention. We also include two papers that do not focus on a specific technology but discuss the potential future effects of smart farming in arable production in general (Lieder and Schröter-Schlaack, 2021) and precision technology in land and soil management (Paul et al. 2019). Despite the few papers, we identify induced S&B change through all mechanisms but risk. Table 4.4 displays the S&B change derived from the literature review. More details are provided in Table 4.5 in Appendix 2.

Table 4.4 Induced structural and behavioural (S&B) change in crop production

Reference	Technology trait	Effect	Mechanism	Outcome
Schimmelpfennig (2019)	VRA	Rebound effect	Increased efficiency of conservation agriculture	Increased practice of conservation agriculture
McFadden er al. (2022)	Information	Rebound effect	Increase efficiency of production	Increase output
Tenreiro et al. (2023)	Indivisibility	EoSi	Costs can be minimised at larger farm sizes	Expansion to minimise costs
Monzon et al. (2018)	VRA	Rebound effect	Increased efficiency of production	Increased input usage
		Rebound effect	Increased efficiency of production	Increased production of high-yield crops
Lieder and Schröter-Schlaack (2021)	Information	EoSc	Diversification is enabled	Increased diversification of crops
	VRA	Rebound effect	Increased fertilizer use efficiency	Increase fertilizer usage and increase intensity on heterogenous fields
		Rebound effect	Increased efficiency of production	Increased cultivation of high-value crops
		Rebound effect	Increased water use efficiency	Increased water usage
Paul et al. (2019)	VRA	Rebound effect	Increase efficiency	Increase input usage

Lowenberg-DeBoer et al. (2022)	Autonomy	EoSi	With higher supervision-time, costs are lowered at larger farm sizes	Expansion to minimise costs
Zhang and Mishra (2024)	Information	Rebound effect	Increase land and labour productivity	Increased commercialization
MacPherson et al. (2025)	Investment cost	Risk	Need to pay off debt	Work more
	Information	Risk	Reduced production-risk of diversification	Diversify output
		EoSc	Increased opportunities for crop diversification	Diversification
Lowenberg-DeBoer et al. (2021)	Capacity	EoSi	Possibility to farm on smaller and irregularly shaped fields	Expand to fields previously unprofitable to farm
	Capacity	disEoSi	Possibility to farm on small and irregularly shaped fields	Decreased incentive to expand to minimise costs
Smith (2024)	Information	Rebound effect	Increased control over workers	Restructure labour - Intensify and specialise tasks

EoSi is identified in three papers. Tenreiro et al. (2023) identify EoSi regarding a threshold for when VRA of fertilizers has an economic advantage compared to uniform applications in their sample of Spanish wheat farms. Lowenberg-DeBoer et al. (2021) find that by using autonomous technology for grain production; profitable production is also enabled on smaller and more irregularly shaped fields. However, this can lead to farm expansion onto fields that were previously too high-cost. In later work, Lowenberg-DeBoer et al. (2022) show that fleet robotics used with current requirements of supervision time will enable decreasing costs under the condition that farms expand, where the benefit of larger farm sizes increases the higher the required supervision time is. Lieder and Schröter-Schlaack (2021) and MacPherson et al. (2025) identify the effects driven by EoSc, where smart arable farming can provide information to maintain and increase crop diversification.

