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Characterising Farming Resilience Capacities: An Example of Crop Farms in the United Kingdom

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Improving the resilience of farmers against external shocks is a priority for policy makers. This paper measures the resilience of a sample of farmers in the United Kingdom to assess the impact of the 2011-12 drought on their productivity and income. The analysis allows for the distinction of four resilience capacities: to prepare; to absorb the immediate impact of the shock; to adapt farming practices to a new environment; and to transform the business model, and improve productivity and income in the longer term. Results show that a single farm rarely performs strongly across these four capacities, and that those farms that best absorb the impact of the drought, perform poorly in transforming their business after the shock. While size and diversification improve absorption and adaptation, innovation is a key driver of long-term resilience to keep the pace of productivity gains. In the past, policies on agricultural risk management focused on the absorption capacity of farms and on stabilising income. Forward-looking resilience policies today need to prioritise other capacities, in particular preparedness, adaptation and transformation.

Key words: Agricultural productivity, Drought, Risk management, Adaptation, Transformation

JEL codes: D24, O31, O33, Q12, Q18

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Key messages

- Policy makers seek to enhance the resilience of farmers. However, this requires considering the different dimensions of resilience. Policies focused on improving only one aspect of resilience – e.g. the immediate capacity to absorb a shock – may deny other important capacities that would allow farmers to be better prepared in the longer term.
- Farm level resilience can be measured by assessing the impact of a shock on productivity and income at different stages in the process to capture the following four resilience capacities:
    - the capacity to *prepare* to a particular shock
    - the capacity to *absorb* the immediate impact of the shock
    - the capacity to *adapt* the practices to the new environment after the shock
    - the capacity to *transform* the business model, become stronger and benefit from the new opportunities to improve productivity and income in the longer term
- An empirical investigation of UK crop farms after the droughts of 2011-12 shows that a single farm very rarely performs strongly across the four resilience capacities. Those farms that perform best in absorption perform poorly on transformation. This could be because a good absorption of the shock may limit incentives to do more, but also due to other policy or financial barriers to transformation. On the other hand, those farms with weak capacity to absorb impacts on income show stronger adaptation and transformation capacities.
- These empirical trade-offs have implications for farm managers and policy makers who may need to prioritise one or other targeted capacity. In the case of UK crop farms, being well prepared can in principle improve performance on all other resilience capacities, but in practice this requires careful balancing. There are practices and farm characteristics that contribute to each of these capacities. While size and diversification improve absorption and adaptation capacities, innovation is a key driver of resilience to keep the pace of productivity and enhance longer term transformation.
- Government payments, as a stable source of farm income, are found to have a positive effect on improving the capacity of UK farms to absorb the impacts of droughts on income. However, they do not contribute to the absorption of the impacts of shocks in terms of keeping the level of productivity, nor to enhance the longer-term adaptation and transformation of the affected farms. Government technical assistance is likely to have more positive impacts on resilience, particularly if targeted to resilience absorption, adaptation and transformation capacities, though this could not be measured in this case.
- Crop farms that are resilient across all three capacities in the United Kingdom share a few common characteristics. In particular, high resilient farms tend to have a relatively high share of net investment and a lower debt-equity ratio. Farms that are resilient with respect to a farm income shock have higher land and total assets to rely on. In contrast, farms resilient to productivity shocks have experienced technical changes.

Executive summary

Enhancing the resilience of farmers with respect to adverse events is a priority for policy makers. Agricultural risk management policies have traditionally focused on the absorption capacity of farms, and stabilising income in the aftermath of an adverse event. In contrast, resilience policies prioritise the preparedness of farmers, together with their capacity to adapt to the shock and to undertake transformation.

This paper develops a method to estimate the resilience performance of farms using farm level data. The framework of analysis takes into account the multifaceted nature of the concept of resilience distinguishing between four different resilience capacities: *ex ante* preparedness, and *ex post* absorption, adaptation and transformation. These capacities can be measured at farm level through the impact on, and dynamics of two reference variables: productivity and income. A sample of crop farms in the United Kingdom – England and Wales – is used to measure these capacities in the context of two adverse events: droughts and floods. The results discussed in this paper are specific to this case study; further work would be required to assess their applicability in other countries with other shocks.

