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Conceptualization of How Adopting Novel Technology Induces Structural and Behavioral Changes on Farms

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Predicting the effects of technology adoption, particularly smart farming, is challenging as farmers often alter their behavior and farms once using a new technology. We derive incentives for structural and behavioral change triggered by technology adoption by considering features of smart farming technology and economic theory. As a result, we contribute a conceptual framework describing processes of change linked to technology features. Specifically, we focus on rebound effects, economies of size and scope, and risk balancing. To provide examples of how our framework applies, we conduct a literature review of previous research studying farm-level effects of smart farming.

Key words: agricultural technology, conceptual framework, rebound effects, structural change

Introduction

Digital innovation is transforming the agricultural industry (Klerkx and Rose, 2020). The European Union's Common Agricultural Policy for 2023–2027 reflects a desire to promote digital and smart farming technology to modernize agriculture through innovation and knowledge (European Commission, 2022). One of the outcomes sought by increasing the use of digital technology is enhancing resource use efficiency and halting biodiversity loss (European Commission, 2022). However, whether increasing the adoption of digital and smart farming technology will provide these desired outcomes of increased sustainability is uncertain (Klerkx, Jakku, and Labarthe, 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 behavioral (S&B) adaptations follow after adoption.

In this article, we use economic theory and insights from previous literature to conceptualize 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. 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.

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This study contributes to understanding S&B change induced by smart farming. Specifically, we provide insights into how novel smart technology motivates farm-level S&B changes and the outcomes this can yield. Our objectives are therefore to construct a theoretically derived conceptual framework that describes and conceptualize mechanisms that can create incentives for S&B change and 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 formulated in this article to smart farming in livestock and crop production. Findings from the literature review are analyzed 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 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 through 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, Von Hobe, and Musshoff, 2020; Shang et al., 2021; Gabriel and Gandorfer, 2023; Khanna et al., 2022, 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 labor 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 changes from smart farming have 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 labor 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 from 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 benefit the agricultural sector. Nevertheless, none of these previous contributions include smart-farming-induced S&B change. Instead, the majority of 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 have not yet been 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: (i) it informs empirical research, (ii) provides information for modeling, and (iii) informs policymakers in their efforts to promote sustainable development through smart farming. Specifically, we assume that induced S&B change can arise from changes in economies of size (EoSi) and scope (EoSc); changes in risk and rebound effects arising from increasing resource use efficiency are considered.

Structural and Behavioral Change Induced by Smart Farming Technology

To increase understanding of how the adoption of smart farming can incentivize farm-level S&B changes, we do not focus on farmers' intentions when adopting the technology but instead aim to understand how attributes of technology can create incentives for S&B change, disregarding whether the farmer was targeting these changes before the adoption of the technology. There is already a vast literature on farmers' intention to adopt smart and precision farming technology (Tey and Brindal, 2012; Pathak, Brown, and Best, 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 us to evaluate how certain technology characteristics induce S&B change. We do not evaluate whether the induced changes are desirable 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 the International Society of Precision Agriculture (2024) defines 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.

However, robotic and fully automated systems are also increasingly being developed and adopted to farms, playing another crucial role in the transition toward smart farming (Moysiadis et al., 2021). Therefore, this study also focuses on autonomous technology, and 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.

Theoretical Foundations of Induced Structural and Behavioral Change

Our 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 that we include in our conceptualization do not encompass all potential effects of novel

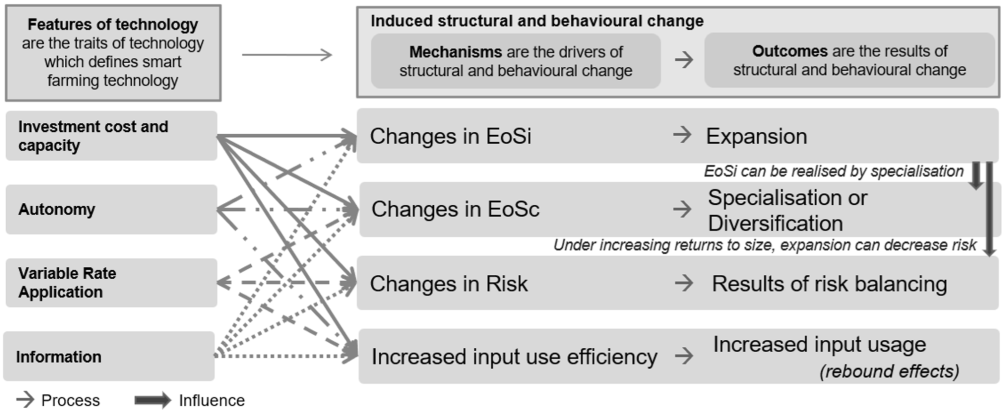

Figure 1. Theoretically Derived Conceptual Framework of Induced Structural and Behavioral (S&B) Change

Notes: 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.

