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The evolving profile of new entrants in agriculture and the role of digital technologies

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Note by the Secretariat

In November 2022, OECD Ministers of Agriculture called on the OECD, through the Committee for Agriculture, to work on inclusiveness under the third food systems challenge of "Ensuring inclusive livelihoods." The work proposed, responds at least partially, to three "call" items in the declaration:

- 41. "…support inclusive and gender responsive policies and standards to accompany the transition of new entrants into the sector…"
- 44. "Identifying innovation policies and accompanying institutions, investments and knowledge transfers to catalyse efficient progress towards agricultural productivity, sustainability and resilience contributing to rural development."
- 45. "Assessing the opportunities, barriers and policy levers for broader adoption of digital technologies towards sustainable and inclusive transformation of agriculture and food systems."

This paper contains the work under Expected Output Result 3.2.1.2.2 "Innovation" of the 2023-24 Programme of Work and Budget (PWB) of the Committee for Agriculture as discussed in the scoping paper [TAD/CA/APM/WP(2023)8] in the May 2023 APM. The paper focuses on identifying the profile of new entrants to the farming sector, investigating the role of digital technologies on their skills and wellbeing and analysing what farmers will look like in the future.

The revised paper accounts for comments received on the first draft version presented to the APM in November 2023 and in May 2024. It builds on previous work on changes in agricultural labour and skills in OECD countries and on digitalisation as a driver of some of these changes. The work also contributes to skills and digital topics included in the PWB Expected Output results 3.2.1.2.3 on "Rural development."

This paper has benefited from co-operation and inputs from Jonathan McFadden (USDA-ERS), Alicia Rosburg (University of Northern Iowa), Emilio Pindado (Madrid Polytechnic University), Masayasu Asai (OECD), and participants at the 31st session of the Farm Level Analysis Network (FLAN) in March 2023.

This document was APPROVED and DECLASSIFIED during the 92nd Session of the Working Party on Agricultural Policies and Markets in May 2024.

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Key messages

- New entrants into agriculture can be key players in transforming food systems. They are younger, have higher levels of education and entrepreneurial skills, and are more likely to adopt new technologies, which can enhance agricultural productivity and competitiveness.
- Several obstacles hinder entrance in the agricultural sector. These include capital constraints; limited access to land, sometimes exacerbated by existing policies; regulatory complexities; and lower access to services compared to other sectors. Negative perceptions of farming as old-fashioned, characterised by hard physical work, loneliness, isolation and high levels of risk can also discourage new entrants.
- Agricultural digitalisation could help to alleviate these constraints. Under certain conditions, digital technologies can enhance agricultural productivity and sustainability, and have the potential to improve farmers' lives. They could make farming more attractive to youth and to both new entrants and established farmers by decreasing menial tasks and physical labour, and by enabling more flexible work schedules. Agricultural digitalisation could also reduce health risks and has the potential to support diversification of on-farm activities such as tourism and hospitality services.
- The adoption of digital technologies is challenging, involving costs and risks that differ across farmers and countries. To make digital access inclusive, governments could consider policies that facilitate equal access to infrastructure and services, as well as investments in life-long training, education, and skills development for marginalised groups.
- Embracing digital technologies requires prospective farmers to refine their existing skills and to acquire new ones. Evidence suggests that in the United States human capital is the main driver of digital technology adoption, and yet current educational and training systems may not sufficiently cover the skills needed for agricultural digitalisation. Governments should therefore build ambitious long-term skill strategies to identify and tackle emerging gaps in the agricultural sector.
- Foresight studies analysing macro trends and challenges to a sustainable, digitalised, and inclusive future can be a useful policy tool to anticipate farmer skillset needs and to transform mindsets for the future of agriculture. While future farmers are expected to be diverse, they will need higher levels of education, the capacity to learn and adjust quickly, as well as new entrepreneurial and digital skills.
- Governments can make progress on their objectives for food systems by addressing the multiple challenges faced by new entrants. Although different policy levers will be required to address the diversity of issues and contexts, structural policies are more likely to have long-term effects. These include policies that are tailored to strengthen human capital and skills, to improve digital infrastructure services, to promote innovation systems, and remove barriers to entry.

Executive Summary

New entrants to agriculture can play a critical role in the transformation of food systems and in addressing the multiple challenges facing food systems. Yet the profile of new entrants is not sufficiently understood, nor the barriers they face and how technologies and policies could be shaped to enhance their contribution.

This paper uses a broad definition of new entrants and aims to address these issues by analysing the profile of new entrants to agriculture, how that profile is changing, and the impact of digital technologies and other megatrends on agricultural labour via a statistical analysis of existing datasets and a review of the literature.

The analysis finds that new entrants in OECD countries are on average younger than established agricultural entrepreneurs, are mostly male, have greater entrepreneurial skills and higher levels of education, and are more likely to adopt new technologies. New agricultural entrepreneurs have the skills and characteristics that can boost innovation in the agricultural sector and lead to increased productivity and competitiveness.

Potential entrants into agriculture face several barriers, however, including capital constraints, limited access to land, and low profitability of farming, often exacerbated by regulatory complexities. The underrepresentation of women among new farmers suggests that there are relatively more important barriers to entry for women. New entrants in agriculture, while having greater entrepreneurial skills than previously, continue to lag such skills in other sectors, although this cross-sectoral gap is closing. At the same time, negative perceptions of farming persist, which can deter entry into agriculture and the attraction of individuals with valuable skills.

Digital technologies can act as enablers that can contribute to food security and more sustainable systems and impact farmers’ lives. Some types of digital technologies could remove barriers faced by young and new entrants by reducing the need for menial tasks and physical labour, allowing for more flexible work schedules, reducing health risks, improving farm income, and facilitating certain on-farm diversification activities, such as tourism and hospitality services.

At the same time, digital technologies affect the quantity and quality of agricultural labour, and the skills needed on the farm. Farmers will need to refine their existing skillsets and develop new skills required by a more digitalised agricultural economy. An empirical analysis suggests that the main driver of technology adoption in the United States (US) is farmers’ human capital, including education, but that off-farm work also matters, reflecting knowledge spillovers from other sectors and experience. Current educational and training systems may not adequately develop the skills needed for agricultural digitalisation.

By identifying emerging trends, uncertainties, and potential disruptions, foresight analysis and prospective studies can help to identify the characteristics, skills, and knowledge needed to navigate the changing agricultural landscape in a more environmentally sustainable, digitalised, and inclusive future.

The findings in this paper suggest several avenues for policy improvements to facilitate new entrants in agriculture and the related use of digital technologies. While no single policy can address all issues across different contexts, governments should invest in building human capital, reduce the gender gap, address ageing and generational renewal, and bolster the innovation and entrepreneurial drive of new entrants. These efforts should be tailored according to the structural issues affecting new entrants in each country. More work is needed to assess the effectiveness of various policies in tackling concerns related to new entrants, digitalisation, and the emerging skills gaps of future farmers.

1. Introduction

1. Agriculture and food systems are rapidly changing, driven by climate change, technology development and population dynamics, while facing the challenge of ensuring global food security, nutrition, social inclusiveness, and environmental sustainability. In November 2022, OECD Agriculture Ministers committed to addressing the triple challenge for food systems: to ensure food security and nutrition for a growing population, to support the livelihoods of millions of people working in the food supply chain, and to do so in an environmentally sustainable way (OECD, 2021[1]; OECD, 2022[2]). This means that farmers need to respond to these trends, meeting increasing demand in a more sustainable manner while competing in a more volatile world market (Krzysztofowicz et al., 2020[3]).

2. New entrants to the sector are likely to play a crucial role in accelerating the needed adaptations and transformations.[1] They can bring fresh perspectives, innovation, and alternative approaches to farming, contributing to growth, development and sustainability in agriculture (Žabko and Tisenkopfs, 2022[4]; FAO, 2022[5]). They may also contribute to increased diversity and enhanced inclusiveness. New entrants' skills can strengthen the farming sector and make it more dynamic and responsive to the new demands. However, compared with established farmers, new entrants are confronted with strong barriers both before entering and once in the sector. In addition, farming is often perceived negatively as an old-fashioned job characterised by hard physical work, loneliness, isolation, and risk, and these perceptions can discourage new entrants (Ryan, 2023[6]).

3. Digital technologies could help to overcome some of these barriers and perceptions, making farming more attractive to new and young entrants into agriculture by improving farmers' lives and helping to address some of the most pressing challenges of agriculture. Furthermore, digital technologies can increase productivity, help address food security, reduce environmental footprints, and enhance farm resilience (Bacco et al., 2019[7]; OECD, 2019[8]). Despite the challenges, costs and risks of digitalisation (Finger, 2023[9]), many authors agree that if they are successfully mitigated, digital technologies can be powerful enablers, a transformative force in agricultural production systems, value chains, and food systems (Klerkx, Jakku and Labarthe, 2019[10]; Ehlers, Huber and Finger, 2021[11]; Barabanova and Krzysztofowicz, 2023[12]).[2] However, there is limited but increasing empirical evidence on how digital technologies affect the quantity and quality of agricultural labour, skills, and farmers' wellbeing.

4. The analysis presented in this paper is based on a comprehensive literature review and the use of two relevant datasets to answer the following questions. What is the current profile of new entrants to agriculture in OECD countries? How do new entrants differ from established farmers in OECD countries? How do digital technologies affect agricultural labour, skills, and farmers' lives? Do digital technologies help attract new entrants? What is the projected profile of future generations of farmers? Which skills and competencies are needed for farmers to effectively manage sustainable and profitable agricultural operations?

[1] New entrants are defined here as individuals, groups, or organisations that have recently entered farming or agricultural production activities. They can include individuals who are new to farming, such as those who have recently acquired land, inherited agricultural production activities, or are starting a new agricultural enterprise from a different sector. They can also include firms or groups introducing new technologies, products, or services to agriculture, and investors entering agricultural production for the first time. Given the heterogeneity between different types of new entrants and across OECD countries, this paper uses a broad definition, but focuses on farmers. See Section 2 for more details.

[2] They can also affect rural areas, although the effect of digitalisation on rural development is beyond the scope of this paper. See Salemink, Strijker and Bosworth (2017[85]) for a review.

5. Section 2 analyses the profile of new entrants in agriculture in OECD countries compared to established farmers, identifying opportunities and obstacles for new entrants, generational renewal, and transformation. Section 3 examines the relationship between digital technologies, labour, skills, and farmer wellbeing. By recognising the various effects of digitalisation, the paper discusses why and how digital technologies can help to attract new entrants into farming. Section 4 discusses the possible profiles of future farmers under scenarios linked to environmental sustainability, inclusiveness, and increased digitalisation in the agricultural sector. This implies considering characteristics and skills that future farmers may need in an increasingly dynamic and complex farming sector. Finally, Section 5 discusses the implications of the evidence on new entrants and digitalisation for the evolving profile of farmers and policy issues that deserve attention in order to achieve a more sustainable and inclusive agricultural system.

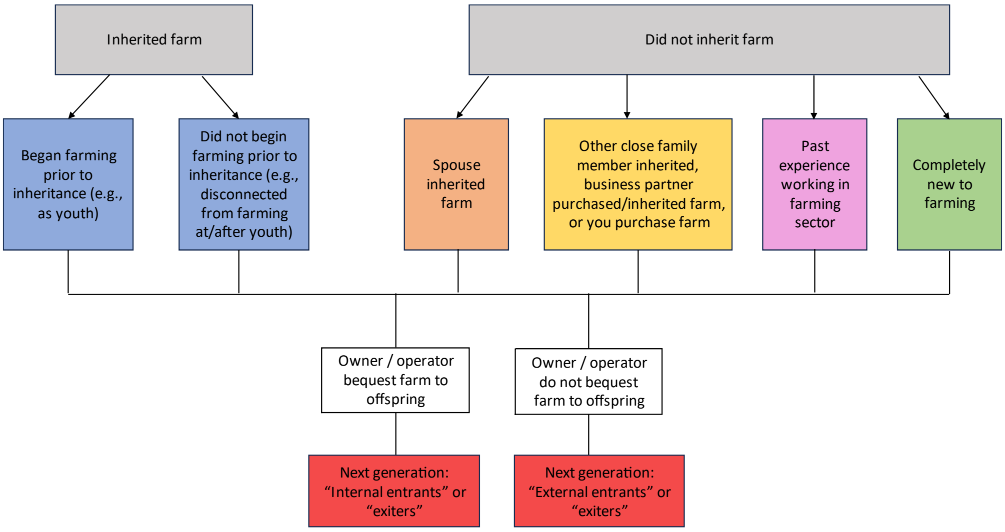
2. New entrants to agriculture

2.1. Definition of new entrants

6. There is no consensus on the definition of "new entrants," with varying interpretations amongst researchers and governments (Pindado et al., 2018[13]; Sutherland et al., 2023[14]; Creaney, Hasler and Sutherland, 2023[15]). Some researchers define new entrants as individuals starting new farms without prior agricultural experience (Sutherland et al., 2015[16]), while others also include those creating new start-ups, innovative farming products, or urban farming practices (Dieleman, 2017[17]).

7. Entry into the sector occurs in a variety of ways. Creaney, Hasler and Sutherland (2023[15]) highlight different stylised points of entry and trajectories for becoming a farmer (Figure 2.1). New entrants can inherit the farm as direct successors or enter through the extended family. They can also become farmers after some work experience in agriculture or be entirely new to the sector. These different paths make it difficult to identify new entrants in practice and to have one unique definition. New entrants can have heterogeneous degrees of off-farm experience (Zagata and Sutherland, 2015[18]), or can also be individuals who return to a family-held farm later in life (Sutherland et al., 2015[16]). Newcomers may or may not introduce innovations in farm operations, diversify, and remain employed off-farm, regardless of whether they are successors or coming from outside agriculture (EIP-AGRI, 2016[19]).

Figure 2.1. Different types of new entrants into farming



Note: This figure abstracts away from considerations of full-time or part-time operation and generally considers owners to be operators (i.e. owner-operators). As such, it does not consider absentee landlords. The figure is a representation that does not consider all possible paths and focuses primarily on inheritance as the main point of entry into farming. "Internal entrants" refer to those that enter the sector by inheriting, while "external entrants" are those that enter without inheriting the farm. "Exiters" refer to those that abandon the farming activity.
Source: Authors' elaboration based on Creaney, Hasler and Sutherland (2023[15]).

8. Governments also define new entrants differently based on policy contexts and needs, often based on factors like age, family succession, or years of farming experience. An EU initiative[3] defines new entrants as "anyone who starts a new farm business or becomes involved in an existing one". These individuals span various ages, have diverse experience and resource availability, and can start farming at any point in their professional lives. Newcomers share common barriers,[4] including securing access to land, labour, capital, housing, and markets, as well as acquiring the knowledge and networks necessary to obtain these resources and face regulatory complexities (Helms, Pölling and Lorleberg, 2020[20]; Žabko and Tisenkopfs, 2022[4]; Creaney, Hasler and Sutherland, 2023[15]).

9. For policy purposes, age often serves to identify new entrants as "young farmers", but the correlation between the average age of farmers and new entrants varies across countries. For instance, in the European Union, there is a difference between young farmers and new farmers. The EU's Common Agricultural Policy (CAP) provides support to young farmers, defined as those aged below a certain threshold, with Member Countries setting the exact upper age limit between 35 and 40 years old.[5] The term "new farmer" refers then to a non-young farmer who is "head of the holding" for the first time in that year.[6] However, a study based on a focus group of new farmers in the European Union concluded that new

[3] "New Entrant Network: Business models for Innovation, entrepreneurship, and resilience in European agriculture" (NEWBIE), http://www.newbie-academy.eu/.
[4] In this study, we refer to barriers or obstacles as factors that create disadvantages for individuals willing to enter agriculture and for farmers who have recently entered the sector. Both potential and new farmers can face multiple barriers or difficulties beyond those faced by established farmers.
[5] See https://agriculture.ec.europa.eu/common-agricultural-policy/income-support/young-farmers_en.
[6] See https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32021R2115.

entrants could be of any age and, therefore, definitions of new entrants should include all ages (EIP-AGRI, 2016[19]).

10. The United States Department of Agriculture (USDA) focuses on the operation of the farm rather than on the operators' age, defining new entrants or "beginning farmers" as those who have operated a farm for ten years or less (Creaney, Hasler and Sutherland, 2023[15]).[7] A beginning farm is defined as one on which all operators have had no more than ten years of experience as an operator on any farm (e.g. USDA-Economic Research Service) or as one in which the principal operator (as opposed to all operators) has no more than ten years of experience on the farm they are currently operating (as opposed to on any farm) (e.g. USDA-National Agricultural Statistics Service) (Key and Lyons, 2019[21]).

11. Some authors claim that the definition matters in developing supporting measures (Creaney, Hasler and Sutherland, 2023[15]). Therefore, it is essential to proceed with conceptualisation and empirical analysis of the characteristics of new entrants, with a shared understanding of the definition, while recognising there may be country-specificities (EIP-AGRI, 2016[19]). To the extent possible, this common conceptualisation should remain sufficiently broad to capture a range of different situations. To this end, this paper considers new entrants as individuals, groups, or organisations that have recently entered farming or agricultural production activities, regardless of their age or entry path.