The effect we identify most frequently is related to rebound mechanisms. Rebound mechanisms increase efficiency in five ways, leading to six different outcomes. First, increasing input use efficiency increases output (Monzon et al. 2018; McFadden et al. 2022) or, if producing another crop becomes more profitable, a shift towards growing more high-value and input-intensive crops (Monzon et al. 2018; Lieder and Schröter-Schlaack, 2021). Second, increasing the output per hectare increases land use efficiency, which drives land use expansion or intensification (Monzon et al. 2018; Paul et al. 2019; Lieder and Schröter-Schlaack, 2021). The third technology feature that drives S&B change through rebound mechanisms is the increased efficiency of operating heterogenous fields, which (Lieder and Schröter-Schlaack, 2021) identified. This is listed as a separate effect, as it highlights a shift where farmers, apart from re-investing benefits from increasing output per hectare into intensification or expansion, can also expand their production to land that was not previously profitable to farm. Smith (2024) find that labour can be better supervised with new technology, which can motivate a re-structuring of labour to more specialized tasks. The fifth and last feature to drive rebound mechanisms is that the benefits of conservation agriculture can be increased using PA, motivating farmers to expand the land farmed (Schimmelpfennig, 2019). This differs from previous specifications of rebound effects where the conditions are that an increase in efficiency should lead to higher consumption of that input for which efficiency was increased (Paul et al. 2019). In our definition, all change motivated by increased efficiency is considered a rebound effect, independent of the outcome.

Finally, from one paper, we can derive S&B change due to changes in risk (MacPherson et al. 2025). As farmers invest in new information technology, they face pressure to increase production to pay off the debt. Further, as information technology can decrease the risks of diversifying outputs, this can motivate farmers to diversify what crops are produced (MacPherson et al. 2025).

Summarising, we identify rebound effects to occur most frequently as effects of smart farming in arable production. The few responses due to changes in risk or EoSi and EoSc likely reflect the literature’s focus on more immediate effects. While rebound effects can arise in the short run, changes in farm structures as responses to EoSi, EoSc and risk are visible only in the long term, which requires studying technology usage for a longer time after adoption. In some of the included studies, this is enabled by using modelling approaches (Lowenberg-DeBoer et al. 2021; MacPherson et al. 2025).

4.6 Conclusion

Identifying and understanding induced S&B change is essential to assess how novel technology can contribute to sustainable development. The concept of induced S&B change provided in this paper enables predicting what effects smart farming technology might have in the future, given the features of the technology. On the one hand, technology may incentivize expanding and intensifying production through EoSi, rebound effects or changes in risk. On the other hand, technology can improve the efficiency of smaller and more diversified farms through EoSc. It is important to consider the relative importance of these effects for realizing farm structural development policy objectives and for modelling when making predictions about farm developments after technology adoption. By understanding S&B change induced by smart farming technology, decision-makers are better equipped to steer and predict future developments.

The results from the literature review distinguish between livestock and crop production. Despite their differences, comparing them provides valuable insights. One of the largest differences in smart farming adoption between the two specializations is that we identify more and earlier studies on autonomous livestock farming in the form of AMS (Table 4.3). In contrast, only one study is identified to discuss the effects of fully autonomous technology in arable farming (Table 4.4). Due to the high initial investment associated with AMS adoption, farmers are motivated to increase milk production to be able to afford the investment (Vik et al. 2019) and when financing the investment with a loan, the increased debt can create pressure to increase productivity (Schewe and Stuart, 2015). However, this effect is not identified in arable smart farming, likely as the technology in the reviewed studies requires smaller investments than AMS. Nevertheless, as farmers adopt more autonomous and robotic technology in arable farming, investment costs might increase, creating developments towards expansion.

Our literature review connects the theoretical foundations and previous literature on the effects of smart farming to derive examples of how the framework applies. While we find support for S&B through EoSi, EoSc, risk and rebound effects, future research can extend the framework to also consider other effects. Particularly, several studies highlight the absence of effects due to a lack of trust in the technology and unwillingness to give up control (Jacobs and Siegford 2012; Steeneveld et al. 2015; Eckelkamp and Bewley 2020). Including the possibility of the farmer not acting on the provided information is an avenue for future research extending the provided framework. Another avenue for future research, highlighted and enabled by this study, is to conduct empirical research on the farm-level smart farming-induced S&B change.