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.'s (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 (see Figure 1) is the basic premise of the framework presented in this study. 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. Unlike Lange et al. (2021), who focused exclusively on the rebound effect, this article considers a broader range of mechanisms and focuses to the specific features of smart farming technology.

We focus on four mechanisms. As depicted in Figure 1, we consider that S&B change will be induced if a novel technology changes the cost-minimizing size of the farm (i.e., changes EoSi), changes the cost-minimizing scope (i.e., changes EoSc), increases or decreases risk and uncertainty (i.e., changes risk), or increases input use efficiency (enabling reinvestments, giving rise to rebound effects). These mechanisms change the status quo on the farm, and the outcomes will be structural or behavioral changes following the economic concepts listed. Notably, there are overlaps between the effects discussed in this article. In particular, EoSi and rebound effects overlap in the sense 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 the concepts are, however, the mechanisms through which the features of technology generate the outcomes which are distinct for the different economic theories and will be elaborated on. 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 1.

Economies of Size and Scope as Incentives for Structural and Behavioral Change

Technological development has encouraged expansion toward larger and more specialized farms (Bowman and Zilberman, 2013). EoSi are 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 toward becoming larger and more specialized under the economic rationale to pursue EoSi and increase technical efficiency rather than focusing on diversification (de Roest, Ferrari, and Knickel, 2018), smart farming technology can also enable both increased and new forms of diversification of production (Walter et al., 2017) and enable preserving smaller-sized farms 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 and EoSc necessary to study on a farm level as potential mechanisms of S&B change.[1] EoSi are present when costs per output can be decreased by increasing the size of production in any cost-minimizing way, and EoSc are 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). The following sections describe EoSi and EoSc with respect to 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 production are 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).

Recent literature has studied 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 further expansion would otherwise 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).

[1] The idea of economies of size 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 differences between the concepts.

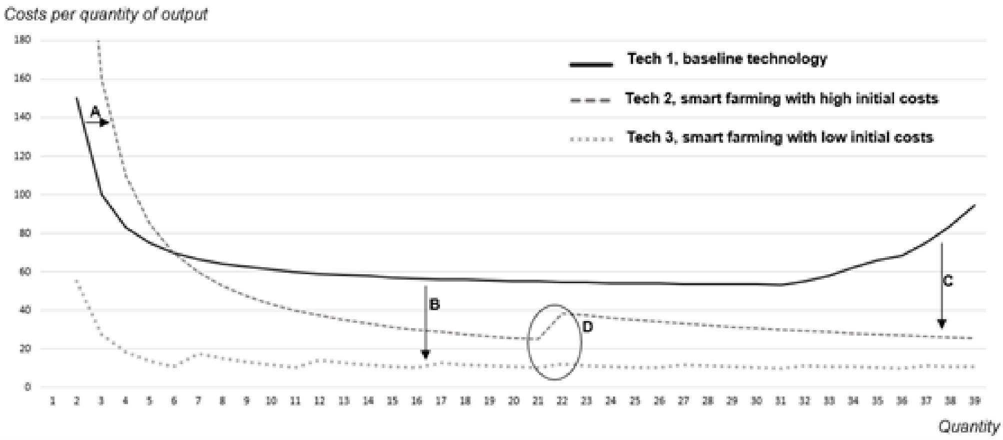

Figure 2. Illustration of Economies of Size (EoSi) for Different Features of the Technology

Notes: The three curves illustrate three different hypothetical technologies and show how average costs might change as novel technology is adopted. Figure 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.