Empirical results confirm that resilience is not a monolithic concept and estimates of different resilience capacities differ for the same farm. Farms in the sample are generally strong only on a few of the four capacities and most often farms that successfully absorb shocks are weak in adapting and transforming their activities to the new environment after the shock. The existence of these practical trade-offs implies that farm managers and policy makers need to prioritise to invest scarce resources in some or other capacities. For instance, prioritising the capacity to absorb income shocks may imply weaker adaptation and transformation of practices and business models. Furthermore, once the farm has absorbed the shock, there appears to be less incentive to transform. When using the term resilience, it would be more accurate and meaningful to specify which of the resilience capacities is being referred to.

Preparedness has the potential to enhance all other resilience capacities. A composite indicator of *ex ante* characteristics of the farms is proposed to measure their potential to be resilient *ex post*, after the adverse event. It includes increased diversification of activity and larger asset holdings. This preparedness indicator is found to be significantly positively correlated with the *ex post* income resilience absorption, adaptation and transformation performance of farms in the United Kingdom. However preparedness, as measured by this composite indicator, is found to be less associated with productivity resilience.

The yearly resilience preparedness index for UK crop farms significantly decreases in the last three decades driven by reductions in investment and in the equity/debt ratio. There is also evidence of ongoing divergence in preparedness levels of crop farms in the United Kingdom. This means that the difference between the most and the least resilience-prepared farms has grown in the last two decades.

Most of the farms in the sample are resilient with respect to only one of the *ex post* capacities. It is rare that the same farms are most resilient in all phases of absorption, adaptation, and transformation. The farms that are best performing in absorbing impacts on productivity, are badly performing in transformation, while the second worst performing quartile in absorption are the best performing in transformation. These results are consistent with the loss of incentives to transform after the shock if its impact was smoothed. The results on income dynamics show an even clearer distinction between the farms that perform well on absorption and those performing well in adaptation and transformation.

The drivers of different *ex post* resilience capacities are also different. For instance, it is found that farm size may contribute in different directions to absorption (positively) and transformation (negatively) aftershocks on productivity. Government payments to UK farms help to get through periods of income loss and are found to enhance the income absorption capacity of farms, but do not contribute to the adaptation and transformation required in the longer term. Some farm characteristics like productivity and innovation have positive effects in almost all resilience capacities, while age seems to have general negative impacts.

The profile of the most resilient crop farms in the United Kingdom, those few farms that are in the best performing groups of the four resilience capacities, is characterised by a high share of net investment and low debt equity ratios. In absolute terms, most income resilient farms have high land and total assets, but most productivity resilient farms have high values of technical change and net investment.

According to the results on the resilience of the UK crop farm sector, the most productive farms are more capable of absorbing negative impacts on income, while the least productive farms are quite weak in both adaptation and transformation capacities. For the aggregate crop sector, the preparedness capacity is declining over time, while the sector dynamics shows a strong transformative capacity to move less productive farms into more productive pathways after the drought.

While the proposed method herein offers a robust means to analyse resilience at farm level, it is more appropriate for some types of adverse events and data than for others. In particular, the method performs well for systemic events that evolve over time, such as droughts. For more localised and sudden events, such as floods, methodologies that use a control group are more appropriate. Understanding the performance of methodologies across different types of adverse events would require their application to more sectors or countries in order to compare resilience indicators beyond a single case. When data availability permits, analysing the response to repeated shocks would provide additional information on the robustness of the results.

The analytical framework and the empirical approach to measure preparedness, absorption, adaptation and transformation capacities at farm level are also relevant for the analysis of food system resilience. Further research would be needed to investigate if more complex systems show the same trade-offs between different resilience capacities.

1. Introduction

Policy makers are concerned about fostering greater resilience and enabling farmers to cope with more frequent and unpredictable adverse events (OECD, 2022[1]). Resilience at farm level is "the ability to prepare and plan for, absorb, recover from, and more successfully adapt and transform in response to adverse events" that significantly affect farming (OECD, 2020[2]). These adverse events include natural hazards that become more frequent with climate change, but also market disruptions and human-made disasters. Targeting policies to farm resilience objectives requires the capacity to measure the complex concept of resilience that has different characteristics or capacities. The purpose of this paper is to respond to this need by developing a methodology for measurement and applying it to farm level data from the United Kingdom.