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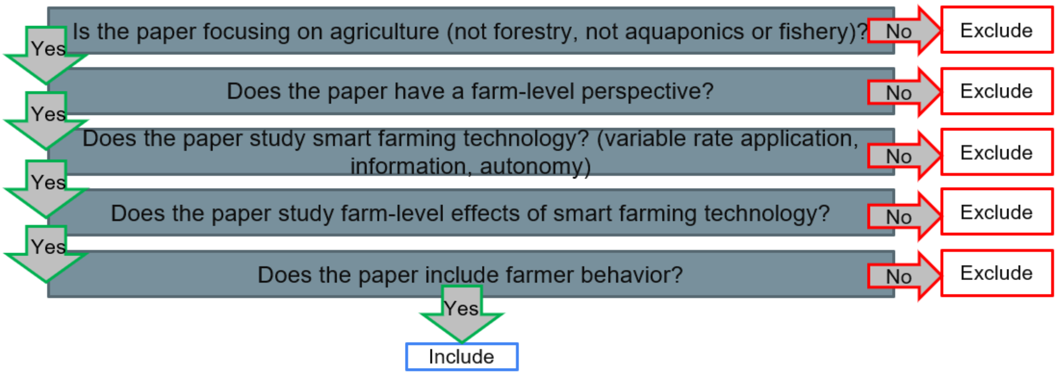
4.8 Appendix 1: inclusion criteria and labelling

When screening the papers for inclusion, the following protocol was used:

Figure 4.4: Protocol used for the literature review



The researchers screening the papers were then appointed to read the papers deriving mechanisms and outcomes and labelling these as EoSi, EoSc, rebound effects or risk balancing, or other if the effects did not fit into any of the a priori defined mechanisms.

4.9 Appendix 2: details of included records

Table 4.5shows the induced S&B change derived from each paper together with an extract from that paper where the effects are identified. The square brackets indicate additions made by the author of this paper to clarify abbreviations or other aspects not clear from the short quote in Table 4.5.

Table 4.5: Induced S&B change derived from each paper extracted from the literature review

Livestock production

References and details	*Label*	*Identification in text*
Tangorra et al. 2022 **Country:** Italy **Data:** Survey: 62 dairy farmers adopters of AMS **Tech:** AMS	Scope effects (invest more in dairy farming → to optimise technology)	"In 29% of farms, the adoption of the milking robot required the construction of a new barn" "in accordance with the switch to Automatic milking, most farmers chose to build new freestall barns and improve their facilities".
	Size effects (increase herd size → minimise costs of labour)	"The number of FTE ["full-time employee"] in cluster 3 ["large sized farms with high milk production"] was significantly higher (P < 0.05) than the other 2 clusters due to the higher number of lactating cows and AMS installed (Table 2). In cluster 3, a single FTE produced 115% and 30% more milk annually than clusters 1 ["small farms with low milk production"] and 2 ["medium farms"], respectively. This is consistent with the findings of Hadley et al (2002), where increasing herd sizes resulted in improved labor efficiency due to several factors such as labor-saving technology adoption, skilled and managerial personnel employment, better facilities use, and economies of size (Bewley et al., 2001; O'Brien et al., 2007).
Rotz et al. (2003) **Country: USA** **Data:** Simulations, historical weather data, regional information **Technology:** AMS	Size effects (increase herd size → minimise costs)	"Highest farm net return to management and unpaid factors was when AMS were used at maximal milking capacity. Adding stalls to increase milking frequency and possibly increase production generally did not improve net return" "At 50- to 60-cow farm sizes, a single AMS unit was better utilised, providing an equal or greater return than traditional milking systems" "A primary disadvantage is that they [the AMS] require a large initial investment"
Qi et al. (2022) **Country:** China **Data:** Survey data	Size effects (no increased costs for management for larger herds → expansion)	"herd size significantly negatively impacts dairy cow yield; second, the adoption of digital technology can attenuate the negative impact of herd size on dairy cow yield"