Given EoSi and previous studies on how novel technology can change average costs and thus change EoSi, we identify four ways in which 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 achieve minimized average costs (Lowenberg-DeBoer et al., 2022). Third, suppose the novel smart farming technology can provide higher managerial capacity, allowing farms to grow more before encountering diseconomies of size, or even grow without encountering diseconomies of size, as in the case for 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 use of the technology cannot be increased gradually but only stepwise. Figure 2 illustrates these three potential effects of smart farming technology.

For illustration, Figure 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 (point A in Figure 2), creating hurdles for further expansion (point 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 (point B). Finally, information gathering and provision and variable rate application (VRA) can alleviate the managerial limitations at large farm sizes, enabling farms to continue growing without running into decreasing returns to size (point C).

Economies of Scope (EoSc)

We follow the definition of EoSc as sharable, or complementary, inputs (Panzar and Willig, 1981), which 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) categorize sharable inputs as (i) elements of productive capacity (e.g., electricity), (ii) indivisible equipment usable for producing more than one good, and (iii) human capital or other inputs that inevitably offer coproducts (the typical example being sheep offering mutton and wool). Similarly, Oude Lansink (2001) exemplifies sharable inputs such as labor, farm structures and machinery. Knowledge is also 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 and Chavas and Barham build their formulations of sharable inputs on Panzar and Willig.

Smart farming technology can generate both increasing and decreasing EoSc, depending on whether it increases or decreases the usage of sharable inputs. While EoSc have barely been studied in the context of the effects of technology, Takeshima, Hatzenbuehler, and Edeh (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 (i.e. when technology is sharable). On the one hand, if technology has high indivisibility, replaces labor, 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 1 illustrates that all technology features can affect EoSc, as long as the feature increases or decreases sharable inputs.

Rebound Mechanisms as Drivers of Induced Structural and Behavioral Change

Rebound effect is a broad term initially developed to explain the difference between potential and actual energy savings (Sorrell, 2007), but the definition can 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 reinvested into expanding production, changing production processes, or allocation elsewhere (Paul et al., 2019). A common distinction of rebound effects is between income and substitution effects. Income effects indicate a situation in which cost savings can be reinvested and substitution effects indicates substituting processes toward using more of the process by 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 (Song et al., 2018; Albizua, Pascual, and Corbera, 2019; 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, capacity, autonomy, VRA, and information can all 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 whether 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 labor efficiency. Autonomous technology replaces the need for some labor tasks, where cost savings can generate rebound effects in other inputs. Decreases in labor 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. These savings can be reinvested to change farm structures; however, the exact outcomes generated through rebound mechanisms are not inherent in the theory but vary depending on how the farmer chooses to reinvest the cost savings.

Risk Balancing as a Driver of Induced Structural and Behavioral 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 Gabriel and Baker's (1980) risk-balancing principle and focus on two broad types of risk: business and financial risks (Komarek, De Pinto, and Smith, 2020). Risk-balancing behavior 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, De Pinto, and Smith, 2020). Farmers identify farm survival and profit maximization as two objectives to optimize 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. Risk balancing is conceptualized 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):

$$\frac{\sigma}{cx} + \frac{\sigma I}{cx(cx - I)} \leq \beta, \tag{1}$$

where 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, where risk is increased by fixed financial obligations such as the obligation to repay a debt (Gabriel and Baker, 1980; Komarek, De Pinto, and Smith, 2020), where I denotes the fixed debt servicing obligation. If σ increases, 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 decreases, 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 in which a smart farming technology can affect behavioral 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 acceptable to the farmer. Recent findings indicate that production and financial risk are independent of each other, such that a farmer's attitude toward production risk is a poor predictor of their attitude toward financial risk (Finger, Wüpper, and McCallum, 2023). This indicates that farmers handle different types of risks separately, which could imply that the adoption of 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 (1), slack can motivate farmers to adapt their behavior to increase profits by increasing the standard deviation 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 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 (see Figure 1). Figure 1 also illustrates an influence between risk balancing and changes in EoSi. Under increasing returns to size, farmers can opt to expand; if there is also a slack in the risk constraint, a farmer can be motivated to expand even further than is feasible from the perspective of EoSi.

When Risks Are Too High

If technology increases risks and the left-hand side of equation (1) is higher than β, a farmer is motivated to decrease risks to meet the constraints. This situation can arise if the technology requires a large investment and the farmer must take a loan. Griffin, Shockley, and Mark (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 (breeding stock and animals crucial for production, such as dairy cows), land and machinery (Harwood et al., 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 behavior can provide an additional drive to utilize size effects as a way to lower risks. However, increased debt could lead farmers to be more cautious with further investments on the farm.