A significant body of literature documents the increasing relevance of the concept "resilience" in agricultural policy making. The concept is multifaceted and is often applied at different sectors or to different levels or actors in a given sector (OECD, 2020[2]; OECD, 2020[2]). This report builds on previous work on agricultural risk management and resilience (OECD, 2020[2]) and develops a robust statistical method to measure the different resilience capacities at farm level. It is complementary to two other OECD reports that apply the same concept of resilience to two other policy relevant contexts: climate change adaptation policies and system-wide resilience in agro-food value chains.

Most of the academic literature is focused on the socio-ecological and climate change adaptation aspects of agricultural resilience, often using a descriptive approach. Quantitatively motivated management and economics based research attempts are rare (see, for example, Darnhofer (2014[3])). The quantitative characterisation of the different resilience capacities has been undertaken following an *ex ante* evaluation approach rather than measuring the performance of farms after experiencing an external shock (Slijper et al., 2021[4]). The work in this paper aims to close this knowledge gap by presenting a quantitative approach that measures the different capacities according to *ex post* data from farms covering a large time period before, during and after the occurrence of a systemic adverse event. Resilience capacities are then estimated based on *ex ante* characteristics (preparedness) and on the dynamic performance of the farms during the absorption, adaptation and transformation period.

Section 2 presents the framework to analyse these different resilience capacities using farm level data on response and performance after a systemic shock affecting many farms in one country or region. The framework is applied to crop farms in the United Kingdom – a sample of farms in England and Wales – for the drought 2011-12 with results discussed in Sections 3 to 8. The same approach is applied to floods with the same sample in a final section. The results are relevant for the United Kingdom, but the method aims to be a contribution to the resilience literature, framing and measuring the concept across countries. A series of country case studies covering other countries), as well as other agricultural types of production would help to investigate the robustness of the results.[1]

2. A framework to analyse resilience capacities using farm level data

The analysis in this paper provides empirical evidence for the performance of farms with respect to their different resilience capacities, and identifies characteristics of farms or farming sectors that are associated with higher levels of each resilience capacity. The applied measurement strategy uses micro data to measure how much capacity different farms have to be resilient to climate hazards, in particular, measuring four different resilience capacities: preparedness, absorption, adaptation and transformation. It then estimates the main characteristics that drive resilience across the four capacities among farms. The analysis is applied to a sample of UK crop farms using Farm Business Survey[2] data for the two examples of droughts and floods.

Farm and sectoral characteristics affect the dynamic adjustment of farms in response to significant shocks and their different resilience capacities. Outcomes and methods of previous work conducted in cooperation with the OECD Farm Level Analysis Network and the OECD Secretariat – the identification of different productivity drivers and the analysis of the dynamics of productivity performance (see (Sauer and Moreddu, 2020[5]; Sauer et al., 2021[6]; Antón and Sauer, 2021[7]) – are exploited to substantially enrich this work.

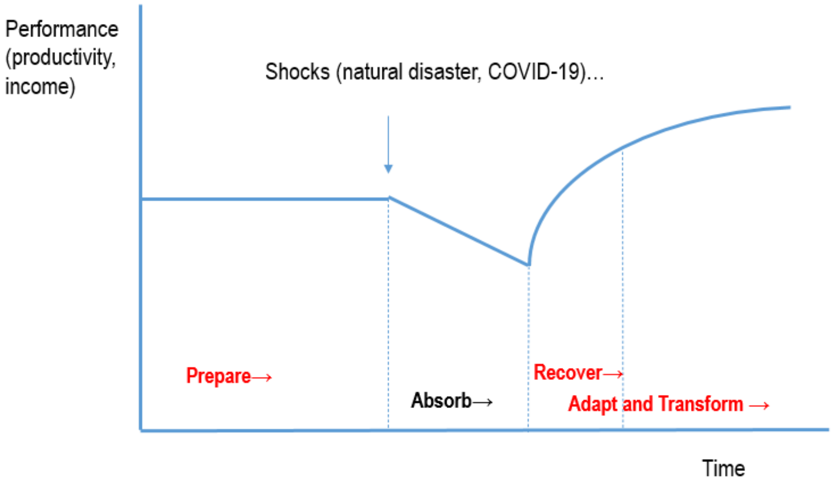
The main framework for analysis is based on the idea that resilience capacities are revealed in a dynamic manner when an external shock occurs. Statistical methods allow grouping the affected farms according to their performance over time in relation to two reference performance variables: productivity and income. This performance is measured in different periods of time in relation with the date of the external shock.