Technology: Automatic oestrus detection		"The negative impact of herd size on dairy cow yield diminishes with the adoption of digital technology."
Schewe and Stuart (2015) **Country**: USA, the Netherlands and Denmark **Data**: Interviews with 35 adopters **Technology**: AMS	Size effects (want to maximise profitability → invest in increasing herd size, Size effects (increased capital costs → expansion)	"Priorities to maximize profitability and extent of debt load resulted in decisions to increase heard size or convert from a pasture-based operation to year-round confinement" "one-half of adopters interviewed have increased herd size, all with the ultimate goal of increasing production to offset capital investment."
	Risk (increased debt → increased productivity)	"our findings demonstrate that AMS may increase the debt load, undermining farm resiliency and increasing the environmental intensity of production". "Pressure to increase production to compensate for the high cost of AMS and possible reduced resilience resulting from debt was a central concern for many adopters." "Those farmers with less acquired debt did not feel the same pressures to increase productivity and maintained a higher degree of perceived financial resilience".
Steeneveld et al. (2015) **Country**: the Netherlands **Data**: Survey to 512 farms. 202 farms had sensor systems and 310 farms did not have **Technology**: Sensor system	Size effects (increased capital costs → expansion)	"Farms with sensor systems had a significantly larger average herd size than farms without sensor systems. This suggests that sensor systems may be adopted by farms who wish to pursue a herd expansion strategy". "Farms without any sensor system had an average herd size of 104 cows in 2013, compared with 114 cows for AMS farms with sensor systems and 147 cows for CMS farms with sensor sys- tems (data not shown)."
	Rebound effects (increased labour efficiency → expansion)	"The finding that the FTE ("Full-Time Employee") did not decrease after investment might have several explanations. First, farms in the current dataset may be more focused on expansion than on having more free time, thus a decrease in FTE does not show as they plan a transition to more cows".

Castro et al. (2012) **Country**: Spain **Data**: Collected data from AMS units **Technology**: AMS	Size effect (expansion → increased efficiency)	"the milk yield could be maximised by milking the maximum number of cows per AMS with a value of between 2.40 and 2.60 milking per cow per day".
Jacobs et al. (2012) **Country**: USA **Data**: Literature review **Technology**: AMS	Scope effects (structural change → optimise technology)	"Enough evidence exists to suggest that a delicate balance must be achieved, with cows motivated to voluntarily approach the AMS to decrease farm labor while avoiding unproductive visits to help promote an efficient system and maximise use of the AMS" "without a well-managed traffic situation, the potential for a bottleneck or absence of cows at the AMS increases, resulting in a less efficient milking system (Wiktorsson and Spörndly, 2002)".
	Scope effects (changed management → optimise milk yield)	"if the cow does not participate voluntarily in the milking and feeding routine, labor is required to complete these processes. Therefore, the cow's ability and motivation to individually access the milking stall become important to the overall success of the system (Hogeveen et al., 2001). The success of various strategies for encouraging voluntary milking visits will be reviewed in future sections of this document".
Hogan et al. (2023) **Country**: Ireland **Data**: Survey **Technology**: Automatic calf feeder	Size effects (labour efficiency can increase for larger herds→ expansion)	"Results showed an increase in total farm time input in 2021 compared to 2019, but this was accompanied by an improvement in labour efficiency on farms. This finding corroborates previous labour research, which showed an economy of scale effect was present with regard to labour efficiency; as herd size increased, time input increased and labour efficiency improved (O'Donovanetal., 2008; Demingetal.,2018; Hoganetal.,2022a)."
Rodenburg et al. (2017) **Country**: Europe	Scope effects (structural change → optimise usage)	"This paper offers a practical overview of labor organisation, management strategies, and design of robotic milking facilities that contribute to labor efficiency and cow comfort and productivity"