Worth noting here is that the literature often highlights other risks associated with smart farming, such as the potential marginalization 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 farm autonomy can be associated with risks that 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.

Empirical Foundations: Literature Review

To provide examples of how the conceptual framework applies, we review previous research on farm-level effects of smart farming . We first 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 listed in Table 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 attempt 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 1.

Results

We searched the databases a final time on January 8, 2025. The literature search resulted in 10,546 papers. Following Šarauskis et al. (2022), we refined our searches by topic. After excluding duplicates and papers based on irrelevant meso-topics (WoS) and subject area (Scopus),[2] 3,263 papers remained to screen for inclusion. Figure 3 illustrates this process. Next, we formulated a protocol for what qualifies a record to be included in the literature review (see the online supplement at www.jareonline.org). Many papers were excluded after screening titles and abstracts, as they focus on adoption determinants, contribute to developing technology, or do not consider smart farming technology.

Notably, when considering the 196 articles for full reads, few studies include the potential of smart farming to induce S&B change. As seen in Figure 3, most papers were excluded at this stage because they consider the future potential of a smart farming technology (25 studies on the farm level and eight 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). We identified any discussion of S&B change generated by smart farming technology in 34 papers. We were able to identify the S&B mechanisms and outcomes in our conceptual framework (Figure 1) in 27 of these studies. The seven papers indicating S&B change that 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

[2] 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.

Table 1. Keywords for the Literature Search

Group		Search Terms	No. of Studies
1 – specify context (joined by AND). All papers should include some elements of agriculture, technology and structural change	Agriculture (from Shang et al., 2021)	TS = agricultur* OR farm* AND	
	Identify the technology context (also from Shang et al., 2021, 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 behavioral change (joined by OR). All papers should also include an element of EoS, risk or increasing input use efficiency	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’	
	Risk	TS= ambiguity OR hazard OR uncertain* OR risk* OR variab* OR volatil* OR stabil* OR vulnerab* OR resilien* OR robust* OR 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’	= 1,660 (filtered for papers in English)

Notes: TS indicates title search. The asterisks (*) indicate a wildcard replacing zero or more characters in a search string. The dollar sign ($) indicates a single-character wildcard (e.g., labo$r will find both labor and labour). These wildcards allow for broader searches.

commitment to climate change mitigation (Citra Irawan et al., 2023; Mao et al., 2024). Two papers state that the adoption of smart farming technology generates S&B change but do not specify the mechanisms triggering the changes (Martinsson et al., 2024; Wang et al., 2024).

We listed the mechanisms and outcomes for each paper, then considered whether it fits as one of the processes identified from the theory. Many of the included studies only briefly mention the mechanisms through which smart-farming-induced S&B change occurs or refer to them indirectly, requiring us to deduce them from the motivations for change described in the papers. Few studies include the possibility for S&B change; of the few studies that do, many refer to such change indirectly, highlighting the need for more research on this topic. Future research on smart-farming-induced S&B change can make use of our conceptual framework. For transparency, the online supplement reports quotes from the papers in which we identified the induced S&B change.