2.2. Links between age, generational renewal, and new entrants

12. In many countries, farm succession and inheritance are the primary means of accessing agriculture, impacting both family life on the farm and the broader agricultural sector. Consequently, intergenerational farm transfer after retirement is critical for the sustainability, adaptation and transformation of agriculture (Conway et al., 2016[22]; Leonard et al., 2017[23]). Generational renewal, understood as the successive retirement of older farmers who are replaced by a younger or newer cohort of farmers, is essential for farming and new entrants are called to have a relevant role as ageing farmers are retiring (Leonard et al., 2020[24]; Creaney, Hasler and Sutherland, 2023[15]).

13. OECD countries have a steadily ageing farming workforce and a low number of new entrants to the farming sector (Jöhr, 2012[25]). For many countries, ageing is a crucial challenge for the agricultural sector. The average age of farm owners or managers in the United Kingdom rose to 60 years in 2016, and 25% of Canadian farmers will be 65 or older by 2025. The average age of farmers in Japan is amongst the highest in OECD countries, with an increase from 66 years in 2010 to 68 years in 2020 (Ryan, 2023[6]). In the United States, the average age of farm producers increased from 57.5 to 58.1 years from 2017 to 2022, and new and beginning farmers are 47.1 years old on average (USDA NASS, 2024[26]).

14. Several EU countries are also experiencing a rising average age of farmers and a decreasing number of farmers under 40, driven partially by young people moving from rural to urban areas (Leonard et al., 2017[23]; Kalantaryan, Mazza and Scipioni, 2020[27]). This demographic trend is of concern because younger farmers are often, although not always, associated with more efficient production practices (Leonard et al., 2017[23]) and

[7] Specifically, a "beginning farmer or rancher" is defined as a person who "has not operated a farm or ranch" or "has not operated a farm or ranch for not more than ten years" and "meets such other criteria as the Secretary may establish," according to the US Food, Agriculture, Conservation, and Trade Act of 1990. However, the last clause of this legal definition gives USDA agencies some leeway in considering more restrictive definitions of a beginning farmer or rancher (Callahan and Hellerstein, 2022[161]).

with more entrepreneurial capabilities compared to established agri-entrepreneurs (Pindado and Sánchez, 2017[28]). Some studies find that in some European countries the age of farmers relates to the size of their farms, with young farmers managing larger farms, employing more labour, and generating higher value (Zagata and Sutherland, 2015[18]). Larger and more profitable farms are also more likely to have successors (Lobley and Baker, 2012[29]).

15. Although the European Union tends to conflate young farmers with new entrants, significant national variations exist. In Germany, 5% of farm holders are in the 65 and older age group, but more than 46% in Portugal are in that age group. About 2% of Portuguese farm holders are young (under 35 years), but this figure is almost 15% in Poland. In countries where small-scale holdings are more prevalent, particularly in Portugal, Italy, Romania, and Greece, there is a high proportion of older farm holders and a low proportion of young farm holders (Zagata and Sutherland, 2015[18]). In brief, the problem of generational renewal in Europe reveals a high heterogeneity. Furthermore, Pindado and Sánchez (2017[28]) find that, on average and compared to other sectors, age is positively related to agricultural entrepreneurship; individuals above the mean age are more likely to start agricultural ventures and this probability increases with age.

2.3. New entrants as transformative agents

16. Attracting new entrants to agriculture can be transformative, given that newcomers can bring diverse resources and experiences from different backgrounds beyond farming, including skills, networks, financial capital, and new organisational and business models. These characteristics can spur innovation, more sustainable farming systems, and increased connections between farming and the local community, stimulating local economies by creating jobs and business opportunities (EIP-AGRI, 2016[19]).

17. OECD (2022[30]) indicates new innovative entrepreneurs in agriculture are already conducting disruptive innovations (new entrants that radically change incumbent competitors' business models) or more incremental changes towards adopting best practices in product and process innovation to be competitive in the market. Some authors claim that new entrants to agriculture (for example, the so-called career changers who move into agriculture from other occupational and educational backgrounds) bring skills, experience, and networking from other industries (Žabko and Tisenkopfs, 2022[4]). New entrants from other occupational and educational backgrounds often usher technological, social, and entrepreneurial innovations (Helms, Pölling and Lorleberg, 2020[20]). Other authors show that new entrants create more value added to the sector and rural areas than established farmers (Vik and McElwee, 2011[31]; Zagata and Sutherland, 2015[18]). For example, Lobley, Butler and Reed (2009[32]) show that new entrants are more likely to be involved in alternative and value added farming, such as organic farming. Similarly, some studies show that on-farm diversification activities are more frequent among new entrants (Barbieri and Mahoney, 2009[33]).

18. Several studies have found more entrepreneurial abilities and managerial strengths among new entrants into agriculture than among established farmers. Those with personal relations or social networks with existing entrepreneurs and having invested in other businesses are confident in their own skills and abilities and see opportunities to become agricultural entrepreneurs (Pindado et al., 2018[13]). New entrants show more entrepreneurial behaviour than established farmers, which is especially relevant for the competitiveness and sustainability of the agricultural sector (Seuneke, Lans and Wiskerke, 2013[34]; Pindado and Sánchez, 2017[28]).

19. In the context of climate change, some individuals could be inclined to begin sustainable farming or work for sustainable agribusinesses as a personal choice to contribute to reducing agriculture's environmental footprint. Young entrants are more likely to have strong environmental awareness (Baiardi and Morana, 2021[35]). Farmers' perceptions about environmental sustainability can be transformative because their livelihoods, and those of future generations, depend on their commitment to sustainable environmental practices (Carmichael et al., 2023[36]). New entrants are often associated with more sustainable farming systems (for example, in Japan (Zollet and Maharjan, 2021[37])) and with potential job creation and livelihoods in countries such as South Africa (Brooks et al., 2013[38]).

2.4. The profile of new entrants to agriculture

20. Characterising the attributes of new entrants is important to understanding their role as transformative agents and targeting policy programmes. Assessing the evolving profile of new entrants and their related skills helps understand their potential to bolster the future sustainability and transformation of the agricultural sector.

21. The literature indicates differences between new entrants into agriculture and established farmers. The "Global Entrepreneurship Monitor"[8] (GEM) is one of the most detailed sources of information for studying entrepreneurial behaviour and activity at the international level, containing data on the entrepreneurial attitudes, activity, and aspirations of 1 793 688 individuals in 37 OECD countries.[9] GEM classifies entrepreneurs by industry using the International Standard Industry Classification (ISIC), which enables the identification of agricultural business owners (Álvarez, Urbano and Amorós, 2013[39]).[10] A subsample of the GEM database is used to empirically analyse the attributes of new entrants and established farm entrepreneurs in OECD countries from 2003 to 2019. GEM follows the occupational perspective of entrepreneurship, in which farmers are entrepreneurs and profit-maximising decision makers (Phillipson et al., 2004[40]; Sternberg and Wennekers, 2005[41]; Pindado and Sánchez, 2017[28]). The database also incorporates specific variables that facilitate the analysis of entrepreneurial behaviour among both new and established business owners (Koellinger, Minniti and Schade, 2007[42]; Bosma and Schutjens, 2010[43]).

22. The survey enables the identification and classification of people involved in entrepreneurial activity within each country, according to the categorisation of "new" or "early-stage" entrepreneurs and "established entrepreneurs", outlined by Reynolds et al. (2005[44]). Following Pindado and Sánchez (2018[13]), the analysis considers "new agri-entrepreneurs" as individuals currently owning and managing an agricultural business that is less than 42 months old (i.e. 3.5 years), while "established agri-entrepreneurs" are individuals who have successfully operated in the market owning/managing a farming business for more than 42 months. Within the sample, a subset comprising 16 763 new (early-stage) agri-entrepreneurs and another subset of 17 874 established agri-entrepreneurs have been identified, covering most OECD countries.

[8] See https://www.gemconsortium.org/data.

[9] Unfortunately, the database does not include information for Australia's agricultural sector.

[10] GEM data are gathered through interviews with adults aged 18 to 64, drawn from representative samples of at least 2 000 individuals per country. The primary objective of the GEM adult population survey is to establish a representative sample of the population in each country and ascertain the proportion of individuals who own or manage a business or are in the process of initiating one. Participants are then asked follow-up questions, which aid in creating a profile of these individuals and their respective companies (Koellinger, Minniti and Schade, 2007[42]).

23. The definition of "new agri-entrepreneurs" based on 3.5 years of activity might differ from policy definitions in the United States or in the European Union (see Section 2.1). In the GEM database, firms that have been active for over 42 months are considered established because they have survived the "liability of newness", that is, the risky existence of emerging organisations, many of which would not survive their early days (Reynolds et al., 2005[44]). The database does not contain information on specific aspects, such as generational renewal, family context, or new entrants' social or professional origin. Table 2.1 shows summary statistics of some indicators of interest for the subsample of new entrants and established agricultural entrepreneurs in OECD countries. The average of the following indicators is higher for new entrants than for established agricultural entrepreneurs: household income, education, several entrepreneurial characteristics and technology adoption.

Table 2.1. Summary statistics on new entrants and established agricultural entrepreneurs across OECD countries for the period 2003 to 2019

Variable	Description	New agricultural entrepreneurs			Established agricultural entrepreneurs		
		Observations	Mean	St. Dev.	Observations	Mean	St. Dev.
Age	Age measured in years	16 763	39.23	11.44	17 874	47.78	10.15
Gender	Gender (male = 1, female = 0)	16 763	0.77	0.42	17 874	0.66	0.47
Household Income	1. Lowest 33%. 2. Middle 33%. 3. Upper 33%	14 122	2.24	0.79	13 155	2.18	0.80
Education Level	The education level is a scale ranging from 0 to 4 (0 = "none", 1 = "some secondary", 2 = "secondary degree", 3 = "post-secondary", 4 = "graduate experience")	16 763	2.24	0.97	17 874	2.01	1
Education Level Secondary	Dummy variable indicating whether individual has at least secondary education or higher	16 763	0.79	0.4	17 874	0.68	0.46
Recent Entrepreneurial Experience	Variable indicating whether the individual has experienced a business failure in the last 12 months	16 763	0.05	0.22	17 874	0.02	0.15
Opportunity Alertness	Variable indicating whether the respondent believes that, in the next 6 months, there will be good opportunities for starting a business in the area in which they live	16 763	0.45	0.50	17 874	0.29	0.46
Entrepreneurial Self-efficacy	Variable indicating whether the individual believes they have the knowledge, skills, and experience required to start a business	16 763	0.77	0.42	17 874	0.70	0.46
Entrepreneurial Social Capital	Variable indicating whether the individual knows someone who has started a business in the last two years	16 763	0.56	0.50	17 874	0.39	0.49
Technology Adoption	Variable indicating whether the respondent believes that the technologies used to obtain his/her products became available in the last 12 months	16 763	0.08	0.28	17 874	0.03	0.17

Note: Averages are calculated over the period 2003 to 2019.
Source: Authors' own description based on a subsample of GEM data (https://www.gemconsortium.org/data).

New entrants are younger, mostly male individuals

24. Figure 2.2 shows differences among OECD countries. The OECD average age of new agri-entrepreneurs is 39.2 years, while established agri-entrepreneurs average 47.8 years. For all countries, the average age of new entrants is lower than that of established entrepreneurs, which is not surprising as age is expected to be negatively related

to the probability of becoming an entrepreneur. The age structure of entrepreneurs varies widely across OECD countries. In some countries (for example, Iceland, Korea, and Norway), new entrants and established agri-entrepreneurs are older than the OECD average – suggesting ageing sectors – and the age difference between the two is smaller. In contrast, the new vs. established age gap is greater in other countries such as Estonia, Latvia, and Lithuania, which have younger established and new entrant farmers, suggesting that these countries are attracting relatively young farmers to the sector.

Figure 2.2. Differences in age, gender, and household income between new entrants and established agricultural entrepreneurs across OECD countries

Note: Averages are calculated over the period 2003 to 2019. OECD is the average of OECD countries (excluding Australia).
The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.
Source: Authors' calculations using GEM data (https://www.gemconsortium.org/data).

25. Most agricultural entrepreneurs are male. In many countries, new entrants have a slightly higher share of men than established agri-entrepreneurs, which might indicate

greater difficulties for women to start a new farm. This aligns with the findings of Arenius and Minniti (2005[45]) and Pindado and Sánchez (2017[28]) and with evidence on barriers to women's participation, as discussed in Giner, Hobeika and Fischetti (2022[46]). Interestingly, the EIP-AGRI (2016[19]) shows that new entrants in their innovation sample include a higher percentage of women, who have been historically more active in more modern forms of agriculture, such as organic farming and certain on-farm diversification activities, although most new entrants in European countries are men. In all countries, there is a clear gender gap in both groups, which implies that the bias against the participation of women remains even within the generational renewal.

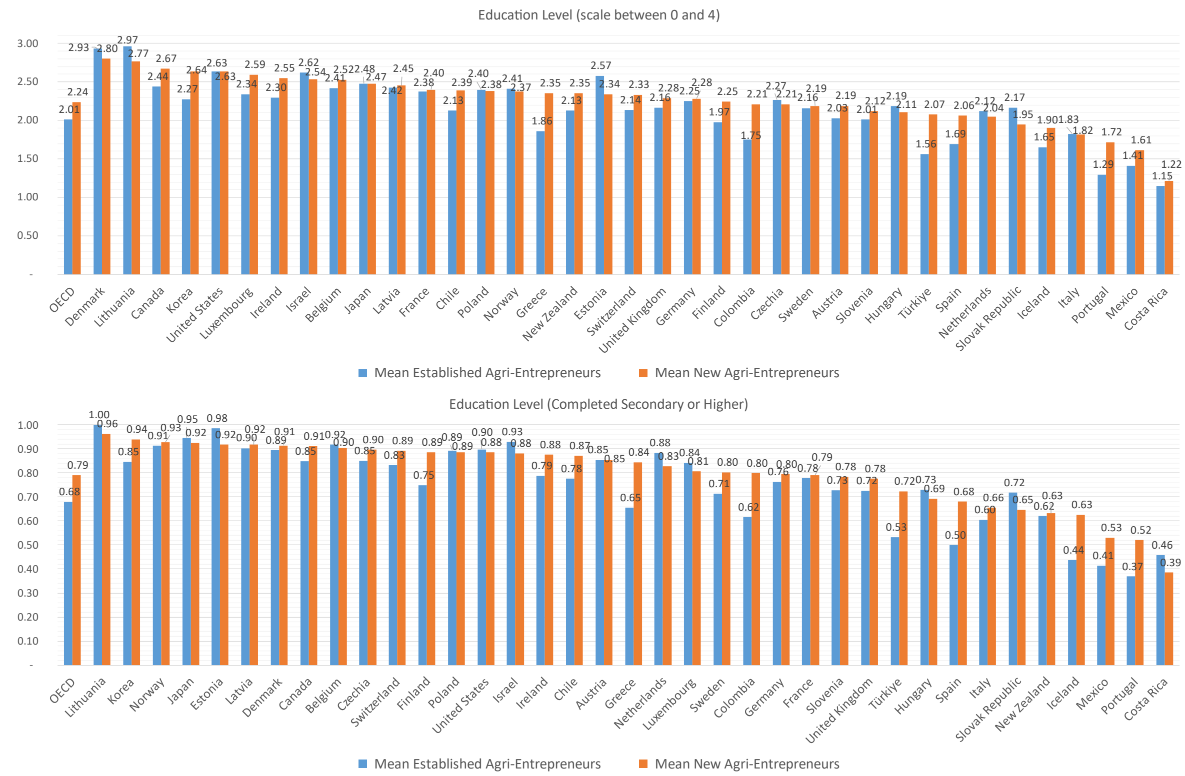
26. In some countries, established agri-entrepreneurs have, on average, higher household income levels than new ones, while in other countries, the opposite is true. There are arguments in both directions. Low-income levels might enhance the incentive to become an entrepreneur actively searching for opportunities. Conversely, high-income levels reduce financial constraints, increasing the likelihood of becoming an entrepreneur (Arenius and Minniti, 2005[45]). For EU countries, Pindado and Sánchez (2017[28]) find a negative relation between household income and the probability of becoming an agri-entrepreneur.

New entrants have higher education levels than established agricultural entrepreneurs in most countries

27. There are also differences between new and established entrepreneurs in terms of education (Figure 2.3).[11] For most countries, the education level tends to be higher for new entrants, although, in some countries, established entrepreneurs have a higher education level. In countries such as Greece, Colombia, Türkiye, Spain, Iceland, Mexico, and Portugal, there is a clear pattern of new entrants with higher general education levels compared to established farmers, which holds implications for the structural change of the sector (Caskie, 2018[47]). Individuals with higher education are more likely to perceive opportunities for profitable business and have greater abilities to exploit them (Hormiga, Batista-Canino and Sánchez-Medina, 2010[48]; Pindado et al., 2018[13]; Pindado, Sánchez and García Martínez, 2023[49]). In some countries, the higher education level of new entrants may be linked with specific policy instruments. For example, ten EU Member States included additional formal qualification criteria for support payments to young farmers (under 40) (OECD, 2023[50]).