Data: Literature review **Technology**: AMS		"Further research in these areas and the potential to select for milking frequency will undoubtedly result in new opportunities to improve robotic milking outcomes in terms of labor savings as well as milk production per milking stall and per cow".
Hansen et al. (2015) **Country**: Norway **Data**: Interviews with 19 dairy farmers adopters **Technology**: AMS	Size effects (structural and managerial change → optimise usage)	"The majority of the farmers had expanded their production significantly and built new cowshed or refurbished their cowsheds as part of installing the AMS."
Martin et al. (2022) **Country**: No geographical limitation **Data**: Literature review **Technology**: Agricultural robots (main focus on AMS)	Size effects (improve economic viability → expansion)	"At the farm level, this production increase is part of changes to make investments in AMS structurally and eco- nomically viable (Vik et al., 2019). Moreover, the farms that tend to adopt AMS are not the most labor-intensive ones but instead those oriented towards increasing milk production (Heikkila et al. 2012)"
	Diseconomies of size (maintain economic viability → do not expand)	"For a given robotic milking capacity, the milking frequency decreases when the herd size increases, so the profitability decreases when the farm size increases"
	Size effects (increase herd size → increase profits)	"there is a size range in which investing in AMS is economically attractive: medium- sized farms"
Vik et al. (2019) **Country**: Norway **Data**: Interviews with 36 farmers, and secondary literature **Technology**: AMS	Size effects (high initial costs → expansion to spread out fixed costs)	"In practice, investing in AMS implies investing in a new or renovated cowshed. The interviews show that, for many, the investment is partly financed by increased production. To afford a new cowshed, the volume of milk produced must be increased, as the profit per litre is difficult to increase to a sufficient degree, and this has a significant impact on daily life on the farm"
	Size effects (expansion → finance investment, spread fixed costs)	"Installing AMS is often associated with other investments, such as automatic feeders and modernised cowsheds, and the investments are partly financed by increased production".

	Scope effects (invest more in dairy farming → increase efficiency)	"Installing AMS is often associated with other investments, such as automatic feeders and modernised cowsheds, and the investments are partly financed by increased production".
(Lyons, Kerrisk, and Garcia, 2014) Country: - Data: Literature review Technology: AMS	Size effects (technology underutilized → increase herd size)	"Only when system utilisation levels are low and there is spare milking robot time available, then the farmer can aim at increasing the number of milkings performed per day (Hogeveen et al., 2001; Rotz et al., 2003)." "In a report from van Dooren et al. (2004b), an indoor-based AMS that allowed 24 h grazing with 2 daily fetchings, operated 18.2 h per day and had the potential to reach full utilisation (milking 22 h per day) by adding 14 additional cows to the herd and harvesting an additional 336 kg milk/d"
(Lee et al. 2024) **Country**: South Korea **Data**: Secondary farm-level economic data **Technology**: AMS	Rebound effects (labour savings → invest more in management)	"The significant differences in ATT on calf production suggest that adopting smart farming, specifically robotic milking systems, has led to labor input savings, allowing increased effort to be invested in the management of individual dairy cows, which could have resulted in improved calf productivity in the Korean dairy industry."
Arable production		
Reference and details	*Label*	*Identification in text*
(Lieder and Schröter-Schlaack, 2021) **Country**: No geographical limitation **Data**: Literature review and expert interviews **Technology**: smart farming (SF)	Scope effects (information enable diversification → more diverse systems)	"SF can greatly simplify the move away from monoculture and the planning of diverse crop rotations. Appropriate advisory services or platforms for the exchange of know-how promote the implementation of ecological crop rotations, which can also lead to efficiency gains"