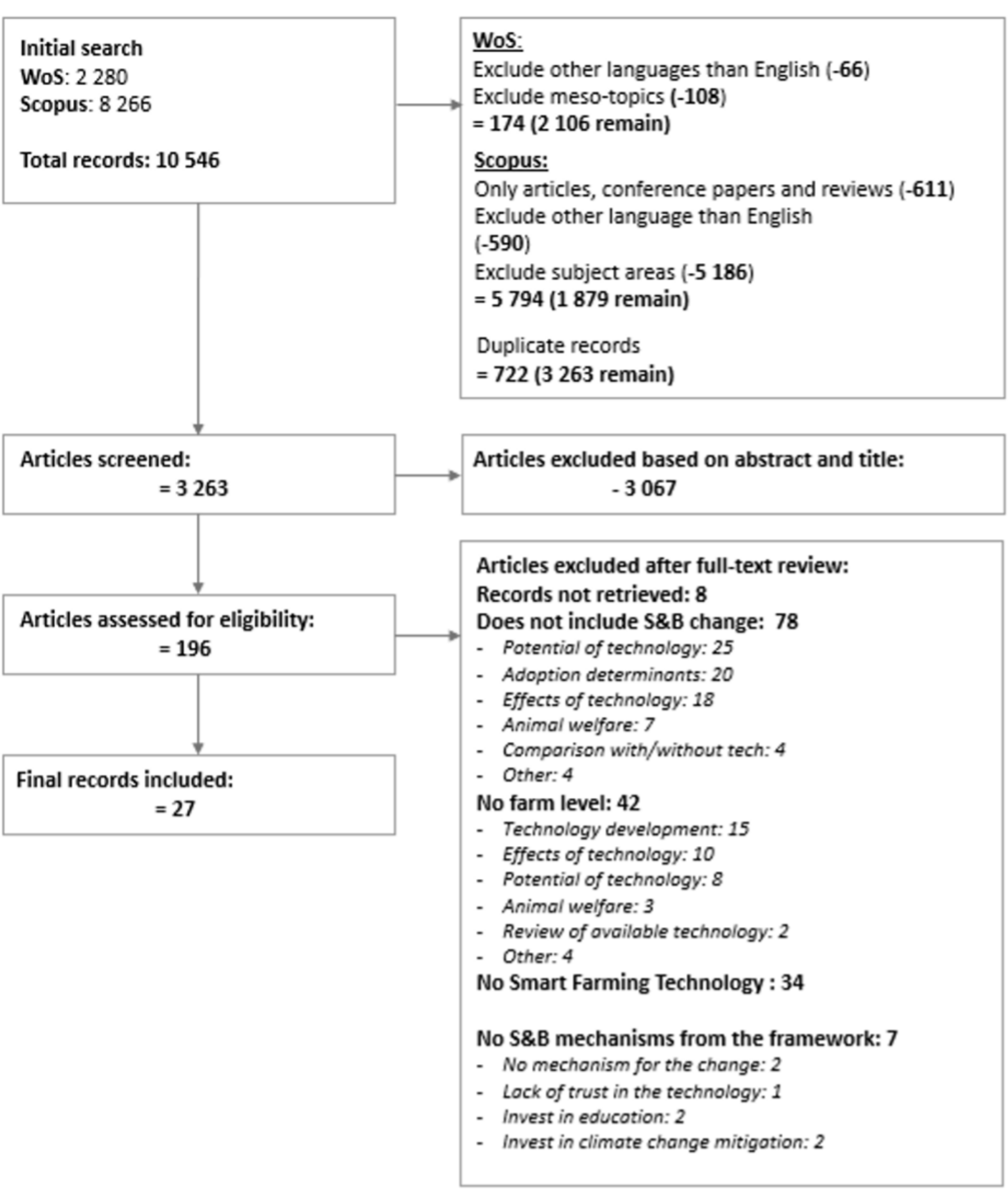

Figure 3. Structural and Behavioral (S&B) Change

Table 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. Table 2 presents an overview of the results of labeling 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 2. Induced Structural and Behavioral (S&B) Change Derived from the Literature

Reference	Technology	EoSi	EoSc	Rebound	Risk
Livestock production					
Tangorra et al. (2022)	AMS	X	X		
Rotz, Coiner, and Soder (2003)	AMS	X			
Qi et al. (2022)	Automatic oestrus detection	X			
Schewe and Stuart (2015)	AMS	X			X
Steeneveld, Hogeveen, and Oude Lansink (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, Kerrisk, and Garcia (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					
Schimmelpfennig (2019)	PA in rice production			X	
McFadden, Rosburg, and Njuki (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	

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

Induced Structural and Behavioral Change in Livestock Production

Of the 27 included papers, 16 focus on livestock farming. Of these, 13 evaluate automatic milking systems (AMS). The remaining articles focus on technologies to improve animal monitoring in dairy farming (Steeneveld, Hogeveen, and Oude Lansink, 2015), automatic estrus detection (Qi et al., 2022), and smart calf feeders in cattle and dairy farming (Hogan et al., 2023). Automatic estrus detection is a technology worn by the cow (Qi et al., 2022) and thus does not have the same structural requirements as AMS. Sensor systems are a broader category of technology that can be either stationary and coupled with an AMS or set up as activity meters placed directly on the cows (Steeneveld, Hogeveen, and Oude Lansink, 2015). Thus, the sensor systems, including the automatic estrus 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 (see Table 3). Table S1 in the online supplement provides more detail on the effects derived from each paper. In ten of the 13 papers, we identify effects from EoSi, which arises after