[11] The educational level illustrated in the first panel of Figure 2.3 is on a scale ranging from 0 to 4, with increasing levels of education. The second panel indicates whether the individual has a secondary education or higher.

Figure 2.3. Differences in education levels of new entrants and established agricultural entrepreneurs across OECD countries

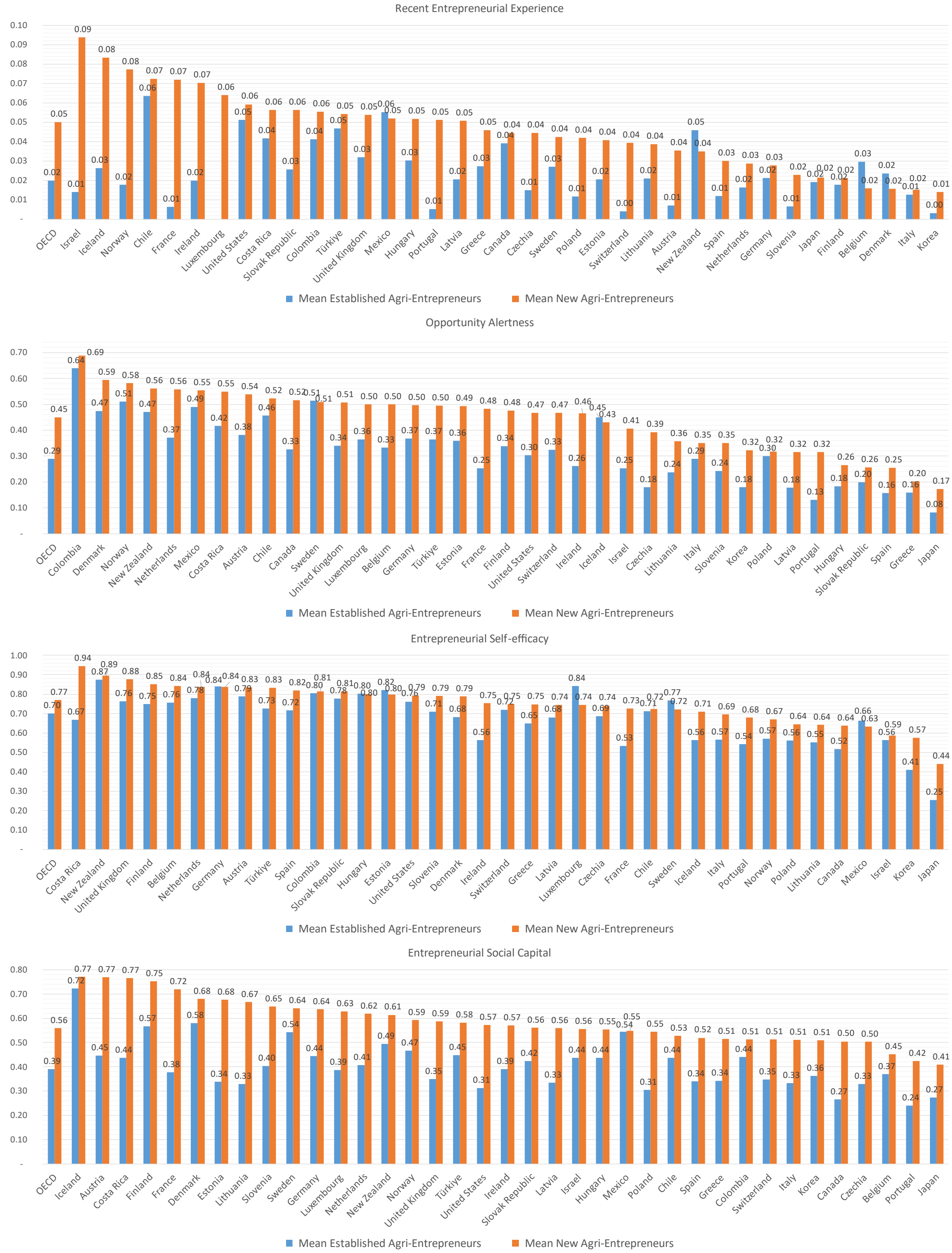


Note: Averages are calculated over the period 2003 to 2019. OECD is the average of OECD countries (excluding Australia).
Source: Authors' calculations using GEM data (https://www.gemconsortium.org/data).

Entrepreneurial skills and technology adoption are higher for new entrants than for established entrepreneurs in most OECD countries

28. "Recent entrepreneurial experience" indicates whether the new entrant has experienced a business failure in the last 12 months, capturing expertise in new ventures (Elston and Weidinger, 2018[51]). Recent entrepreneurial experience is higher for new entrants than for established entrepreneurs in most countries (Figure 2.4). Similarly, there are differences in "opportunity alertness", which indicates whether the respondent believes that in the next six months, there will be good opportunities for starting a business. Both recent experience and opportunity alertness have heterogeneous levels across countries as they both tend to be highly affected by the institutional, economic, and cultural national context.

Figure 2.4. Differences in entrepreneurship-specific skills and social capital between new entrants and established agricultural entrepreneurs across OECD countries

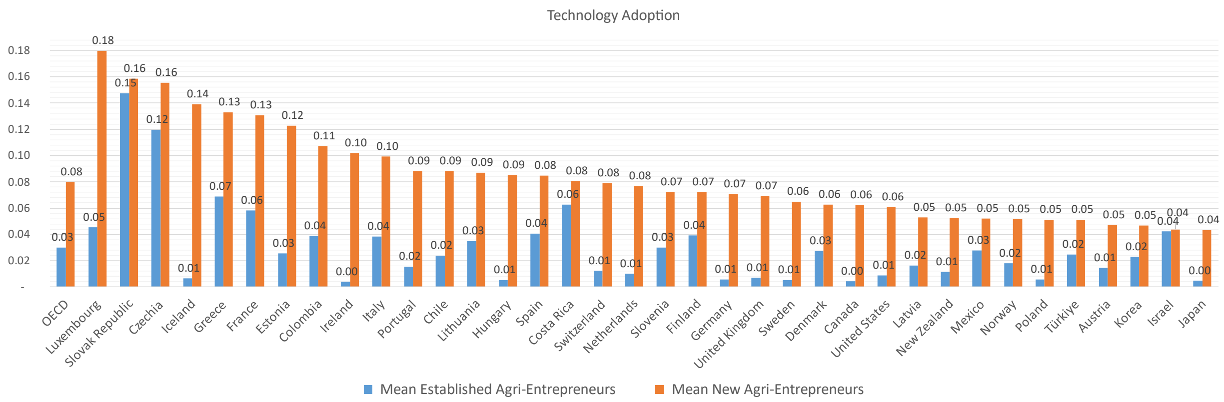


Note: Averages are calculated over the period 2003 to 2019. OECD is the average of OECD countries (excluding Australia).
Source: Authors' calculations using GEM data (https://www.gemconsortium.org/data).

29. “Entrepreneurial self-efficacy” indicates whether the new entrant believes they have the knowledge, skills, and experience required to start a business. In most countries, new entrants are more confident in their entrepreneurial skills than established entrepreneurs. Similarly, new entrants tend to have a higher average score for ‘structural social capital’, which measures whether the entrepreneur knows someone who has started a business in the last two years. This indicator captures access to information and thus advantages in identifying entrepreneurial opportunities (Pindado et al., 2018[13]). Importantly, Lastra-Bravo et al. (2015[52]) have shown that social capital increases the willingness to adopt agri-environmental schemes.

30. New entrants and established Agri-entrepreneurs also differ in “technology adoption” (Figure 2.5), which indicates whether the entrepreneur believes that the technologies used to obtain their products became available in the last 12 months. This reveals how adopting the latest technology serves as a growth and survival strategy for new entrants (Bosworth and Mcelwee, 2010[53]).

Figure 2.5. Differences in technology adoption between new entrants and established agricultural entrepreneurs across OECD countries

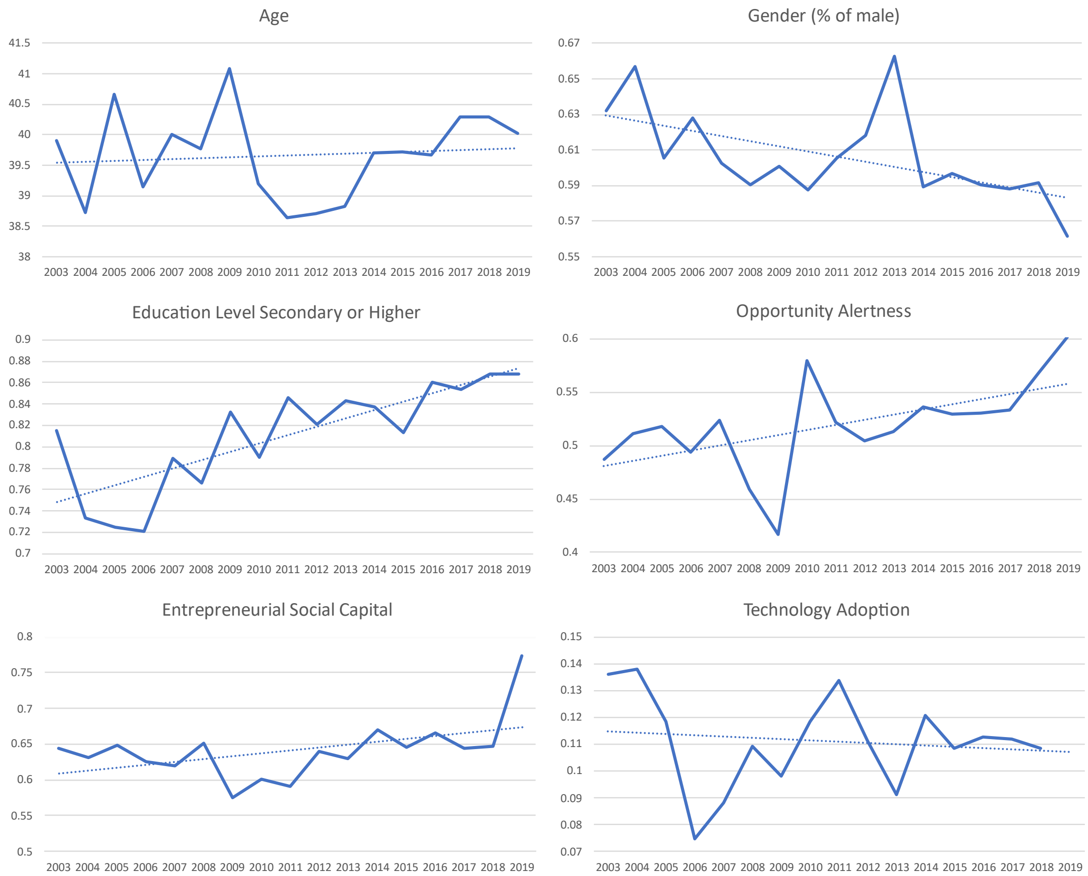


Note: Averages are calculated over the period 2003 to 2019. OECD is the average of OECD countries (excluding Australia).
Source: Authors’ calculations using GEM data (https://www.gemconsortium.org/data).

Over time, new entrants are slightly older, with increasing education and entrepreneurial skills and the gender gap might be slowly narrowing

31. The evolution between 2003 and 2019 of select indicators characterising new agricultural entrepreneurs reveals interesting evidence (Figure 2.6). Age slightly increased while the share of men declined, which implies a rising participation of women and a reduction in the gender gap among new agricultural entrepreneurs over the period. Notably, the education level and the indicators of entrepreneurial skills improved for new entrants. Technology adoption, however, did not change much over this period.

Figure 2.6. Evolution of indicators characterising new agricultural entrepreneurs

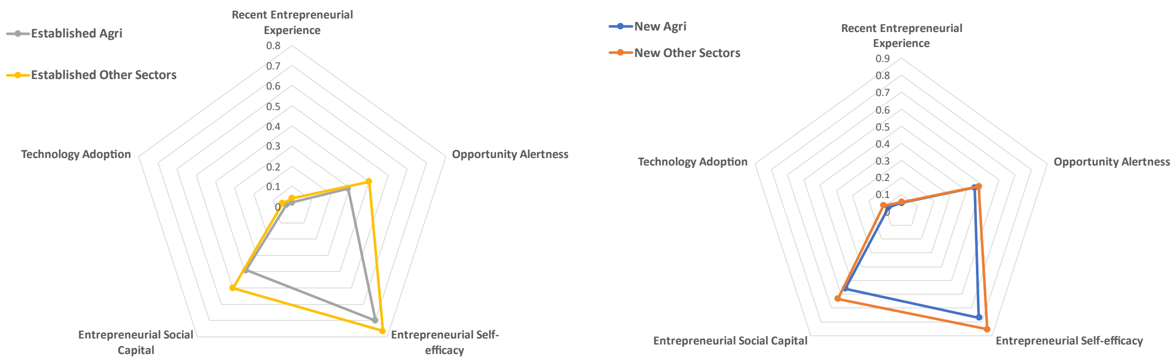


Note: The data point for each year represents an average over OECD countries (excluding Australia).
Source: Authors' calculations using GEM data (https://www.gemconsortium.org/data).

Agri-entrepreneurs have less entrepreneurial skills than in other sectors, but the gap is smaller for new entrants

32. It is also important to put the agricultural sector into a broader context by comparing the two groups of agri-entrepreneurs with other economic sectors (Figure 2.7). Agriculture has noticeable differences in entrepreneurial skill indicators such as "entrepreneurial social capital", "entrepreneurial self-efficiency", and "opportunity alertness". In contrast, the differences in "technology adoption" and "recent entrepreneurial experience" are smaller. While the agricultural sector seems to perform worse in the indicators of entrepreneurial skills, it is interesting to note that the cross-sector differences are lower for the group of new entrants. This evidence implies that new entrants into farming are more dynamic than established agri-entrepreneurs and that new entrants might be helping to narrow the gap with other sectors in terms of entrepreneurial skills.

Figure 2.7. Differences between established and new entrepreneurs in agriculture and other sectors for OECD countries



Note: Averages are calculated across OECD countries (excluding Australia) for the period 2003 to 2019.
Source: Authors' calculations using GEM data (https://www.gemconsortium.org/data).

33. To sum up, the analysis shows that, across most OECD countries, new entrants into agriculture show consistent differences from established agricultural entrepreneurs. New entrants are younger than established entrepreneurs. Women are underrepresented in both groups, particularly among new entrants, indicating more substantial barriers to entry for women. Still, there is an increasing average trend in female new entrants in the OECD.

34. In most OECD countries, new agricultural entrepreneurs have higher education levels and better entrepreneurial skills and are more likely to adopt the latest technologies. The OECD averages of education and self-assessed entrepreneurial skills increased between 2003 and 2019. Although the agricultural sector scores lower on indicators of entrepreneurial skills relative to other sectors, this cross-sector gap is smaller for new entrants, indicating that the farming sector is becoming more dynamic.

2.5. Is farming attractive?

35. Several obstacles hinder the entry of new participants into the farming sector (see Box 2.1). Some of these barriers may continue once new entrants start farming activities, creating disadvantages compared to established agri-entrepreneurs. Furthermore, negative perceptions of the farming profession and the sector as being characterised by hard physical work, loneliness and isolation, and risk due to uncertain economic and weather conditions, may discourage entry (Hounsome et al., 2011[54]).

36. According to an OECD report (Ryan, 2023[6]), labour and skills shortages are significant in the agri-food sector across OECD countries. This challenge is compounded by negative perceptions of the sector, relatively low wages, and limited career prospects. Moreover, the study argues that the farming profession is often perceived as a job of the past, lacking dynamism, with ageing farmers, and little space for innovation and entrepreneurship. However, there can be a perception that farmers are set in their ways and resistant to change, making the adoption of new practices and technologies difficult.

37. This negative perception can affect the choice of agriculture as a career and contribute to the difficulties faced by the farming profession in attracting youths (Unay-Gailhard and Brennan, 2023[55]). For example, potential careers in the agri-food sector are not popular for most Dutch students for many reasons, including the general negative social perceptions of agriculture as a career choice (Ryan, 2023[6]; OECD, 2023[56]). There is also evidence of similar negative perceptions of agriculture in non-OECD countries. A recent

survey indicates that some university students in Indonesia view farming as an occupation for individuals with low education levels (Nainggolan and Rommel, 2023[57]). In many OECD countries, work is ongoing to assess the skills gaps, the current and future demand for skills, the inflow of workers and the sector labour mobility to improve the attractiveness of agriculture (Ryan, 2023[6]).