	Rebound effect (increase efficiency → expansion)	"SF technologies for fertilizer application may also bring along rebound effects. Schieffer and Dillon concluded in a model experiment that effective cost savings create incentives to increase fertilizer use. According to Ahlefeld, there is also a risk of increasing intensity on heterogeneous fields, which could hardly be fertilised before".
	Rebound effect (increase efficiency → more high-value crops)	"The increase in efficiency could contribute to farmers cultivating higher-value crops than before with regard to a desired profit maximisation and thus increase fertilizer intensity overall"
	Rebound effect (increased efficiency of irrigation → increased irrigation)	"Rebound effects from digital innovations in irrigation have often been studied as it seems particularly susceptible to rebound effects [132]. For example, Sears et al. [117] show that increasing irrigation efficiency can lead to an increase in water use by making it less expensive to irrigate marginal lands."
(Tenreiro et al. 2023) **Country**: Spain **Data**: Experimental farm trial **Technology**: VRA	Size effects (expansion to reach profitable size → minimise costs)	"Under current conditions (S1), a relative advantage associated with VRA adoption was computed but only for an annual area sown as wheat larger than 567 ha year−1 (Table 5). This is considerably larger than representative European (arable) farm sizes, which typically range from 4 to 62 ha"
(Monzon et al. 2018) **Country**: Argentina **Data**: Single case study 5000 ha farm **Technology**: Precision Agriculture (PA)	Rebound effects (increase efficiency → intensification)	"These novel technologies can lead to i) input use reductions and preservation of resource base without yield penalties, ii) increases in production while maintaining the levels of input use and, when necessary, iii) increases in input application without reductions in input use efficiency (Byerlee, 1992). This paper presents a clear example of this type of technologies driving a substantial increase in production in areal farm". Table 4: Precision management increased farm output (between 25%-39% and decreased variation in farm output between 0%- -28% (depending on the zone).
		"The gross margin of San Lorenzo was 112 US$ ha−1 year−1 higher than that for Tandil (Fig.7). This

		difference was related to a 244 US$ ha−1 year−1 higher net income in San Lorenzo despite132US$ ha− 1year−1 higher total cost. This difference in total cost relates to a higher cropping intensity in San Lorenzo (1.32 vs 1.16 crops per year), a lower frequency of Soy1 (a less expensive crop to grow), and a greater frequency of the more expensive maize and winter crop/Soy2 compared to Tandil”. *[Comment: Tandil is the region and San Lorenzo the farm where the PA is used.]*
(Schimmelpfennig, 2019) **Country**: USA **Data**: US national farm-level production data (USDA **Technology**: Precision agriculture (soil and yield mapping, VRT, GPS**)**	Rebound (conservation agri more efficient →increase conservation agri)	“PrecAg is linked to stewardship through BMPs (best management practice) including conservation tillage and erosion control” “The conclusion from the analysis is that profitable and cost-effective implementation of PrecAg in rice production improves average on-farm natural resource stewardship, and lowers the environmental burden of intensive crop management practices”.
(McFadden, Rosburg, and Njuki, 2022) **Country**: USA **Data**: USDA **Technology**: Yield and soil maps	Rebound (increase efficiency → increase output)	“All productive inputs (labor, nitrogen, capital, and other materials) generally increase across the four adoption scenarios. For example, field-level nitrogen applications increase from 6,120 pounds on unmapped fields to 12,611 pounds on fully mapped fields. This large difference is partially driven by field size differences. However, even after accounting for field size, average nitrogen application rates are higher on fully mapped fields than unmapped fields. This variation in input use may reflect some degree of unobservable field or farmer attributes that play a role in map use.” “we find that output increases with the use of maps because of their frontier-shifting and efficiency-increasing effects” “…over the long run as agricultural digitalization deepens, there may be implications for farm structure.