Preparedness takes place before the shock and can be measured with the *ex ante* strategies of the farm that could strengthen all or some of the *ex post* capacities. The resilience capacities will differ across farms and would be reflected in alternative shapes of the curve in Figure 2.1. Absorption is the capacity of coping with the immediate consequences of the adverse event and, therefore, contributes to ensure stability: some farms would be able to absorb better than others, smoothing the impacts and having smaller reductions (a smaller down spike) in the reference performance variable: productivity or income. After the shock, farms need to recover, which requires flexibility to adapt and transform: adapting the production processes to the new environment – including the changing risk profile due to climate change – in order to reach at least the level of performance prior to the shock; and transforming their activities to new business models that respond better to the evolving opportunities in the longer term, allowing enhanced income or productivity as compared with the period before the shock.

[1] The work within the Farm Level Analysis Network (FLAN) foresees potential analysis on: crop farms in Australia, rice farms in Korea, pig farms in Denmark, and dairy farms in Sweden and the Czech Republic.

[2] The Farm Business Survey (FBS) is the source of the FADN data in the United Kingdom.

Figure 2.1. Resilience capacities according to impact of shock on reference performance variable

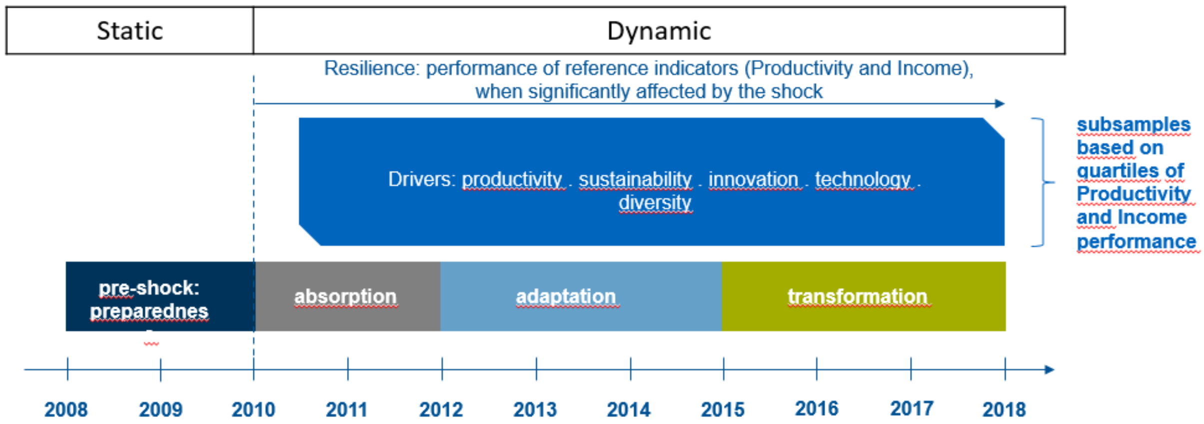


The various capacities characterising resilience at farm and sector level (i.e. preparedness, absorption, adaptation and transformation) are measured using various indicators and empirical methods that estimate relative performance of the reference variable compared to the period before the shock. Two potential sources of risk are considered with a particular emphasis on adverse events related to climatic hazards: drought and floods. The applied method is, however, intense in terms of data requirements. This is the case of the floods example.

A static analysis of *ex ante* factors that can potentially contribute to resilience is undertaken using the information on farms referring to the time before the shock (Figure 2.2). A dynamic analysis of the impact of the adverse event on productivity and income is then undertaken for the following periods of time or phases of adjustment after the shock. During the time of the shock, the capacity of absorption is measured by the degree to which the farm's income or productivity is relatively stable. In the years after the shock, the capacity to recover is measured in the medium run as adaptation capacity, and in the longer term as transformation capacity to create new opportunities for productivity or income growth.