Table 3. Induced Structural and Behavioral (S&B) Change in Livestock Production

Reference	Tech 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	Labor use efficiency can be improved for larger farm sizes	Expansion to increase efficiency
Rotz, Coiner, and Soder (2003)	Capacity	EoSi	Potential to increase economic viability at full utilization	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, Hogeveen, and Oude Lansink (2015)	Autonomy	Rebound effect	Increased labor use efficiency	No decrease in labor input
Castro et al. (2012)	Capacity	EoSi	Potential to increase economic viability	Increased herd size to full utilization
Jacobs and Siegford (2012)	Autonomy	EoSc	Potential to increase efficiency	Increased labor 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 Increase production
Vik et al. (2019)	Investment cost	EoSi	Need to finance the investment	Increase specialization in dairy
		DisEoSc	Need to finance the investment	Increased herd size to full utilization
Hogan et al. (2023)	Capacity	EoSi	Potential to increase labor use efficiency	Increased herd size to full utilization
Lyons, Kerrisk, and Garcia (2014)	Capacity	EoSi	Potential to increase economic viability	Increase production
Martin et al. (2022)	Investment cost	EoSi	Potential to increase economic viability	Maintain production
	Capacity	DisEoSi	Potential to maintain economic viability	Adapt farm structures to the AMS (specialize in dairy)
Keeper et al. (2017)	Capacity	DisEoSc	Potential to increase milking efficiency and reduced labor requirements	Adapt farm structures to dairy
Bach and Cabrera (2017)	VRA	DisEoSc	Need to optimize the technology	Invest to improve productivity
Lee et al. (2024)	Autonomy	Rebound effect	Labor savings	Invest to improve productivity

adopting AMS (Rotz, Coiner, and Soder, 2003; Castro et al., 2012; Lyons, Kerrisk, and Garcia, 2014; Vik et al., 2019; Martin et al., 2022; Tangorra et al., 2022) but also after adopting livestock sensor systems (Steeneveld, Hogeveen, and Oude Lansink, 2015) and automatic calf feeding (Hogan et al., 2023). We also include automatic estrus detection technology because 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) find 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 previously outlined, 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 AMS usage (Jacobs and Siegford, 2012; Hansen, 2015; Bach and Cabrera, 2017; Keeper et al., 2017; Rodenburg, 2017; Tse et al., 2018; Tangorra et al., 2022). Second, to adapt to the AMS, Martin et al. (2022) point out that farmers are motivated to adopt other complementary technology, creating a feedback effect in which 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 reinvested or used to substitute less efficient processes. One process was identified through which rebound effects can arise, driven by increasing labor use efficiency and where the cost savings can be reinvested in expanding or intensifying production (Steeneveld, Hogeveen, and Oude Lansink, 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 pay back the debt. This aligns with the behavior 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 of the prospect of lower costs and increased benefits if herds are larger and because AMS generates cost savings, which can be reinvested (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 15 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 that the effect is absent.

Induced Structural and Behavioral Change in Arable Production

We identify 11 papers focusing on arable production, including studies on yield and soil mapping for maize production (McFadden, Rosburg, and Njuki, 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 that enable intrafield intervention. We also include two papers that

Table 4. Induced Structural and Behavioral (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, Rosburg, and Njuki (2022)	Information	Rebound effect	Increase efficiency of production	Increase output
Tenreiro et al. (2023)	Indivisibility	EoSi	Costs can be minimized at larger farm sizes	Expansion to minimize 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 heterogeneous 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 minimize costs
Zhang and Mishra (2024)	Information	Rebound effect	Increase land and labor 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 minimize costs
Smith (2024)	Information	Rebound effect	Increased control over workers	Restructure labor - Intensify and specialize tasks

Notes: No effects were detected for risk balancing.

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 small number of papers, we identify induced S&B change through all mechanisms but risk. Table 4 displays the S&B change derived from the literature review. Table S2 in the online supplement provides more details.