Paul el at. (2019) **Country**: - **Data**: Literature review **Technology**: Precision technology	Rebound (increase efficiency or input to yield → increase output)	"For precision farming, strong direct producer-side rebound effects in the form of higher total fertilizer inputs are possible. In general, an important component of precision farming is calculating the spatially differentiated nutrient demand of plants. In cases of relatively low fertilizer intensities before the implementation of the technology, a higher production potential in some areas of a field with corresponding higher nutrient needs can overcompensate for the reduced fertilizer application in areas with a lower production potential (Flessa et al., 2012)." "efficiency gains from improved crop varieties, intercropping and precision farming/decision support systems could come with direct rebound effects (substitution) if they motivate farmers to reduce tillage and substitute mechanical weed control with pesticide application."
(Lowenberg-DeBoer et al. 2022) **Country**: Great Britain **Data**: Simulation data **Technology**: Swarm robotics	Size effects (decreased average costs from expansion → motivate larger farm-sizes)	"The cost curves show that increasing human supervision time accentuates the economies of scale for larger farms, compared to either the 10% field time autonomous equipment scenario or the conventional scenario" [note: cost/ton wheat and farm size. 100% supervision time ~170£/ton, farm size of 100 ha, ~120£/ton farm size of 500 ha. Conventional technology ~170£/ton, farm size of 100 ha, ~135£/ton farm size of 500 ha.] "For the smallest farm, the 100% supervision scenario has higher production costs than the conventional equipment cost curve, and for the 500 ha farm it is about £11/ton lower. The implication of higher human supervision time for farm size is that the economic pressure for "bigger is better" is accentuated by requiring increased human supervision."
(Zhang and Mishra, 2024) **Country**: China	Rebound effect (increase productivity of land and labour →	"…farm households adopting ICT increased the percentage of marketed farm output in total farm production, are more commercialized, and have an

Data: Secondary economic data (China Household finance survey) **Technology**: Information and Communication Technologies	increase farm commercialisation)	increased tendency to maximize profits in agricultural production”
(MacPherson et al. 2025) **Country**: Germany **Data**: modelling and stakeholder input **Technology**: Digital agriculture	EoSi (need to scale up to stay competitive → scale up) Risk (need to pay off debt → increase production)	“the adoption of digital agriculture could also result in a ‘technology treadmill’, where the need to scale up operations to stay competitive arises because technological advancements often lead to increased productivity, driving down prices and forcing farmers to expand their operations, thereby increasing their workload (Cochrane, 1958; McGrath et al., 2023). Additionally, the financial investments required to adopt costly digital technologies could result in capital lock-in, where farmers are financially bound to pay off debts, compelling them to work more.”
	Risk / EoSc (reduced production risk of diversification → diversify)	“The participants agreed that better decision support could reduce production risks associated with introducing new crops as well as provide better market analytics on consumer demand for new products. In turn, crop diversification could improve economic stability (von Czettritz et al., 2023) and ecosystem functionality (Tamburini et al., 2020).”
(Lowenberg-DeBoer et al. 2021) **Country**: UK **Data**: Simulation data **Technology**: Crop robotics	EoSi (decrease costs of smaller and irregular plots → expand into these areas)	“An additional benefit of using smaller equipment sets, whether they be conventional or autonomous, would be their ability to better handle in-field obstacles (e.g. trees, power poles) and smaller irregularly sized fields [...] With a much-reduced impact of smaller and irregularly sized fields on the operating efficiency of smaller equipment sets, and as this study indicates, comparable costs of production and more profitable scenario outcomes, adoption of such systems would reduce or even lead to a reverse in the impacts of agricultural intensification and large scale mechanisation.”

	Dis-EoSi (cost minimised at smaller farm sizes → maintain farm size)	"The estimated wheat production cost curve with autonomous equipment achieves almost minimum levels at a smaller farm size than the conventional equipment cost curve." "The ability to achieve near minimum production costs at relatively smaller farm sizes, and with a modest equipment investment, means that the pressure for farming businesses to continually seek economies of scale (i.e. to "get big or get out") is diminished."
(Smith, 2024) **Country**: UK **Data**: Interviews, expert knowledge and review of industry grey literature **Technology**: digitalisation (Agtech)	Rebound effect (more control over workers → intensify and specialise tasks)	"'AgTech' is not leading to significant reduction in demand for seasonal migrant labour and so not governing in a meaningful manner the regulation of migrant flows. Rather it is focused on growers seeking to govern the regulation of the workplace through adopting 'AgTech' to attempt to intensify and specialise tasks."