Box 2.1. Obstacles to entry into agriculture

New entrants face several obstacles to entering the agricultural sector. Some of these obstacles are inherent to farming activities and are shared by new entrants and established farmers. However, important constraints can also discourage potential new entrants. The most frequent barriers highlighted in surveys, academic studies, and policy reports are capital and financial constraints, land availability, and low profitability (Jack et al., 2019[58]; EIP-AGRI, 2016[19]).

Farming is highly capital-intensive and demands substantial upfront investment in land, equipment, modern farming technologies, and infrastructure, posing challenges for those with limited credit history, especially young farmers (FAO, 2014[59]; EIP-AGRI, 2016[19]; Žabko and Tisenkopfs, 2022[4]).

Securing affordable land is challenging, particularly when ownership is concentrated among large-scale farmers or prices are steep (EIP-AGRI, 2016[19]). Policies like payments based on area can also contribute to high land prices. Inheritance may grant access to land but not necessarily the resources to farm (land, machinery, infrastructure) (Creaney, Hasler and Sutherland, 2023[15]). Older generations might be hesitant to pass on the business due to a lack of provision for retirement or concerns about how the business will be run when handed over (Jack et al., 2019[58]). To overcome the difficult access to land, in many places such as in the United Kingdom or Argentina, contract farming is a potential entry point whereby the contractor owns the machinery, provides labour and makes decisions on land management with varying degrees of autonomy from the land owner (Lobley and Potter, 2004[60]; Senesi et al., 2017[61]).

Housing, labour, skills, and social networks also pose hurdles (Sutherland et al., 2015[16]). Given that entry into a new sector is knowledge and resource intensive, knowledge and experience gaps can be significant barriers, particularly for those without a farming background, who can be at a considerable disadvantage in terms of finding networks and information (Žabko and Tisenkopfs, 2022[4]; Creaney, Hasler and Sutherland, 2023[15]; Sutherland et al., 2023[14]). Established market channels, dominant players, and stringent quality standards may hinder market access. Building relationships with buyers, establishing distribution networks, and meeting market demands can be challenging, particularly for small-scale or niche producers. New entrants need to have high entrepreneurial skills to be competitive (Vesala and Vesala, 2010[62]; Seuneke, Lans and Wiskerke, 2013[34]).

Regulatory complexities, bureaucratic processes, and compliance requirements can also be barriers for new entrants as they can be time-consuming and expensive, especially for those unfamiliar with the regulatory landscape (EIP-AGRI, 2016[19]). Some studies show that the regulatory framework can be a barrier to the adoption of innovative sustainable practices (Leitheiser et al., 2022[63]) and that the regulatory apparatus and bureaucracy are a significant source of stress for farmers (Jaye et al., 2021[64]).

Lesser services (e.g., access to education, health, and digital technologies) and insufficient infrastructure in rural areas can also discourage new entrants. Some studies show that young people in rural areas generally have access to fewer services and do not have the same opportunities to get involved in work and non-formal learning opportunities as their peers in urban areas (Șerban and Brazienė, 2021[65]). Similarly, cultural and lifestyle factors could also prevent the farming sector from being attractive to young people.

Addressing these barriers requires a comprehensive and tailored approach that may include supportive policies, access to financing, training, mentorship programmes, land reform initiatives, improved infrastructure, and market linkages. A recent study has shown that the European Union's CAP generational renewal measures positively impact the number of young farmers, business performance and local employment, varying from very minor to significant according to the local context (Dwyer et al., 2019[66]). Notably, aid is found to be most effective and efficient when delivered in mixed-measure packages that combine planning, investment, collaboration and advice, and are conditional on beneficiary training. The impact is also enhanced where institutional and fiscal policies ease access to land and capital. In marginal areas, aid for rural diversification and services aid are also vital. The study recommends a more holistic, flexible, and strategic approach to generational renewal.

38. Several factors contribute positively to the attractiveness of the agricultural sector. For example, the desire to become independent is often a driver of mobility towards agriculture (Paranthoën, 2015[67]). Despite hard physical work, some farmers claim they find time to relax and enjoy life and nature on their farms (Quinn and Halfacre, 2014[68]). Moreover, ongoing changes and trends in agricultural digitalisation could change the sector's attractiveness, especially for young people. Notwithstanding the need for digital skills and the fact that certain innovations can be disruptive, digitalisation has enabled entrepreneurs, including those in agriculture and food systems, to change and grow, transforming entrepreneurial opportunities (Dias and Rocha, 2023[69]). FAO (2022[5]) highlights the potential benefits of digital technologies and agricultural automation, which can make agri-food systems more efficient, productive, resilient, sustainable, and inclusive.

3. Digitalisation, labour, and skills in agriculture

3.1. Defining the scope of digitalisation

39. Digitalisation includes a broad range of technologies (precision farming, the Internet of Things (IoT), remote sensing, unmanned aerial vehicles, data-driven applications, AI, digital twins, robotics, and others) with the potential to be used in all fields of agriculture (Jouanjean, 2019[70]; OECD, 2019[8]). The process of digitalisation can be understood as datafication, compilation, and (re-)combination of electronic information, paired with high-dimensional analysis, algorithmic generation of management recommendations, and automation (Klerkx, Jakku and Labarthe, 2019[10]; McFadden et al., 2022[71]). Different concepts are used in the literature to embed specific forms of digitalisation applied to agriculture (Box 3.1). This study considers digitalisation in a broad sense – including a broad array of technologies.

Box 3.1. What does "digitalisation" of agriculture mean?

Agricultural digitalisation refers to integrating and applying digital technologies in several aspects of agriculture, including farming practices, management, and supply chain operations. Overall, agricultural digitalisation aims to modernise and optimise agricultural processes through the adoption of data-intensive technologies and devices. The broad nature of digitalisation in agriculture, value chains, and food systems has led to the emergence of several related concepts that highlight particular features of digital technologies and the digitalisation process (Klerkx, Jakku and Labarthe, 2019[10]). There are no unique criteria for determining what constitutes agricultural digital technologies.

Table 3.1 lists common digital technologies and examples for crops and livestock. Digitalisation also includes more general but relevant technologies, such as the Internet, cell phones, and digital platforms.

Table 3.1. Examples of digital technologies for crop and livestock production

Technology	Example
Robotics	Self-driving machinery, berry picking robots, high precision equipment based on real time kinematic (RTK) global positioning system (GPS)
Robotics: plant protection products (PPP)	GPS guidance for applications of PPP
Band spraying of PPP	Equipment for band spraying of PPP
Variable rate techniques	VRT for fertilisers, PPP, weeding, sowing, planting
Precision crop monitoring	Weather station data, digital mapping, soil scanning, yield monitors
Soil analysis	Testing of core samples performed on-farm or sent to laboratory; testing from on-farm soil sensors
Welfare and health monitoring of animals	Camera monitoring, sound monitoring, alert systems, activity sensors, animal tracking, health monitoring, feeding registration, drinking registration
Grinder mixer for animal feeding	Portable or stationary mills that proportion ingredients, grind, and mix feed, with various mill types
Automatic feeding systems	Equipment for pushing feed closer to livestock or fully automated delivery of feed
Automatic regulation of barn climate	Barn automation systems that control ventilation, lighting, and/or cooling of the housing environment
Milking robots	Automated milking systems for various housing types, with or without sensors that monitor cow health

Source: Extracted and adapted from the questionnaires of the Integrated Farm Survey (2023) (https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32021R2286&from=EN).

Smart farming focuses on integrating various technologies and automation (Walter et al., 2017[72]; Wolfert et al., 2017[73]). These include the IoT, sensors, robotics, AI, and data analytics to monitor and manage farm operations. Smart farming aims to optimise resource use, automate processes, and enable data-driven decision-making to achieve more efficient and sustainable agricultural practices.

Precision agriculture is a similar concept but emphasises precise input management (Griffin, Shockley and Mark, 2018[74]). It aims to maximise crop productivity, minimise input waste, and reduce environmental impacts by applying the right quantity of inputs in the right place and time.

Decision agriculture focuses on using data and analytics to support informed or data-driven decision-making in agriculture (Yost et al., 2018[75]) and across the agricultural value chain (Basso and Antle, 2020[76]).

Agriculture 4.0 or *Agri-Food 4.0* emphasise the application of advanced technologies from Industry 4.0* in agriculture or in agri-food supply chains (Valle and Kienzle, 2020[77]; Lezoche et al., 2020[78]).

Note: * This includes technologies such as the IoT, cloud computing and analytics, machine learning, and AI in production facilities and throughout manufacturing sectors' operations.

40. Digitalisation has far-reaching consequences within and beyond the farm gate (Jouanjean, 2019[70]). The entire agricultural sector and food value chains are being fundamentally transformed, including field- and farm-level production systems, storage and transportation of commodities, processing into feed and foodstuffs, and sales and marketing (Lowenberg-DeBoer, 2015[79]; McFadden and Schimmelpfennig, 2019[80]). Although this transformation is far from complete, especially in low- and lower-middle-income countries, and there are different degrees of digitalisation in other activities.[12] But its myriad effects are felt broadly, enabling upstream research and development (R&D) for new agricultural technologies, and potentially improving farmers' productivity, sustainability, and resilience (McFadden et al., 2022[71]).

41. National policy makers and inter-governmental organisations are increasingly aware of the role that sound digital and data policies can play in fostering innovation, guarding against anti-competitive behaviour, especially in input markets, and correcting negative externalities from agricultural production (OECD, 2019[8]; Guerrero, 2021[81]; Schroeder, Lampietti and Elabed, 2021[82]; McFadden et al., 2022[71]). A combination of new actors and public policies could accelerate the supply of digital agricultural technology, manage market concentration threats, and harness the opportunities of digital agriculture for all. In addition, established companies that develop and provide digital solutions using open innovation are interesting players that can help address these challenges (Piot-Lepetit, 2023[83]). Well-designed policies will be critical in ensuring the benefits and preventing potential negative impacts of digitalisation.

3.2. The challenges of digital adoption

42. The use of digital technologies has been increasing in quantity and variety (Walter et al., 2017[72]; MacPherson et al., 2022[84]; McFadden et al., 2022[71]). However, the adoption of digital technologies has been uneven between and within countries and production systems, depending on the characteristics of farmers and the agricultural sector (Salemink, Strijker and Bosworth, 2017[85]; Bronson, 2019[86]; Basso and Antle, 2020[76]). Recent OECD work has analysed the extent to which digital technologies are being adopted in agriculture and identified common barriers to their adoption, including up-front investment and recurring maintenance expenses, lack of relevance and user-friendliness, high operator skill requirements, mistrust of algorithms, and technological risk (McFadden et al., 2022[71]; McFadden, Casalini and Antón, 2022[87]).

43. The digitalisation process in agriculture has costs and risks, with economic, social, and ethical dimensions (Finger, 2023[9]). There exist inequalities in access to digital technologies related to costs, training, age, or network coverage. The digital divide can become a significant challenge that affects not only the most sophisticated technologies, but also basic tools such as mobile phones and general internet access (Rotz et al., 2019[88]; Mehrabi et al., 2020[89]). Lack of broadband or internet access and infrastructure occurs not only in less developed countries, but also in remote rural areas of many OECD countries (Williams et al., 2016[90]; de Clercq, D'Haese and Buysse, 2023[91]). Some farmers lack access to the necessary infrastructure or training to effectively use digital technologies (Birner, Daum and Pray, 2021[92]), and there can be large upfront costs associated with

[12] In fact, digitalisation is not universally applicable or a natural progression for all farming practices. In some cases, farmers would prefer to avoid using it. For instance, in pursuing specific geographical indications that yield substantial price and quality differentials for farmers, applying technology to automate tasks is restricted. For example, harvesting Corsican clementines must be done manually to qualify as "from Corsica". However, digital technologies can also benefit this type of activity, for instance facilitating traceability and marketing.

acquiring and implementing digital tools that can reduce profitability (Bolfe et al., 2020[93]). Investments in human capital (e.g. training and learning-by-doing with trial and error) are also costly (Miller et al., 2018[94]), and significant continuous education to keep up with advances in the technology is required. Such costs increase if the technology lacks general user friendliness and adaptability to the specific needs of the farmers or if there is a mismatch between the farm worker's level of human capital and the skills required to operate the technology safely and efficiently. These potential mismatches are highly relevant as governments design and implement training and education initiatives to fully realise the benefits of digitalisation (Nedelkoska and Quintini, 2018[95]).

44. Some studies mention the risk that the overreliance on big data will erode traditional farming checks and balances, exacerbated by algorithmic opacity and unequal benefits distribution (Visser, Sippel and Thiemann, 2021[96]), the privatisation of information (Miles, 2019[97]), and concerns regarding data privacy and security, and trust (McFadden, Casalini and Antón, 2022[87]). The use of AI and robots in agriculture can also raise ethical questions, which have been insufficiently investigated to date (Ryan, van der Burg and Bogaardt, 2021[98]). Despite the opportunities it offers for market access by small players, some authors warn that digital agriculture will increase the market power of large agribusiness enterprises by creating monopolistic conditions and concentrating power in major companies, thereby increasing the digital divide (Fleming et al., 2018[99]; Birner, Daum and Pray, 2021[92]). Some researchers also raise questions about the ability of small-scale farmers to adopt digital solutions in order to benefit from digitalisation (Vecchio et al., 2020[100]), leading to a situation that can endanger the viability of small-scale farming (Lioutas, Charatsari and De Rosa, 2021[101]).

45. While there is a growing body of literature on the potential benefits and challenges of digital technologies in agriculture (e.g. Khanna (2021[102]), FAO (2019[103]), Deichmann, Goyal and Mishra (2016[104])), there is limited empirical evidence on how they affect agricultural labour,[13] skills, the quality of work, job satisfaction of farmers, and farmers' wellbeing in general (Comi, Becot and Bendixsen, 2023[105]). Specific studies suggest that digital technologies can help reduce inequalities in terms of the age and gender composition of agricultural labour, both operators and hired labour (OECD, 2018[106]) and impact farmers' wellbeing (OECD, 2019[107]) with positive effects in their working and private lives (Goller, Caruso and Harteis, 2021[108]). They can also potentially shape the career paths of younger generations, including attracting young people into farming (Unay-Gailhard and Brennen, 2022[109]).

46. Understanding how digital technologies might affect farmers' lives and livelihoods is essential and can help to develop policies and initiatives supporting a sustainable and inclusive agricultural system. The remainder of this section discusses the available evidence and the most relevant issues related to digital agriculture, agricultural labour, skills, and farmers' wellbeing.

3.3. Impacts of digitalisation on labour

47. Digitalisation affects the quantity and quality of labour in agriculture. FAO (2022[5]) claims that autonomous processes, machinery, and robots are expected to carry out a large quantity – and different types – of activities, replacing human operators with no decision makers directly involved. The "Hands Free Hectare" and "Hands Free Farm" in

[13] The focus is on farmers and new entrants. However, sometimes, references to agricultural labourers are made when relevant. In this report, there is no difference between hired labour and operators' labour. The analysis focuses on the effect of digitalisation on tasks developed on the farm regardless of who performs them.

the United Kingdom are examples that show how automated machines can grow, manage, and harvest crops fully autonomously (Maritan et al., 2023[110]). The adoption of these tools has been rising since the early 2000s, most notably in North America and Western Europe, but regulatory issues and low profitability still limit adoption, particularly in developing countries where most of the world's agriculture takes place (Bronson, 2019[86]; Basso and Antle, 2020[76]; Lowenberg-DeBoer et al., 2021[111]).

48. Some digital technologies, such as automated guidance systems, automatic section control, controlled traffic farming, variable rate input applications, robotic milking, automated animal tracking, and unmanned aerial vehicles, are labour-saving, substituting capital for labour and may reduce the number of work hours needed to produce. Speciality crops are traditionally more labour-intensive and have been slow to mechanise and digitalise because of potentially irregular field shapes (e.g. orchards, vineyards, and horticultural plots), obstruction of wireless signals (e.g. from trees, vines, bushes), and damage from equipment to high-value crops. However, robots are expected to enhance production while compensating for the lack of labour, reducing production costs, taking over unattractive (risky, heavy, and dirty) jobs and reducing the burden of food production on the environment (Ryan, van der Burg and Bogaardt, 2021[98]).

49. The diffusion of labour-saving technologies can have both advantages and drawbacks. A careful assessment and balance of where, when, and how to implement AI robots within different agricultural practices is needed (Ryan, 2023[6]). Some technologies can replace low-skilled jobs and create social challenges in some regions (Carolan, 2020[112]), but could benefit both employers and workers in other areas where labour scarcity is increasing and wages are rising (FAO, 2022[5]). The magnitude of these labour-saving effects remains unknown primarily due to data limitations, although recent evidence from the United States suggests there can be substantial reductions in work hours (Shockley, Dillon and Stombaugh, 2011[113]; McFadden, Njuki and Griffin, 2023[114]).