EoSi are 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 as required supervision time rises. 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, which increase efficiency in five ways, leading to six outcomes. First, increasing input use efficiency increases output (Monzon et al., 2018; McFadden, Rosburg, and Njuki, 2022) or, if producing another crop becomes more profitable, a shift toward 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). Third, Lieder and Schröter-Schlaack (2021) identify increased efficiency of operating heterogeneous fields as a feature that drives S&B change through rebound mechanisms. This increased efficiency is listed as a separate effect, as it highlights a shift where farmers, apart from reinvesting 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 labor can be better supervised with new technology, which can motivate a restructuring of labor to more specialized tasks. Fifth and finally, 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 are able to 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).

Summarizing, 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 modeling approaches (Lowenberg-DeBoer et al., 2021; MacPherson et al., 2025).

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 article enables researchers to predict the effects that 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 modeling 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 3), while only one study is identified to discuss the effects of fully autonomous technology in arable farming (Table 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 the increased debt can create pressure to increase productivity when financing the investment with a loan (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 toward 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 consider other effects as well. 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, Hogeveen, and Oude Lansink, 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 farm-level smart-farming-induced S&B change.

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Online Supplement: Conceptualization of How Adopting Novel Technology Induces Structural and Behavioural Changes on Farms

Elin Martinsson and Hugo Storm

Inclusion Criteria and Labeling

When screening the papers for inclusion, the protocol in Figure S1 was used.

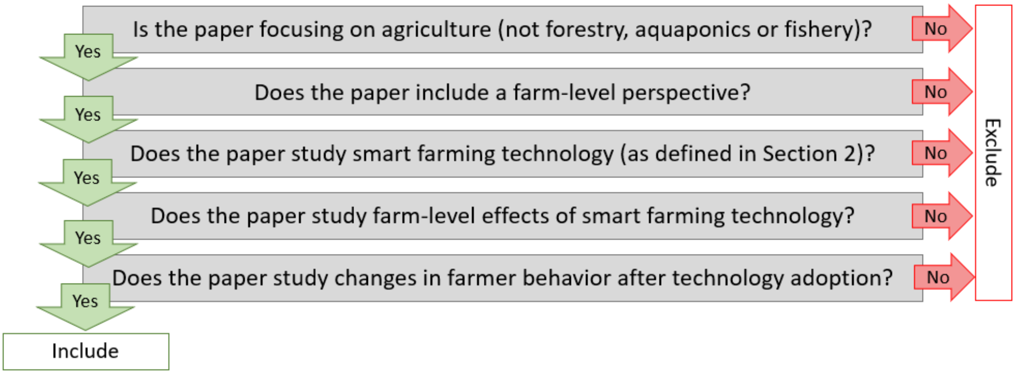

Figure S1. Protocol Followed When Screening the Papers for Inclusion

In the last step depicted in Figure S1 the reviewers were asked to assess whether the paper include changes in farmer behavior after the technology is adopted. Specifically, we look at changes in behavior which can be related to the four mechanisms included in our conceptual framework: changes in economies of size and scope, changes in risk or changes in input use efficiency (triggering rebound mechanisms). The researchers screening the papers were appointed to read the papers deriving mechanisms and outcomes and labeling these as EoSi, EoSc, rebound effects or risk balancing, or other if there where structural and behavioral change which did not fit into any of the *a priori* defined mechanisms.

Details of Included Records

Table S1 shows 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 authors of this article to clarify abbreviations or other aspects not clear from the short quote in Table S1.

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

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Table S1

Panel A. 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 optimize technology)	"In 29% of farms, the adoption of the milking robot required the construction of a new barn." (p. 7543) "In accordance with the switch to Automatic milking, most farmers chose to build new freestall barns and improve their facilities." (p. 7546)
	Size effects (increase herd size → minimize costs of labor)	"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)." (p. 7546)
Rotz et al. (2003) Country: USA Data: Simulations, historical weather data, regional information Technology: AMS	Size effects (increase herd size → minimize 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." (p. 4167) "At 50- to 60-cow farm sizes, a single AMS unit was better utilised, providing an equal or greater return than traditional milking systems." (p. 4174) "A primary disadvantage is that they [the AMS] require a large initial investment." (p. 4167)
Qi et al. (2022) Country: China Data: Survey data Technology: Automatic estrus detection	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." (p. 13) "The negative impact of herd size on dairy cow yield diminishes with the adoption of digital technology." (p. 11)