50. Apart from the quantitative effects, several potential qualitative effects result from these technologies. Digitalisation may create new tasks and jobs that require higher or different skills (see Section 3.4). It can increase farmers' work quality and imply lower health risks, improving safety and reducing farmers' displeasure from specific menial farm tasks that can be fully or partially automated (e.g. steering equipment, milking dairy cattle, monitoring livestock fertility, scouting for pests, shutting off input applicators on sections of fields that have already been treated) (Nedelkoska and Quintini, 2018[95]; Marinoudi et al., 2019[115]). For example, robots are increasingly used in dairy farming, which involves arduous tasks and a rigid work organisation given twice or thrice-daily milking duties (Martin et al., 2022[116]). A study on the impact of automated milking in Norway revealed that farmers' investment in robots was primarily driven by quality of life factors , such as a more flexible work schedule, reduced physical labour, and a desire to align with the future standards of dairy farming (Vik et al., 2019[117]). Some studies have shown that automated milking systems help farmers live a modern lifestyle (Hansen, 2015[118]) and contribute to the attractiveness of the dairy sector for the younger generation (Karttunen, Rautiainen and Lunner-Kolstrup, 2016[119]).

51. Applying inputs more efficiently or by unmanned aerial vehicles instead of manually can also impact farmers' wellbeing (Finger, 2023[9]). For example, using robots and unmanned aerial vehicles for pesticide application can avoid adverse impacts on human health associated with long-term exposure (Mogili and Deepak, 2018[120]). Robotisation can avoid the extensive amounts of hand weeding necessary for certain crops, particularly in organic cultivation, which physically strains workers (Sørensen, Madsen and Jacobsen, 2005[121]). However, reducing physical labour also means lower physical activity, which is

not necessarily replaced by exercise elsewhere (Josse et al., 2023[122]). This can lead to adverse health outcomes, including increases in obesity rates (Gu et al., 2014[123]).

52. While the relationship between implementing field crop robotics and health benefits is inconclusive, some evidence points to reduced farmer stress and related illnesses (Spykman et al., 2021[124]). For example, the time savings may reduce workload (Sørensen, Madsen and Jacobsen, 2005[121]), leading to a better lifestyle, allowing for more time for family and social life (Tse et al., 2018[125]), and increasing leisure time on family farms (Redhead et al., 2015[126]). Conversely, frequent alerts from digital tools, a perceived loss of autonomy, an increasing dependence on machines, and data overload can reduce wellbeing in terms of mental health (Hansen, Bugge and Skibrek, 2020[127]).

53. A recent survey in Switzerland aimed to determine the level of adaptation of farm managers to digital technologies and the stress they felt in the process (Rapport Agricole, 2022[128]). Approximately 6% of operations managers surveyed felt "always" or "often" stressed due to digital adoption, while 34% of respondents "sometimes" suffered from stress. The perceived stress level depended on the farmers' adaptation phase; the more farmers adapted to digital, the less they felt stress, although there was an upsurge during the experimental phase. Operations managers who said they knew nothing about digital technologies or were only beginning to know about them felt more stress than those who had adopted them. Farmers who were adopting digital technologies felt less stressed than those who did not use them at all. However, an Austrian survey indicated that farmers with higher levels of farm automation faced more difficulty finding a vacation replacement, which might generate a new source of stress (Strauss, Quendler and Zollitsch, 2014[129]).

54. Digital technologies might also facilitate on-farm diversification activities, such as tourism and hospitality services, which can attract young people seeking a certain rural lifestyle (Barbieri and Mahoney, 2009[33]) and allow for better planning of daily activities on the farm (Bolfe et al., 2020[93]). By providing broad access to knowledge and peer networks, digital technologies can also partially compensate for new entrants' lack of knowledge and experience, particularly when they do not come from an agricultural background. Digital technologies can strengthen connections amongst farmers and with society in general, which could reduce the sense of loneliness and promote social sustainability.

3.4. Digitalisation and skills: Improving traditional competencies and developing new proficiencies

55. As the agricultural sector increasingly relies on digitalisation, there is a growing need for both "basic" skills such as literacy and specific high skills (see Box 3.2). This situation can pose bottlenecks for adoption if the required skilled workforce is not readily available or if farmers are not able or willing to acquire the relevant new skills. Conversely, it could also present opportunities for skilled workers and potential new agri-entrepreneurs or farmers to enter or re-enter the agricultural sector (Finger, 2023[9]). New entrants may also have higher levels of human capital and be more able to adopt digital technologies (Section 2.4).

56. Introducing technologies to automate tasks and increase efficiency may lead to the deskilling or displacement of farmers and farm workers with limited digital literacy. This could negatively affect the demand for low-skilled rural labour and have implications for marginalised groups such as migrants (Carolan, 2020[112]; Rotz et al., 2019[88]; Smith, 2020[130]). Some authors claim that digital technologies could reshape the practice of farming and rearrange agricultural labour and expertise, following a more data-driven approach which will require digital skills with less direct management (Eastwood,

Chapman and Paine, 2012[131]; Higgins et al., 2017[132]; Eastwood et al., 2017[133]; Ingram and Maye, 2020[134]). However, other scholars argue that digital technologies can be integrated into existing practices, combining “digital” and “analogue” skills (Burton and Riley, 2018[135]), or give rise to a new form of farming (Blok, 2018[136]). Farmers will need to be smart users of technology. In fact, integrating more traditional and newly acquired skills is likely the most common path in the transformation process. Since agricultural digitalisation began, farmers have needed to adjust; this has been the case, for example, concerning major equipment manufacturers increasingly incorporating digitalisation over the last decade.

57. In the German dairy sector, where farming work has shifted away from manual tasks to working with data processing, farmers need to use computers and other digital devices to monitor and control the processes on their farms (Goller, Caruso and Harteis, 2021[108]). In this case, farmers need to leverage elaborate mental models that connect traditional farming knowledge with knowledge about digital systems.

Adjusting education and advisory services

58. The types of skills necessary for farm work demand a sea change in digital literacy. Implementing and adjusting smart technologies will require different skills, including managing, using, and leveraging digital tools (Higgins et al., 2017[132]). Farmers will need a breadth of basic digital-related skills, such as equipment calibration, basic data analysis, and basic computer programming. They will not necessarily need to become data science experts and it is unlikely that farmers will need to recreate a computer programme or perform a detailed statistical analysis. Still, they will need a sufficient understanding of the general process to interpret the results appropriately and to make data-informed decisions. In a study of the German dairy sector, farmers reported that most of their digital understanding came from instructions offered by technology manufacturers, as well as from informal learning modes. Moreover, most surveyed farmers, including young farmers, indicated that digital technology was not sufficiently covered in their vocational degrees (Goller, Caruso and Harteis, 2021[108]). This indicates that the education system, particularly vocational schools or training institutes, need to be adapted to keep up with the ongoing changes and demand (see Box 3.2).

Box 3.2. Enhancing digitalisation through agricultural education: the role of vocational studies

Improving digital literacy in vocational studies is important to reduce barriers to adopting new technologies

Agricultural vocational training is key in providing farmers with the necessary skills and knowledge for primary agricultural production. Combining practical experience gained on farms with theoretical training provided by vocational schools can create a well-rounded education for young graduates. Digital literacy is not always sufficiently covered in existing vocational schools. These schools could amplify their impact by updating and adapting their content to respond to new skill demands, particularly for digitalisation (Goller, Caruso and Harteis, 2021[108]). Targeted vocational training can empower the next generation of farmers with the skills and knowledge needed to thrive in an increasingly digitalised agricultural sector. By familiarising farmers and young students with digital technologies, vocational schools can facilitate their adoption.

A Case study from Rhineland-Palatinate, Germany

Fachschule Landbau in Rhineland-Palatinate, Germany, provides an example of a vocational school that has successfully integrated a dedicated module on "Digitisation in Agriculture" into its curriculum, designed to progressively build competencies in digital technologies. In the initial years, students learn the basics of using classical digital office applications as well as specialised applications tailored for agricultural contexts. They also gain a fundamental understanding of computer science. Subsequent years focus on advanced, action-oriented competencies in AI (chatbots and machine learning), geo-coded and satellite data, GPS/RTK, robotics, drones, IoT, sensor technology, and network technologies in agriculture.

The curriculum is characterised by flexibility and adaptability, allowing for responsiveness to evolving technologies. This ensures that the teaching modules remain relevant, even in the face of rapid technological changes. The theoretical content derives from professional publications, experiential knowledge, and a knowledge transfer platform on digitalisation in agriculture (*Farmwissen*: www.farmwissen.de, supported by the Federal Ministry of Food and Agriculture in Germany). The platform offers practical examples of digital applications akin to a recipe book, a comprehensive Farmwiki containing a glossary and tutorials, and the Open Data Hof Neumühle (https://odf.ef-sw.de/) that serves as a digital twin of a farm for instructional purposes.

59. To adapt knowledge, acquire skills, and learn, farmers will also likely need adapted advisory services, potentially leading to displaced farm staff and service providers (Eastwood et al., 2017[133]). A more independent and individual way of managing a farm will probably be replaced by a far more structured approach that might include detailed monitoring by agricultural equipment makers, input suppliers, processors, and retailers (Bronson and Knezevic, 2016[137]; Eastwood et al., 2017[133]). Digital agriculture will require new capabilities, support decision-making, and potentially disrupt established modes of knowledge processing. Therefore, digitalisation will likely affect the whole agricultural knowledge and innovation system (Ingram and Maye, 2020[134]).

Combining new and existing skills

60. The shift towards digital skills does not mean that all existing skills will become antiquated; some traditional skills can and will need to remain. For example, farm business owners and operators still need operational and financial management skills to make management decisions. These decisions, however, will become less experience-driven and increasingly informed by automated technologies and other data sources (Klerkx, Jakku and Labarthe, 2019[10]).

61. Farmers will still need sufficient skills to perform routine and general equipment maintenance and to respond to emergency equipment problems. Machinery and equipment will still need repair as, in some cases, waiting for the technician's intervention can result in harvests and income losses. While on-farm repair of specific technologies may be limited by technological lockout or the lack of "right to repair" (Jouanjean et al., 2020[138]), some machinery equipment repairs will be necessary or more cost-effective to perform on-farm.

62. In brief, while the application of these skills will vary with growing digitalisation, farm business owners and operators will still need time management and organisational skills, adaptability, problem-solving skills, and interpersonal skills. Farmers will have to combine these traditional skills with new digital-related entrepreneurial and environmental practices. This combination will enable digitalisation to contribute to a more sustainable agriculture.

3.5. Human capital drives the adoption of digital technologies in agriculture

63. The need to acquire new skills becomes particularly relevant when examining factors influencing farmers' adoption of digital technologies. As farming tasks evolve from traditional manual methods to data-driven processes, the demand for technological proficiency is expected to grow. Several empirical questions deserve further analysis. Are new entrants into agriculture more likely to have the new required skills? Or, conversely, is farming experience a strong driver of digital technology adoption? However, empirical evidence is limited due to data availability.

64. Piot-Lepetit, Florez and Gauche (2023[139]) identify four groups of factors that explain digital adoption in developed countries: individual, organisational, technological and contextual, with individual factors such as education, experience and skills being the highest driving forces. Shang et al. (2021[140]) review several studies that analyse the factors influencing the adoption of precision and digital farming technologies. Many studies focus on farm and operator characteristics, with only a few recent studies emphasising technology attributes (such as compatibility with existing farming equipment, complexity, and data safety) or institutional and psychological factors. These studies conclude that farm size consistently emerges as the factor with the highest average importance, followed by education. In contrast, the relationship between age and adoption appears to be non-linear, as different studies yield varying and inconsistent impacts. Some studies have proven a more obvious link between digital skills and the adoption of digital technologies (Daberkow and McBride, 2003[141]).

An empirical analysis of digital adoption using US data

65. Data from the United States are used in this section to econometrically analyse how several farmer characteristics influence the probability of adoption of digital technologies: the US Department of Agriculture's Agricultural Resource Management Survey (ARMS) for 2006-21, encompassing randomly surveyed fields from more than 10 000 farms across

seven major field crops.[14] The USDA ARMS dataset provides the most detailed data on precision and digital agriculture adoption in the United States.[15] The dataset includes information on the adoption of the following digital agriculture technologies: yield monitors, yield maps, soil maps, variable rate technologies (VRT), automated guidance systems, and imagery from drones, aircraft, or satellites. Unfortunately, similar data on digital technology adoption is not available in other countries. To explain adoption, a set of key variables is analysed:[16] years of farming experience; education with four levels – less than high school, high school graduate, some college, and four-year college graduate or beyond; age; gender; household engaged in off-farm employment at any point in the year; household's total off-farm income (TOTOFI); and farm size as gross cash farm income (GCFI) (Hoppe and MacDonald, 2013[142]).

66. The summary statistics for the ARMS data (Table 3.2) reveal that, of the 10 376 farms in the analysis, 56% used one or more digital agriculture technologies in the production of field crops across the 34 states in the 13 survey years. Among the most widely adopted technologies were yield monitoring (40% of farms) and guidance systems (37%), whereas imagery was the least common (6%). Farmer experience was 31.9 years, on average, while the mean age of farmers – 98% of whom were male – was 56 years. For 37% of the sampled farms, the maximum educational attainment was a high school diploma, while 30% had some college and 28% completed a four-year college degree (or beyond). In nominal terms, the median GCFI was USD 533 000, while the median off-farm income was USD 32 500 – earned by 88% of farm households with off-farm employment. The most widely covered crops in the sample were corn (29% of farms), soybeans (23%), winter wheat (14%), cotton (12%), and rice (8%).

[14] The survey has a multi-phase, stratified, probability-weighted sampling design so that farms of all types and sizes across the United States are adequately represented; calibration of survey weights ensures that sample estimates of population totals hit several dozen targets (total number of farms, distribution of farms by sales classes, physical production quantities, and acreage and/or livestock inventories) (USDA-ERS, 2022[160]).

[15] The analysis does not infer a causal relationship and is carried out for a specific context. While the results help to understand the adoption process of digital technologies (some of which may apply to other contexts or countries), the analysis does not assume that they are generalisable for other OECD countries (similar to any country-specific analysis). Cross-country analyses should be conducted to have comparative results for the OECD. However, reliable and nationally representative data on the adoption of digital agriculture conducted by the national statistical offices in most other OECD countries is currently limited or non-existent (McFadden, 2023[162]).

[16] In the econometric analysis, the type of crop is controlled for in all analyses, and to test the robustness of the results, the estimations include controls for survey year, location (i.e. state, county), and state-by-year effects. These are designed to account for impacts of things that vary over time (e.g. overall price increases), by geography (e.g. local cultures, institutions), and by region over time (e.g. local agricultural policies). Also, possible non-linear effects of some variables are explored. The estimation methods used are ordinary least squares (OLS) and Probit (see Annex A for the estimation results).

Table 3.2. Summary statistics of US farmers' use of digital technologies and their drivers

Variable	Unit	Mean	Std. Dev.	Min.	Max.
Dependent variables					
Digital technologies adoption (aggregate)	1 = adopted, 0 = not adopted	0.561	0.496	0	1
Yield monitor	1 = adopted, 0 = not adopted	0.395	0.489	0	1
Yield map	1 = adopted, 0 = not adopted	0.193	0.395	0	1
Soil map	1 = adopted, 0 = not adopted	0.113	0.316	0	1
Variable rate technologies (VRT)	1 = adopted, 0 = not adopted	0.171	0.376	0	1
Automated guidance systems	1 = adopted, 0 = not adopted	0.371	0.483	0	1
Imagery from drones, satellites, or aircraft	1 = adopted, 0 = not adopted	0.057	0.233	0	1
Indepedent variables					
Years of farming	Decades	3.191	1.342	0	---[b]
Age	Decades	5.605	1.214	2.1	---[b]
Gender	1 = male, 0 = female	0.984	0.122	0	1
Education: Some high school	1= some high school	0.048	0.215	0	1
Education: high school graduate	1 = high school graduate	0.367	0.482	0	1
Education: some college	1 = some college	0.303	0.459	0	1
Education: ≥ 4-year college graduate	1 = ≥ 4-year college graduate	0.282	0.450	0	1
Gross cash farm income (GCFI)[a]	Million nominal USD	0.533	1.759	---[b]	---[b]
Total off-farm income (TOTOFI)[a]	Million nominal USD	0.033	0.220	---[b]	---[b]
Off-farm work	1 = off-farm work, 0 = not working off-farm	0.883	0.321	0	1
Barley	1 = barley field, 0 = otherwise	0.075	0.263	0	1
Corn	1 = corn field, 0 = otherwise	0.289	0.453	0	1
Cotton	1 = cotton field, 0 = otherwise	0.124	0.329	0	1
Oats	1 = oats field, 0 = otherwise	0.057	0.231	0	1
Rice	1 = rice field, 0 = otherwise	0.084	0.277	0	1
Soybeans	1 = soybeans field, 0 = otherwise	0.233	0.423	0	1
Winter wheat	1 = winter wheat field, 0 = otherwise	0.139	0.346	0	1

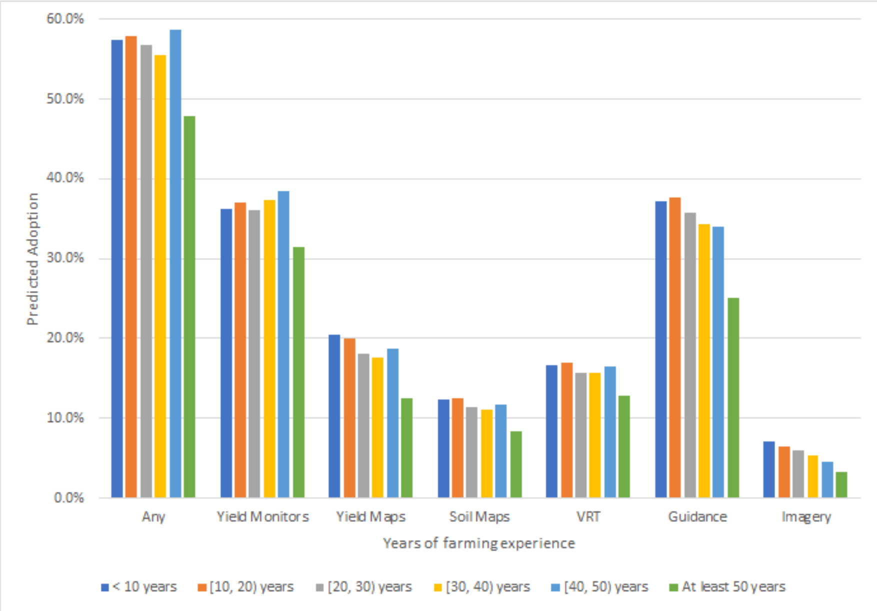
Notes: a To reduce the effects of outliers, median estimates for GCFI and TOTOFI are reported in the mean column. b For confidentiality purposes, maximums for years of farming and age, as well as for GCFI and TOTFI including minimums for these latter two variables) have been suppressed.
Source: U.S. Department of Agriculture, National Agricultural Statistics Service and Economic Research Service, Agricultural Resource Management Survey (ARMS), years 2006-07, 2009-13, 2015-19, and 2021 (https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/).

Human capital drives the adoption of digital technologies

67. The analysis indicates a small and statistically significant positive relationship between years of farming and digital agriculture technology adoption.[17] The predicted effect of years of experience on the adoption of digital technologies reveals some interesting findings (Figure 3.1). The group of farmers with over 50 years of experience is the only group that consistently adopts fewer technologies, on average, than the rest of the farmer groups. Predicted adoption of automated guidance systems and aerial imagery tends to decline with farmers' years of experience. However, in some cases (i.e. yield monitors, yield maps, soil maps, and VRT), there is a higher probability of adoption in the group of farmers between 40 and 49 years old compared to younger farmers.

[17] The positive relationship holds regardless of the specification, including robustness checks that account for other (fixed) effects, non-linear impacts (i.e. squared terms), interactions, and econometric method (see Annex A).

Figure 3.1. Predicted adoption estimates of digital technologies in the United States by years of farming experience

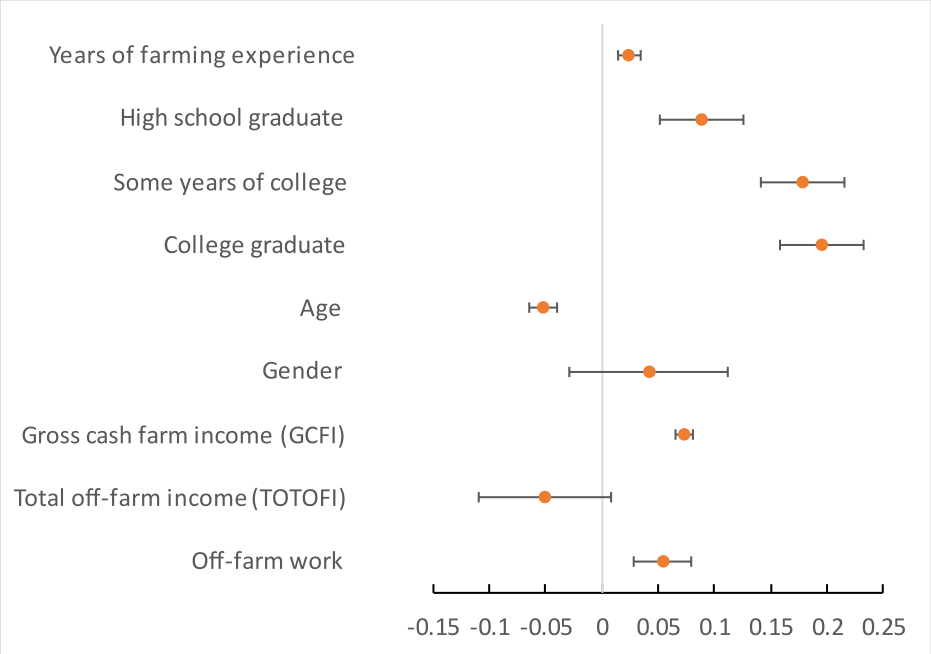


Note: Predicted probabilities for adoption of digital technologies from model (1) with probit estimation method (see Table A.1 in Annex A).
Source: Authors' calculations using data from ARMS for years 2006-07, 2009-13, 2015-19, and 2021. ARMS is available from the US Department of Agriculture, National Agricultural Statistics Service and Economic Research Service (https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/).

68. Figure 3.2 presents the estimated averaged marginal effects for the main independent variables.[18] In the case of years of farming, the regression results indicate that a decade increase in the number of years of farming experience is associated with an increase in digital agriculture technology adoption of around 2.4%. This marginal effect remains statistically significant and similar in magnitude across alternative Probit specifications (2.2% to 2.5%) and slightly higher for OLS specifications (2.4% to 2.8%). Conversely, farmer age has a negative effect on the probability of adopting digital technologies. But similarly, this negative effect is relatively small (-5.2%). Gender is not significant for the adoption of digital technologies, which implies that although there might be fewer opportunities for women in the sector given gender bias,[19] the probability of "success" in terms of technology adoption is not affected by the gender of the farmer.

[18] They are obtained from a simple Probit regression model with no interaction terms or non-linear effects; see model 1 in Table A.1 in Annex A.
[19] Similar gender bias was observed in the analysis of new and established agri-entrepreneurs in Section 2.

Figure 3.2. Marginal effects of human capital, demographics, and farm business characteristics on adoption of digital technologies



Note: Estimated averaged marginal effects (AME) of each determinant from model 1 of the Probit estimations. These are computed using the delta method. Dots represent the point estimate of the marginal effects, and bars are 95% confidence intervals. The x-axis is the marginal effect of the covariate on the probability that a farmer will adopt digital technologies. The y-axis lists the covariates used in the model.
Source: Estimations using data from ARMS for years 2006-07, 2009-13, 2015-19, and 2021. ARMS is available from the U.S. Department of Agriculture, National Agricultural Statistics Service and Economic Research Service (https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/).

69. Education has positive and strong effects that increase in magnitude with higher educational levels, from high school graduate to some college, and college graduate. This is in line with other studies that found that gaps in education and knowledge limit the adoption of digital innovation (Pierpaoli et al., 2013[143]). In the case of the United States, Gyawali et al. (2023[144]) found that the higher a farmer's education level, the more likely they will adopt digital technologies. In line with this, the education variables have the greatest marginal effects on digital technology adoption. Relative to farmers who have not completed high school, graduating from high school increases the probability of adopting digital technologies by 8.9%. In comparison, an additional year of college is associated with an increase of 17.9% in the probability of adopting digital technologies. The highest of all, farmers graduating from college are 19.5% more likely to adopt digital technologies than farmers who did not complete high school (see model 1 in Table A.1 in Annex A).

70. Farm revenues (GCFI), an indicator of farm economic size, significantly and positively affect technology adoption (7.3%). This is in line with the literature that finds that large farms tend to be more likely to adopt and benefit from digital innovations (Jakku et al., 2019[145]; Shang et al., 2021[140]). Further, having a household member engaged in off-farm employment positively relates to digital technology adoption and increases the probability of adoption by 5.4%. This could be linked to the existence of spillovers from other business sectors. For example, Žabko and Tisenkopfs (2022[4]) show that career changers (i.e. new entrants into agriculture from other sectors) bridge several worlds and are often important innovators. However, the income deriving from off-farm work has an estimated negative impact, although not significant in most specifications. This effect was

found to be non-linear, which indicates that at low-to-average levels of off-farm income, the impact on digital technology adoption is positive, but at very high levels of off-farm income (when farm income becomes a small share of household income), the effect is negative (see Table A.2 in Annex A).

71. While the marginal effects are generally robust across specifications, a more detailed examination of regression specifications with squared and interaction terms provides interesting insights into non-linear relationships. For example, there is no evidence of significant non-linear effects with experience; the squared term is negative but insignificant across all specifications. The interaction terms between years of farming experience and education variables, however, are negative and statistically significant. This suggests that the effect of experience on digital technology adoption declines with education (or vice versa), which might indicate some substitutability between farming experience and education. Adoption rates also increase with farm size but at a declining rate in all specifications. Work by other authors shows that adoption rates vary by crop, with the highest adoption for corn, soybeans, and cotton (e.g. Finger et al. (2019[146])).

72. Overall, farmers' human capital is found to be the main driver of technology adoption. Education provides the foundational knowledge required to understand new technologies, while off-farm work introduces farmers to diverse skills and perspectives, enriching their problem-solving abilities. Finally, the years of experience offer practical insights and a deep understanding of local agricultural ecosystems, enabling farmers to tailor practices to their specific contexts. This implies that human capital factors are key in enhancing the farmers' abilities to adopt digital technologies and, more broadly, to make informed decisions, and improve their productivity and sustainability.

3.6. Improving digital-related skills

73. The results in Section 3.5 in the case of the United States point to a small yet robust, positive relationship between farming experience, size and off-farm work, and digital technology adoption. However, while education is the main driver of technology adoption, the literature highlights that education and training systems need to adequately cover the acquisition of skills needed for agricultural digitalisation. Therefore, an important question exists: how can farmers' conventional education and skills be refined, and new skills developed to support a digitalised agricultural economy? The answer is not straightforward, but it implies the engagement of both the private and public sectors in industry-specific and software-related training programmes and education, including training initiatives, reskilling/upskilling endeavours, overarching educational campaigns, and curricula reforms (at the university level and for vocational studies).

74. The private sector has a role to play in facilitating industry or firm-specific skills, including software-specific programmes (e.g. digital platforms) (Birner, Daum and Pray, 2021[92]). Private companies and individuals may not have sufficient incentives to invest in digital technologies and skill development that have spillover effects beyond the firm and the industry, and which can potentially enable innovation with possible benefits for environmental sustainability. Broader development of digital skills could have positive externalities, as is usually the case with knowledge, information, and human capital, suggesting a role for public investment such as for education. Investment can come through several mechanisms, including training, re-skilling/up-skilling programmes, and more general education initiatives. Investment in farmers' digital literacy skills must also be complemented by human capital investment in government staff (e.g. public extension services and policy monitoring) and various computer specialists and advisors (Birner, Daum and Pray, 2021[92]).

75. Adopting digital technologies in farming operations can have large upfront fixed costs, including user training. Addressing potential skill mismatches is particularly relevant for OECD countries as they endeavour to design and implement training programmes and education initiatives that fully leverage the benefits of digitalisation. Given the generally extended duration of their careers and the increasing digitalisation of the agricultural landscape, new entrants to agriculture may be more inclined to invest in digital skills.

76. Farmers should be aware of the opportunities and potential drawbacks of the digitalisation of work processes in agriculture. Providers of agricultural education (like vocational schools or training institutes) should incorporate the knowledge and skills required to work in digitalised environments (e.g. data literacy) into their curriculum (Goller, Caruso and Harteis, 2021[108]). Farmers will also likely need adapted advisory services (Eastwood et al., 2017[133]) and life-long training to adapt to technological changes.

77. The ageing farm manager population might provide an opportunity for cost-effective digital skills investment and development. While some current farmers may be less interested in digital skill development or face insufficient payoffs (especially if retirement is nearing and no succession is planned), incoming farm managers are likely to have greater incentives to invest in digital skills, given the expected length of their careers and the growing digitalisation of the agricultural economy (Khanna, 2021[102]).

78. Adapting skills and acquiring new ones takes time, and it might require defining the needs, objectives, and targets with enough flexibility to adjust them during possible changes in the process. Additional analyses are required to assess how digitalisation will continue to change farming practices and which type of knowledge, as well as skills linked to these developments will be required in the future, considering that there will probably be country or context specificity. Foresight analyses or prospective studies provide a tool to address these far-reaching changes.

4. Prospective analysis on the future of farming and farmers

79. Foresight or prospective analysis is a systematic approach to anticipating and preparing for the future (Prager and Wiebe, 2021[147]; Popper, 2023[148]). It uses various tools and methods, both quantitative and qualitative, to identify emerging trends, uncertainties, and potential disruptions, moving beyond prior data predictions to evidence-based plausible futures (Wiebe et al., 2018[149]). The studies typically adopt a mid- to long-term perspective and seek to anticipate developments that will likely occur over several years. Taking a comprehensive approach allows for systematic consideration of scenarios to anticipate and prepare for future agricultural developments and can thus be helpful in understanding the future and the upcoming challenges of farming, and combining global trends with local solutions and policies (Prager and Wiebe, 2021[147]). Foresight analysis also helps in shaping the future of agriculture, informing decision-makers and policy design to craft effective policies to improve productivity and sustainability (Wiebe et al., 2018[149]; Barrett et al., 2021[150]) and is often used by governments, international organisations, and private companies.

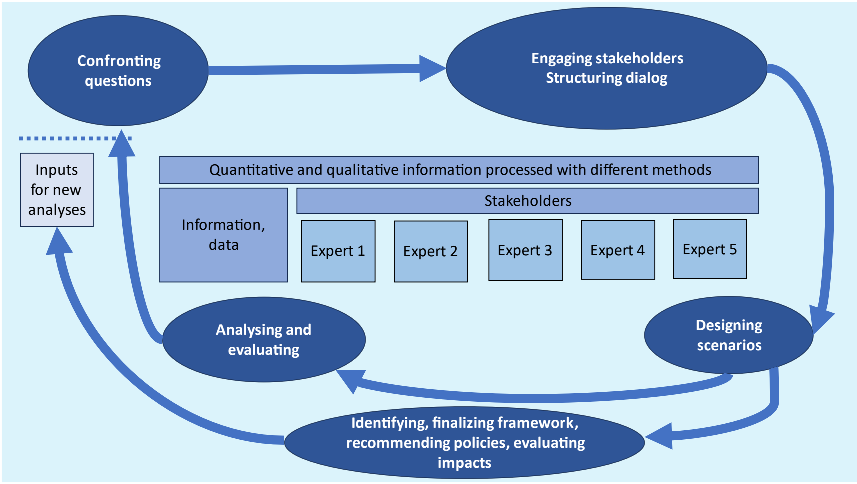
80. This section reviews several studies that use foresight or prospective analysis to discuss the future of agriculture and digitalisation and the evolving role of the farmer or the so-called “farmer of the future”. It focuses on a few studies that are helpful to envisage the possible profiles of future farmers under different scenarios of environmental sustainability, inclusiveness, and increased digitalisation in the agricultural sector.

4.1. Foresight analyses on the future of agriculture

81. The digital transformation is a main driver of the future of food and agriculture, shaping the nature of farm jobs and practices and the attraction of newcomers. The future of farming and food is unknown but can be analysed using prospective techniques. Foresight analysis provides an interesting tool for linking the evidence of new entrants with future farmers, those who will have the capacity to respond to the most likely scenarios for agriculture and digitalisation, requiring improved efficiency, environmental sustainability, and inclusiveness.

82. Scenarios describing alternative plausible futures serve to test what might happen given expected changes or trends (e.g. climate change) and possible responses (i.e. a new policy, a new technology). Foresight analysis is anticipatory in the sense that it allows testing how different present strategies might help better respond to the challenges likely to be faced in the future. A simplified and general conceptual diagram for developing a foresight analysis highlights that the process is nonlinear but circular, with interactions and feedback between the different phases (Figure 4.1).

Figure 4.1. Schematic diagram of foresight analyses or prospective studies



Source: Authors' elaboration based on Cook et al. (2014[151]), Wiebe et al. (2018[149]), and Prager and Wiebe (2021[147]).

83. In practice, the process involves multiple steps with several methodologies and tools. Input collection, scanning, and monitoring are the main steps in defining the subject matter and aims of the study. Input collection includes data and information collection, and exchange and stakeholder engagement. The scanning and monitoring aim to identify and follow the trends and context of the subject of the study and the patterns and possible changes in the factors influencing it. The inputs from these two phases allow key drivers to be identified and thus to develop the scenarios with stakeholders, who can provide their knowledge through a Delphi method based on structured surveys that provide both qualitative and quantitative assessments from experts knowledgeable on a topic or on future scenarios. Successive rounds of surveys and revisions may enable convergence on a consensus about a particular scenario. Assessment, analysis, and evaluation of these scenarios inform policy recommendations and adaptation strategies involving policy makers.