References and Details	Label	Identification in Text
Schewe and Stuart (2015) Country: USA, the Netherlands and Denmark Data: Interviews with 35 adopters Technology: AMS	Size effects (want to maximize 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." (p. 200) "one-half of adopters interviewed have increased herd size, all with the ultimate goal of increasing production to offset capital investment." (p.209)
	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." (p. 211) "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." (p. 209) "Those farmers with less acquired debt did not feel the same pressures to increase productivity and maintained a higher degree of perceived financial resilience." (p. 209)
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." (p. 39) "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 systems (data not shown)." (p. 39)
	Rebound effects (increased labor 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." (p.37)
Jacobs and Siegford (2012) Country: USA Data: Literature review Technology: AMS	Scope effects (structural change → optimize 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." (p. 2232)

References and Details	**Label**	**Identification in Text**
		"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)." (p. 2240)
	Scope effects (changed management → optimize 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." (p. 2229)
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." (p. 936)
Hogan et al. (2023) Country: Ireland Data: Survey Technology: Automatic calf feeder	Size effects (labor 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'Donovan et al., 2008; Deming et al., 2018; Hogan et al., 2022." (p. 8)
Rodenburg (2017) Country: Europe Data: Literature review Technology: AMS	Scope effects (structural change → optimize 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." "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."

References and Details	Label	Identification in Text
Hansen (2015) Country: Norway Data: Interviews with 19 dairy farmers adopters Technology: AMS	Size effects (structural and managerial change → optimize 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." (p. 113)
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)." (p. 12)
	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." (p. 12)
	Size effects (increase herd size → increase profits)	"There is a size range in which investing in AMS is economically attractive: medium-sized farms." (p. 12)
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." (p. 5)
	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." (p. 7)
	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." (p. 7)

References and Details	Label	Identification in Text
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).” (p. 112) “In a report from van Dooren et al. (2004), 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.” (p. 113)
Lee et al. (2024) Country: South Korea Data: Secondary farm-level economic data Technology: AMS	Rebound effects (labor 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.”

Panel B. 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.” (p. 5)
	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”. (p. 10)
	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.” (p. 11)

Reference and Details	Label	Identification in Text
	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 (Paul et al. 2019). For example, Sears et al. (2018) show that increasing irrigation efficiency can lead to an increase in water use by making it less expensive to irrigate marginal lands." (p. 10)
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." (p. 69) 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.] (p. 69)
Tenreiro et al. (2023) Country: Spain Data: Experimental farm trial Technology: VRA	Size effects (expansion to reach profitable size → minimize 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." (p. 869)
Schimmelpfennig (2019) Country: USA Data: US national farm-level production data (USDA Technology: Precision agriculture (soil and yield mapping, VRT, GPS)	Rebound (conservation agriculture more efficient → increase conservation agriculture)	"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." (p. 15)

Reference and Details	Label	Identification in Text
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." (p. 597)
	Rebound (increase efficiency → increase output)	"We find that output increases with the use of maps because of their frontier-shifting and efficiency-increasing effects." (p. 607) "Over the long run as agricultural digitalization deepens, there may be implications for farm structure." (p. 607)
Paul et al. (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)." (p. 1062) "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." (p. 1063)
Zhang and Mishra (2024) Country: China Data: Secondary economic data (China household finance survey) Technology: Information and Communication Technologies	Rebound effect (increase productivity of land and labor → increase farm commercialization)	"Farm households adopting ICT increased the percentage of marketed farm output in total farm production, are more commercialized, and have an increased tendency to maximize profits in agricultural production." (p. 5)

Reference and Details	Label	Identification in Text
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.] (p. 859) "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." (p. 859)
MacPherson et al. (2025) Country: Germany Data: modeling 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." (p. 14)
	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)." (p. 14)
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." (p. 2002)

Reference and Details	**Label**	**Identification in Text**
	Dis-EoSi (cost minimized 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." (p. 2003) "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." (p. 2003)
Smith (2024) Country: UK Data: Interviews, expert knowledge and review of industry gray literature Technology: digitalization (Agtech)	Rebound effect (more control over workers → intensify and specialize 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." (p. 327)

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