84. Continuous monitoring of the (mis)alignment of the scenarios with real-world developments is expected, keeping in mind that foresight analyses do not predict the future but provide possible scenarios depending on different developments. Similarly, the execution of the strategies and the implementation of the measures should be adapted to potential changes in the scenarios. The assessment also includes evaluating the impact of the specific strategies and policies, and the results can be used to refine future foresight analysis.

85. Many studies depict the future of agriculture with alternative scenarios, providing essential insights into potential future challenges and prospects for food and agriculture systems. Table 4.1 presents an overview of the prospective studies or foresight analyses discussed in this section. This set of studies is not intended to provide a fully comprehensive portrait of OECD agriculture or all relevant scenarios envisioned by experts. Rather, it is just a subsample of recent publications.

Table 4.1. Literature review on prospective analysis of agriculture and food

Author (Year)	Context	Scope
OECD (2016)	Discusses alternative futures for global food and agriculture.	Presents three alternative scenarios for 2050, considering economic growth, environmental, and social issues.
FAO (2017)	Explores scenarios for the future of food and agriculture based on key drivers.	Provides policy advice based on alternative trends in income growth, population growth, technical progress, and climate change.
EIP-AGRI (2016)	Analyses new entrants into agriculture.	Emphasises the diversity of future farmers rather than identifying a singular farmer of the future.
Krzysztofowicz et al. (2020)	Analyses the role of farmers and the farmer of the future in Europe.	Combines foresight and design methodologies, involving European farmers and stakeholders to identify megatrends and develop farmer profiles for 2040.
EIP-AGRI (2020)	Analyses the need of new skills for digital farming.	Contributes to the design and implementation of approaches and tools that can help farmers and farm advisers develop the skills they need in the face of the digital transition in agriculture.
Prager and Wiebe (2021)	Discusses the future of agriculture and digitalisation, and the evolving role of the farmer.	Foresight analysis as a tool to link new entrants with the farmer of the future, considering likely scenarios for agriculture, improved efficiency, sustainability, and inclusiveness.
Bock and Krzysztofowicz (2021)	Develops four scenarios that describe possible alternative futures for rural areas in the European Union.	Scenarios range from pronounced depopulation and land use specialisation to diversified and expanding rural areas, considering future developments in demography, multilevel governance, climate change, economic development, and digitalisation.
MacPherson et al. (2022)	Reviews policy and law in the German and European context for leveraging digital agriculture for sustainability.	Uses foresight analysis to reflect on future frame conditions influencing agricultural digitalisation and sustainability.
Ehlers et al. (2022)	Develops and evaluates digitalisation scenarios in the European agri-food sector.	Distinguishes four scenarios of agricultural digitalisation in 2030 and providing implications for policy strategies.
Barabanova and Krzysztofowicz (2023)	Examines the interplay between digital transition, policies, and the resilience of agriculture and rural areas.	Concludes that digitalisation can help cope with shocks, build communities, and adopt systems-related thinking. They can also reinforce inequalities and introduce new rigidities, however. Highlights the need for capacity building for digital skills, fostering an effective digital ecosystem and data governance, investing in infrastructure, and securing adequate funding.
Popper (2023)	Systematic approach to anticipating and preparing for the future.	Identifies emerging trends, uncertainties, and potential disruptions in agriculture to anticipate and prepare for future developments.
Erasmus + FIELDS project (Ongoing)	Creates scenarios for the EU agriculture, food industry, and forestry sectors.	Analyses of socio-economic trends impacting sustainability, digitalisation, bioeconomy, and business models in agriculture.

Source: Authors' elaboration based on a review of the relevant literature.

86. FAO (2017[152]) explored three scenarios for the future of food and agriculture based on alternative trends for key drivers, including income growth and distribution, population growth, technical progress, and climate change. OECD (2016[153]) discussed three alternative 2050 scenarios for global food and agriculture, considering challenges such as feeding a growing, wealthier, and more demanding population while safeguarding delicate ecosystems, bolstering agricultural productivity amidst climate change and other risks, competing for access to scarce land, water, and natural resources, and enhancing the wellbeing of rural areas. The alternative scenarios also differ in how citizens and governments value economic growth and environmental and social issues. Envisioning these scenarios enables a structured discussion and identification of policy and private sector responses to present and future challenges. Bock and Krzysztofowicz (2021[154]) develop four scenarios that describe possible alternative futures for rural areas in the European Union. These range from a significant depopulation and land use specialisation to diversified and expanding rural areas, combining future developments that range from

demography and multilevel governance to climate change, economic development, and digitalisation.

87. Similarly, some studies focus on specific developments in future scenarios, such as agricultural digitalisation.[20] For example, Ehlers et al. (2022[155]) developed and evaluated four digitalisation scenarios in the European agri-food sector in 2030 to guide agricultural policy's strategic development: 1) digitalisation of the sector following current directions at current rates as a baseline scenario; 2) strong digitalisation of a regulatory government; 3) use of autonomous farming technology; and 4) digitalised food business. The findings suggest that the baseline scenario would require strategies to hasten technological ramp-up and institutional infrastructure for digitalisation in 2030. Regardless of the scenario, the authors found it would be beneficial to increase the digital competencies of all stakeholders. Barabanova and Krzysztofowicz (2023[12]) examined the interplay between digital transition, policies, and the resilience of agriculture and rural areas against potentially disruptive and transformative changes. They conclude that digitalisation can catalyse this transformation, helping to better cope with shocks, acquire knowledge, build communities and relations, and adopt systems-related thinking. However, digitalisation can also hinder this process by reinforcing inequalities, creating lock-ins, and introducing new rigidities in the system. Implementing a digital strategy should come with key enablers including capacity building for digital skills and knowledge, fostering an effective digital ecosystem and data governance, investment in infrastructure and connectivity, and ensuring adequate funding and investment.

88. Prager and Wiebe (2021[147]) discussed how alternative investments in agricultural research may function given anticipated futures associated with various drivers, such as climate change, increasing wealth, and changing policy environment. Other studies linked digitalisation scenarios with environmental sustainability. For example, MacPherson et al. (2022[84]) highlighted institutional, societal, and legal preconditions for leveraging digital agriculture to achieve diverse sustainability targets in the German and European context. They concluded that only some policies consider the benefits of digital agriculture and focus on resource use efficiency. Legislation on digital agriculture is emerging but is highly fragmented. And the adoption of digital agriculture to enhance sustainability will depend on future data ownership regimes.

89. Of particular interest are those analyses that focus on the role of farmers in dealing with future challenges in agriculture. Krzysztofowicz et al. (2020[3]) analysed the role of farmers and developed the concept of the "farmer of the future" in Europe. They combined foresight and design methodological approaches, emphasising a participatory process involving European farmers and stakeholders such as academia, civil society organisations, and industry associations. They identified a set of "megatrends" affecting farming and developed 12 farmer profiles for 2040. While climate change and environmental degradation will pose increasing challenges, farmers are expected to adopt more sustainable practices that will become mainstream by 2040. During the transition, farmers are expected to be active contributors to different ways of environmentally conscious farming. Consumers in 2040 will be more demanding and more aware of the consequences of their choices, which will imply changes in the supply chains and business models. They further concluded that technological and managerial skills will be essential as digitalisation increases.

[20] The OECD has been actively involved in the ongoing project on "Long-term Implications of the Digital Transition for Farmers and Rural Communities" carried out jointly by the European Commission Joint Research Centre (JRC) and the European Commission Department for Agriculture and Rural Development (AGRI).

90. An essential feature of this study is that it does not identify a "farmer of the future" but a diversity of future farmers. This is also a relevant feature of the EIP-AGRI (2016[19]) study analysing new entrants into agriculture. Many other initiatives discuss the sociodemographic and economic features of farmers in the future.[21]

91. Other studies focus on the analysis of necessary skills. For example, the Erasmus + FIELDS project "Addressing the current and future skill needs for sustainability, digitalisation, and the bioeconomy in agriculture: European skills agenda and strategy" created scenarios for the EU agriculture, food industry, and forestry sectors, analysing socio-economic trends that impact sustainability, digitalisation, bioeconomy, and business models (including management and entrepreneurship) (Sanna and Fenrich, 2020[156]).

92. In the specific case of digitalisation, an EIP-AGRI seminar on "New Skills for Digital Farming" highlighted the need for cross-cutting skills such as open-mindedness, comprehensive management, communication and collaboration, digital literacy, and advanced digital skills (EIP-AGRI, 2020[157]). Communication and collaboration are particularly important in the digital transition of farmers as they do not take place in a vacuum, and the ability to build networks with other actors is very relevant for the adoption of digital technologies and for the ability to learn and innovate (OECD, 2023[50]). The so-called "soft" skills, such as problem-solving, creative thinking, management, and communication skills, are also relevant in facilitating the digital transition of farmers (OECD, 2019[8]).

4.2. Foresight analyses on the future of farmers

93. Drawing on evidence from the review of different foresight analyses and the need to respond to the triple challenge of food systems (OECD, 2021[1]), this section summarises the main characteristics, needs, expectations, and skills of future farmers. Several analyses of macro-trends identified by the literature are relevant to the future of farmers (e.g. in FAO (2017[152]), Krzysztofowicz et al. (2020[3]), and Ehlers et al. (2022[155])) and permit the exploration of the characteristics of farmers that will evolve within technological, economic, social, and cultural changes.

94. As many studies highlight, specific skills and characteristics are expected to vary depending on factors such as geographic location, type of farming, and individual farm circumstances. Although heterogeneity among farmers is expected to continue shaping the farming sector, an identified set of characteristics and skills will be vital for farmers to succeed in a more productive, sustainable, and inclusive agriculture. Table 4.2 provides a non-exhaustive summary of the macro-trends and challenges expected to affect and change farming and food systems, as well as the associated desired skills and characteristics for farmers, synthesising findings from the literature.

[21] For example, "Future farmers in the spotlight" (https://future-farmers.net/), "Agriculture de Futur" (https://agriculturedufutur.ch/), "Agribusiness in 2035 – Farmers of the Future" (https://www.isi.fraunhofer.de/content/dam/isi/dokumente/ccv/2020/Agribusiness%20in%202035%20-%20Farmers%20of%20the%20Future.pdf).

Table 4.2. Macro-trends and challenges affecting agriculture and associated skills and mindset needs

Macro-trends/Challenges	Skillsets and mindsets for adjusting to or overcoming trend/challenge
Food security and nutrition	- Knowledge of food production and distribution systems - Skills in crop planning and management for reliable food supply - Ability to implement food safety and quality control measures - Familiarity with food storage and preservation techniques - Understanding of nutrition and dietary needs for balanced food production
Inclusiveness	- Cultural sensitivity and awareness - Communication skills to engage with diverse communities - Ability to promote inclusive practices in hiring and working with a diverse workforce - Commitment to fair treatment and opportunities for all stakeholders in the food supply chain - Collaboration and partnership-building skills to work with different groups and stakeholders
Environmental sustainability	- Proficiency in sustainable farming practices - Ability to adapt to changing environmental conditions - Knowledge of conservation techniques and eco-friendly technologies - Commitment to reducing environmental impact - Familiarity with renewable energy and resource-efficient practices
Technological progress and digitalisation	- Strong technological proficiency and digital literacy - Capability to adopt and integrate advanced farming technologies - Ability to use data for decision-making and precision agriculture - Openness to innovation and willingness to embrace new tools - Skills in managing and troubleshooting digital equipment
Consumer awareness and demand for sustainable products	- Understanding of consumer preferences and market trends - Ability to produce and market sustainably produced agricultural products - Communication skills to engage with consumers and explain sustainable practices - Commitment to transparency and ethical production methods
Changing demographics and labour dynamics	- Adaptability to changing labour force dynamics - Knowledge of efficient labour management techniques - Ability to train and manage diverse workforce - Familiarity with technology-driven automation and robotics in farming - Understanding of labour laws and regulations
Policy and regulatory landscape	- Awareness of agricultural policies and regulations - Advocacy and lobbying skills to influence policy decisions - Ability to navigate compliance requirements and obtain necessary permits - Engagement in farming associations and advocacy groups
Globalisation and market access	- Knowledge of international markets and trade dynamics - Skills in market research, export/import procedures, and trade negotiations - Adaptability to meet global quality and safety standards - Networking skills to establish international business relationships
Climate change and resilience	- Capacity to implement climate-resilient farming practices - Knowledge of climate-smart agriculture techniques - Ability to adapt crop choices and farming methods to changing climates - Preparedness for extreme weather events and climate-related challenges - Willingness to participate in climate mitigation and adaptation efforts

Source: Authors' elaboration based on the analysis of the related literature and studies cited in Section 4.

Farmers will be diverse but adaptable, willing to learn and digitally equipped

95. Future farmers will be diverse, but some characteristics, abilities, and skills (such as education, entrepreneurial knowledge, digital skills, technological capabilities, environmental awareness, and understanding of sustainable practices) will likely become increasingly common. As one example, some authors have found that new job postings in agricultural labour markets are increasingly mentioning words like "data", "quantitative", and "[computer] programming" as required skills (Abney, Brewer and DeLay, 2022[158]).

96. Due to the rapid pace of agricultural transformation and the variety of challenges, future farmers will need to be adaptable and willing to learn new skills throughout their careers, for example, participating in training and continuous learning programmes. Past experience is expected to be less critical as more conventional, analogue agricultural production methods become increasingly digitalised. In line with Section 3, prospective studies find that with the increasing digitalisation of agriculture, a large share of future farmers will rely on advanced digital technologies and will need to be proficient in using and managing technology, which includes a broad set of skills related to digital tools and platforms used in modern agriculture.

New skill demands include collaborative networking, environmental knowledge and entrepreneurship

97. To contribute to more inclusive agriculture, farmers are called to ensure their practices are inclusive and equitable for all stakeholders, including farm workers, consumers, and neighbouring communities. Similarly, future farmers will likely need to strengthen their collaboration and networking with other stakeholders in the food system, including supply chain partners, consumers, researchers, local communities, and policymakers. Building solid relationships and partnerships is essential to creating more sustainable and inclusive food systems.

98. Given growing concerns about climate change, resource depletion, and biodiversity loss, farmers are expected to play an active role in using environmentally conscious farming methods. Thus, farmers will need to acquire skills to adopt practices that optimise synthetic chemical use, reduce greenhouse gas emissions, promote soil health, and conserve water. They will need to use precision farming techniques, turn to renewable energy sources, and adopt regenerative practices to restore and enhance ecosystems. Future farmers are projected to become more familiar with and increasingly adopt practices and skills for mitigation and adaptation to climate change, good agricultural practices, efficient use of resources and logistics, and soil nutrient and health management (Mayor et al., 2022[159]).

99. Farmers will benefit from enhancing their managerial skills involving planning, organising, and decision-making needed to run their operations as farming practices evolve and farm outputs and outcomes diversify. Entrepreneurial skills, such as the ability to identify opportunities, take calculated risks, and innovate, are key assets (Mayor et al., 2022[159]). For example, given increasing consumer attentiveness to agricultural production methods and changing preferences, farmers may need to identify and implement opportunities to respond to demands for more sustainable and ethically produced agricultural products.

100. Finally, given that regulations and policies can be increasingly complicated and common, understanding the regulatory landscape, including policies relating to digital agriculture, sustainability, and the bioeconomy, will be essential for future farmers to take advantage of the options provided by policies and regulations. A clear and stable regulatory environment will also be critical to attracting the required human capital and skills.

5. Conclusions and policy linkages

5.1. Improving knowledge of new entrants, digitalisation and the future profile of farmers is critical to shaping policies and food systems

101. Considering the triple challenge of food systems, this paper focused on understanding the characteristics of new entrants to farming, investigating the effect of

digitalisation on farmers' skills, labour, and wellbeing, and reviewing insights from foresight analysis on the profile of future farmers. The study used a broad definition of new entrants to account for their heterogeneity across countries.

102. Results from the analysis of the GEM dataset suggest that in most OECD countries new entrants tend to be younger than established agri-entrepreneurs, and have higher entrepreneurial skills, education levels, and technology adoption rates. These features indicate a greater dynamism that can lead to increased productivity and competitiveness and potentially higher innovation and adaptation. That said, established farmers also have strengths such as greater experience and social capital and, therefore, also play an essential role in agriculture. The sector is predominantly male-dominated, and new entrants have a slightly higher presence of men compared to established agri-entrepreneurs, which might indicate more difficulties for women in starting a new farm business.

103. New entrants face several obstacles as they consider entering the sector and try to settle as agricultural entrepreneurs, including capital constraints, limited access to land, low profitability, and regulatory complexities. At the same time, negative perceptions of farming persist and often deter new entrants. Building a positive image of farming, highlighting the potential for innovation, digitalisation and economic returns, can contribute to changing these perceptions.

104. Digital technologies affect the quantity and quality of agricultural labour, farmers' wellbeing, skills, and the sector's attractiveness for new entrants. More research needs to be undertaken to quantify the impacts of digital technologies on individuals' willingness to enter the agricultural sector, for example, if agriculture was much more automated and less physically demanding. But many studies show that digital technologies can reduce physical work, health risks and stress, leading to a better lifestyle and improving farmers' wellbeing.

105. New entrants with higher human capital appear to be disruptive agents triggering the adoption of digital technologies if barriers to technology adoption are tackled and the necessary skills and human capital are acquired. In the empirical analysis of digital agriculture adoption in the United States, education emerges as a main driver of technology adoption. However, education and training systems may not adequately cover the acquisition of skills necessary for agricultural digitalisation.

106. New entrants in agriculture also have the potential to be strategic and disruptive players in food systems. Foresight analyses suggest that future farmers will be heterogeneous, but specific skills are identified as necessary to respond to macro trends and expected challenges. Research efforts should be directed towards identifying the characteristics, skills, and knowledge that farmers will need to navigate the changing agricultural landscape in a more environmentally sustainable, digitalised, and inclusive future. Foresight analysis is a potentially valuable tool leveraging a comprehensive approach and a macro-level understanding, involving experts and stakeholders, in the search for local solutions.

107. Analysing the evolving characteristics of new entrants to agriculture, how they are impacted by digital technologies, and how new entrants respond to the needs of the farmer of the future is a first step towards better understanding their role. Investing in this analysis will inform policy makers in developing better measures to facilitate the digital and sustainability transformation of food systems and respond to their policy concerns.

5.2. Tailored structural policies are needed to respond to different concerns around new entrants and digital technologies

108. Attracting and supporting new entrants with new valuable skills into agriculture is a shared concern globally. Yet, the specific barriers faced by, and opportunities available to, new farmers can vary significantly based on geographical location, cultural norms, economic conditions, and policies that may affect the dynamics of the sector. The motivations for seeking new entrants and new skills might be formulated differently from country to country: from generational renewal (a concern among European countries) to reducing skill shortages and mismatches, increasing labour supply and improving farmers' livelihoods, promoting sustainable systems, or reducing the gender gap to create a more inclusive sector.

109. Similarly, adopting digital technologies in agriculture is recognised as a crucial opportunity for enhancing productivity and sustainability worldwide. Many digital technologies exist, but not all are necessarily adapted for all kinds of agriculture. Differences in adoption are large across countries and farmers. This raises concerns about the digital divide and inequalities, for instance, in countries such as Brazil and Colombia, which have high inequality of services in rural areas, but also for some EU countries where some low-population areas have limited internet connectivity, or for localities with marginalised groups.

110. While analysing the best policy responses to specific policy concerns was beyond the scope of this paper, the range of policy levers and their effectiveness deserves further analysis. Given the nature of entry and digital transformation, structural policies to strengthen skills and human capital, ensure access to digital infrastructure and services, and enhance agricultural knowledge and innovation systems will likely have the most lasting long-term impact.

111. Acknowledging the different motivations for seeking new entrants can help identify potential areas for action. No single policy is likely to be able to address all issues across different contexts, and tailored policies will be needed.

- *Facilitating new entrants into agriculture to make it more innovative and dynamic*

  New entrants into agriculture can be transformative agents, but they face barriers that affect the sector's capacity to adapt to new market conditions, societal demands, and skills needs. Initiatives to attract and support new entrants are crucial for enhancing the agricultural sector's productivity and sustainability, and they require the adoption of a comprehensive approach, including policies to improve access to finance, training and mentorship programmes, and to enhance infrastructure and digitalisation.

- *Attracting new entrants to boost environmental sustainability*

  New entrants with environmental awareness can improve environmental sustainability in agriculture by adopting better practices. Policies should seek to attract individuals who are willing to engage in sustainable farming through strategies and incentives such as: providing education and training programmes on sustainable farming practices; offering financial incentives and support schemes tailored to new entrants who adopt environmentally sustainable practices; strengthening technical support and extension services on sustainable farming techniques (e.g. training sessions, workshops, and mentoring programs conducted by experienced farmers or agricultural experts); creating market opportunities for sustainably produced agricultural products; fostering a sense of community between new entrants by connecting them with networks of existing sustainable farmers; and encouraging knowledge-sharing, collaboration, and collective action towards environmental goals.

- *Attracting young people to farming to help generational renewal*

In countries where the average age of farmers is increasing, the policy concern of facilitating new entrants is focused on the entrance of young farmers. In some countries, new entry happens almost only by the retirement of older farmers and the takeover of farms by new farmers. Policies could ensure a smooth transition of farmers into retirement and between retiring farmers and the next generation. Initiatives to attract and support young farmers may be crucial for generational renewal and the sustainability of the agricultural sector. Still, as outlined in this report, they need to consider the potential barriers created by existing agricultural policies.

- *Using digital technologies to improve the overall attractiveness of farming*

Improving labour conditions and farmers' wellbeing and reversing negative perceptions about farming can make the sector more attractive for new entrants, particularly young farmers. Digital technologies can reduce physical or menial work, providing opportunities for on-farm diversification and enhancing social connectivity among farmers to reduce perceived loneliness. Digital technologies can also contribute to shaping the career paths of younger farmers, including attracting youths into farming. Changing the perception of farming requires transformation and communication of farming as a dynamic job benefiting from new technologies and contributing to the sustainability of the planet.

- *Addressing challenges and risks to enable digital technology adoption*

Digital technologies are enablers that can enhance productivity, sustainability, and inclusiveness if challenges related to their use are assessed and successfully tackled. For instance, digital devices and data analysis allow farmers and policymakers to monitor performance and better understand the impact of their practices on the environment. They also enable the design of innovative result-based programmes for environmental sustainability. Policies should focus on addressing challenges associated with digital technology adoption, such as reducing upfront costs related to acquiring and implementing digital tools, fostering digital skills through training, addressing the ethical concerns associated with AI and robotics, achieving network coverage and adequate infrastructure in all regions, and ensuring data privacy and security to improve trust.

- *Avoiding new digital and other divides to improve inclusiveness*

The digital transition affects and is adopted asymmetrically by different sectors, regions, and farmers. The possible creation of new basic inequalities is a policy concern in many countries. Policies should analyse the risks of digital divides, address the challenges to digital adoption, mainly when they asymmetrically affect different farmers, and reduce inequalities in access to infrastructure. Policies could consider building a more inclusive environment, particularly for currently marginalised or disadvantaged groups (e.g. new immigrants, Indigenous peoples, women, and persons with disabilities), providing targeted and sufficient investments in life-long training, education, and skills development.

- *Reducing gaps in emerging skills and competencies to face future challenges*

As agriculture undergoes transformation driven by digitalisation, the need for human capital and entrepreneurial skills to adopt digital technologies and more sustainable practices will likely increase in farming and food systems. Governments seeking to ensure the necessary skills and competencies to manage modern agricultural operations effectively will need to analyse and monitor potential skill gaps in the sector and design ambitious skill strategies, including upskilling of advisory services. Investing in training, education, and knowledge-sharing platforms is essential to address emerging skill gaps and to ensure that farmers, especially new entrants, are prepared for the changing demands of the sector.

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Annex A. Econometric estimates

Table A.1. Econometric results: Probit and OLS estimation methods. Simple specifications with different types of fixed effects

Estimation method	Probit				OLS			
Specification	Simple							
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Years of farming experience	0.024***	0.022***	0.022***	0.025***	0.028***	0.026***	0.024***	0.025***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)
High school graduate	0.089***	0.072***	0.039*	0.043*	0.111***	0.098***	0.066***	0.066***
	(0.019)	(0.019)	(0.023)	(0.026)	(0.020)	(0.020)	(0.023)	(0.023)
Some years of college	0.179***	0.144***	0.119***	0.131***	0.212***	0.177***	0.148***	0.146***
	(0.019)	(0.020)	(0.023)	(0.026)	(0.021)	(0.021)	(0.023)	(0.023)
College graduate	0.195***	0.163***	0.131***	0.147***	0.233***	0.202***	0.159***	0.158***
	(0.019)	(0.020)	(0.023)	(0.026)	(0.021)	(0.021)	(0.024)	(0.024)
Age	-0.052***	-0.048***	-0.049***	-0.054***	-0.058***	-0.054***	-0.051***	-0.050***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Gender	0.042	0.045	0.042	0.053	0.048	0.054	0.055	0.053
	(0.036)	(0.035)	(0.039)	(0.043)	(0.035)	(0.034)	(0.036)	(0.036)
Farm revenues (GCFI)	0.073***	0.074***	0.077***	0.090***	0.041***	0.041***	0.038***	0.037***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)
Total off-farm income	-0.050*	-0.037	-0.032	-0.016	-0.041**	-0.030	-0.022	-0.014
	(0.030)	(0.028)	(0.042)	(0.049)	(0.019)	(0.019)	(0.027)	(0.027)
Off-farm work	0.054***	0.039***	0.033**	0.036**	0.048***	0.038***	0.025*	0.023
	(0.013)	(0.013)	(0.015)	(0.017)	(0.013)	(0.013)	(0.014)	(0.014)
Corn	0.675***	0.717***	0.792***	0.843***	0.480***	0.532***	0.511***	0.729***
	(0.066)	(0.066)	(0.084)	(0.240)	(0.031)	(0.033)	(0.037)	(0.139)
Cotton	0.552***	0.740***	0.862***	0.786***	0.456***	0.636***	0.588***	0.720***
	(0.046)	(0.050)	(0.075)	(0.156)	(0.029)	(0.033)	(0.039)	(0.224)
Oats	-0.296***	-0.215***	-0.212***	-0.079	-0.292***	-0.202***	-0.186***	-0.048
	(0.025)	(0.027)	(0.033)	(0.092)	(0.023)	(0.026)	(0.031)	(0.075)
Rice	-0.109***	0.058*	0.132***	0.187	-0.134***	0.023	0.076*	0.127
	(0.024)	(0.029)	(0.038)	(0.146)	(0.026)	(0.031)	(0.039)	(0.230)
Soybeans	0.662***	0.734***	0.839***	0.593**	0.493***	0.571***	0.549***	0.739***
	(0.035)	(0.037)	(0.050)	(0.239)	(0.021)	(0.025)	(0.029)	(0.122)
Winter wheat	0.148***	0.161***	0.154***	0.363**	0.181***	0.191***	0.159***	0.301
	(0.021)	(0.023)	(0.029)	(0.147)	(0.023)	(0.025)	(0.030)	(0.227)
Constant					0.403***	0.160**	0.372*	0.236
					(0.050)	(0.070)	(0.212)	(0.305)
Observations	10 376	10 376	8 741	7 760	10 376	10 376	10 376	10 376
Pseudo R-squared	0.244	0.281	0.355	0.310				
R-squared					0.265	0.302	0.458	0.478

Note: Model (1) includes year fixed effects. Model (2) includes year and state fixed effects. Model (3) includes year, state, and county fixed effects. Model (4) includes year, state, country, and state by year fixed effects. Probit results are the average marginal effects, computed using the delta method, whereas the OLS entries in the right side of the table are coefficient estimates. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Source: Estimation results using U.S. Department of Agriculture, National Agricultural Statistics Service and Economic Research Service, Agricultural Resource Management Survey (ARMS), years 2006-07, 2009-13, 2015-19, and 2021 (https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/).

Table A.2. Coefficient estimates from Probit estimation. Models with squared and interaction terms

Estimation method	Probit							
Specification	Squared variables				Squared variables and interacted variables			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Years of farming experience	0.111**	0.126**	0.108	0.130*	0.337***	0.338***	0.306***	0.325***
	(0.055)	(0.057)	(0.072)	(0.075)	(0.071)	(0.073)	(0.093)	(0.096)
Years of farming experience (Squared term)	-0.006	-0.008	-0.004	-0.007	-0.012	-0.014	-0.009	-0.011
	(0.009)	(0.009)	(0.011)	(0.012)	(0.009)	(0.009)	(0.011)	(0.012)
High school graduate	0.282***	0.237***	0.123	0.124	0.828***	0.781***	0.678***	0.713***
	(0.071)	(0.073)	(0.094)	(0.098)	(0.166)	(0.170)	(0.225)	(0.233)
Some years of college	0.580***	0.481***	0.432***	0.444***	1.329***	1.185***	1.120***	1.146***
	(0.072)	(0.075)	(0.097)	(0.101)	(0.168)	(0.174)	(0.229)	(0.238)
College graduate	0.630***	0.542***	0.477***	0.495***	1.349***	1.230***	1.145***	1.153***
	(0.073)	(0.076)	(0.099)	(0.103)	(0.169)	(0.175)	(0.230)	(0.239)
High school graduate * Years of farming					-0.164***	-0.161***	-0.158***	-0.166***
					(0.043)	(0.044)	(0.058)	(0.059)
Some years of college * Years of farming					-0.228***	-0.211***	-0.200***	-0.202***
					(0.045)	(0.046)	(0.060)	(0.061)
College graduate * Years of farming					-0.220***	-0.207***	-0.195***	-0.189***
					(0.046)	(0.047)	(0.061)	(0.062)
Age	-0.123	-0.161	-0.077	-0.102	-0.121	-0.159	-0.072	-0.097
	(0.110)	(0.113)	(0.141)	(0.148)	(0.111)	(0.113)	(0.142)	(0.148)
Age (squared term)	-0.004	-0.000	-0.010	-0.008	-0.004	-0.000	-0.011	-0.009
	(0.010)	(0.010)	(0.013)	(0.013)	(0.010)	(0.010)	(0.013)	(0.013)
Gender	0.120	0.141	0.132	0.157	0.117	0.139	0.131	0.156
	(0.121)	(0.124)	(0.157)	(0.161)	(0.121)	(0.124)	(0.157)	(0.161)
Farm revenues (GCFI)	0.325***	0.350***	0.412***	0.431***	0.324***	0.348***	0.410***	0.430***
	(0.016)	(0.017)	(0.022)	(0.024)	(0.016)	(0.017)	(0.022)	(0.024)
Farm revenues (GCFI) (squared term)	-0.007***	-0.008***	-0.009***	-0.009***	-0.007***	-0.008***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total off-farm income	0.028	0.110	0.156	0.216	0.039	0.119	0.165	0.223
	(0.152)	(0.157)	(0.212)	(0.219)	(0.152)	(0.157)	(0.212)	(0.219)
Total off-farm income (squared term)	-0.030	-0.039	-0.051*	-0.059*	-0.031	-0.040*	-0.053*	-0.060*
	(0.024)	(0.024)	(0.030)	(0.032)	(0.024)	(0.024)	(0.030)	(0.032)
Off-farm work	0.185***	0.138***	0.131**	0.131**	0.173***	0.127***	0.121**	0.121*
	(0.046)	(0.047)	(0.060)	(0.061)	(0.046)	(0.048)	(0.060)	(0.062)
Corn	2.261***	2.527***	3.154***	3.159***	2.263***	2.531***	3.154***	3.249***
	(0.227)	(0.241)	(0.347)	(0.914)	(0.227)	(0.241)	(0.346)	(0.920)
Cotton	1.837***	2.618***	3.437***	2.890***	1.847***	2.629***	3.451***	2.961***
	(0.160)	(0.185)	(0.305)	(0.580)	(0.160)	(0.185)	(0.306)	(0.584)
Oats	-0.980***	-0.747***	-0.826***	-0.295	-0.981***	-0.747***	-0.829***	-0.263
	(0.086)	(0.098)	(0.133)	(0.341)	(0.086)	(0.098)	(0.133)	(0.342)
Rice	-0.369***	0.230**	0.560***	0.697	-0.376***	0.225**	0.555***	0.737
	(0.080)	(0.105)	(0.153)	(0.543)	(0.080)	(0.105)	(0.153)	(0.545)
Soybeans	2.230***	2.613***	3.347***	2.211**	2.244***	2.628***	3.360***	2.311***
	(0.124)	(0.139)	(0.207)	(0.892)	(0.125)	(0.139)	(0.208)	(0.896)
Winter wheat	0.504***	0.570***	0.619***	1.354**	0.507***	0.570***	0.624***	1.397**
	(0.073)	(0.083)	(0.115)	(0.546)	(0.073)	(0.083)	(0.115)	(0.548)
Constant	-0.553*	-1.512***	0.130	-1.682	-1.210***	-2.146***	-0.574	-2.392**

Estimation method	Probit							
Specification	Squared variables				Squared variables and interacted variables			
	(0.290)	(0.366)	(0.953)	(1.059)	(0.322)	(0.394)	(0.985)	(1.083)
Observations	10 376	10 376	8 741	7 760	10 376	10 376	8 741	7 760
Pseudo R-squared	0.250	0.288	0.361	0.361	0.525	0.289	0.362	0.317

Note: Model (1) includes year fixed effects. Model (2) includes year and state fixed effects. Model (3) includes year, state, and county fixed effects. Model (4) includes year, state, country, and state by year fixed effects. All Probit results listed are coefficient estimates rather than average marginal effects. Standard errors in parentheses. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
Source: Estimation results using U.S. Department of Agriculture, National Agricultural Statistics Service and Economic Research Service, Agricultural Resource Management Survey (ARMS), years 2006-07, 2009-13, 2015-19, and 2021 (https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/).