Figure 2.2. Framework for analysing resilience capacities using FADN data

Example of drought in the United Kingdom (2010-12)



The following analytical steps are applied at farm level in two case studies (Figure 2.2):

1. *Static analysis at farm level*: *preparedness.* Preparedness capacity of resilience is measured *ex ante*, using proxies of variables that could contribute, ex post, to a more resilient dynamic adjustment such as diversification, assets, debt, investment or contracting. This method is similar to the static measurement of productivity and sustainability in previous work and uses indicators calculated under OECD Performance Project Phase I (Sauer and Moreddu, 2020[5]) and II (Sauer et al., 2021[6]). A preparedness resilience index is estimated at farm level based on various indicators and data-driven weights using statistical methodologies, including principal component analysis, limited-dependent panel regression techniques.

2. *Dynamic analysis at farm level: absorption, adaptation, and transformation*. Following the method in (Sauer et al., 2021[6]), resilience is estimated based on the dynamics of farm adjustment in terms of productivity and income performance after these shocks.

    a. *Quantifying the impact of a shock on income and productivity performance.* The change in each of these two reference variables are calculated for all farms in three different phases that are associated with different resilience capacities. Performance over time after the shock captures the extent to which the farms absorb the shock in the short term, but also adapts and transforms along the subsequent years in response to the new risk environment in which shocks may or may not occur[3]. The transformative aspect is better captured by productivity rather than income. In the case of the drought identified in the United Kingdom in 2011-12, these two years are considered as the absorption phase, while the subsequent three years 2013-15 are defined as the adaptation phase; the transformation phase corresponds to the rest of the available data in the sample that is 2016-18.[4] Farmers that are most and least resilient with respect to each of the three resilience capacities (absorption, adaptation, and transformation) are identified as the first and fourth quartiles in each of the two impact variables (productivity and sustainability) for the three *ex post* phases of absorption, adaptation, and transformation. The extent to which a high performer on one capacity is also performing well in another will be quantitatively analysed, showing potential synergies or trade-offs among absorption, adaptation, and transformation capacities.

    b. *Statistical identification of dynamic drivers for resilience capacities at farm level.* The main drivers for more successful shock absorption, adaptation, and transformation among farms are identified. This analysis provides insights on policies to promote the different characteristics of resilience. These results can be compared to the drivers found in the *ex ante* preparedness indicator. Potential trade-offs or synergies between different indices (as e.g. resilience capacities and sustainability) are explored by means of marginal effects analysis.

Whenever data is available, an additional analysis at sector level is conducted. In this case, the sector of crop farms in the United Kingdom is investigated.

3. *Measuring Sector level resilience* This will be done following two alternative methods:

    a. *Descriptive statistics of the three dynamic resilience capacities at sector level*. Using the descriptive information on the size of the farm classes that best perform on each of the three resilience capacities to describe or graph the resilience of the sector.

    b. *Analysis of how the productivity dynamics of the sector are affected by the shock*. Markov type transition matrices will be estimated for productivity dynamics (Sauer et al., 2021[6])

[3] Ideally, the analysis of adaptive and transformative capacities would also investigate the relative effects of repeated shocks of the same or different nature. However, this is not done in this study which focus on adaptation and transformation as capacities to perform better in the new environment after the shock than before. Analysis if repeated shocks could be part of future analysis, but it may be constraint by data availability.

[4] The length of the adaptation and transformation phases is constrained by data availability. The remaining six years available in the dataset after the absorption phase are divided between the medium term adaptation and long-term transformation phases. This is consistent with the analytical frame and with the requirements of the empirical investigation.

before and after the shock. These matrixes will be used to analyse and interpret how the productivity dynamics changes after the shock. The analysis focuses on the extent to which the shock has made the system of farms converge towards larger groups of most productive farms, or has accelerated this convergence.

Finally, the possibility of a composite indicator of the four resilience capacities is explored.

4. *Calculating composite indicators* following different methods. This includes graphical analysis and calculation of correlations between resilience capacities on preparedness, absorption, adaptation, and transformation; and calculating combined indicators for the sector.

The analytical framework outlined above is closely linked to the occurrence of the external shock with respect to time and location. The timing of the different resilience subphases (i.e. preparedness, absorption, adaption and transformation) is determined by the specific date and duration of the shock. While the occurrence of the shock defines the start of the absorption phase, the intensity (in terms of duration and regional spread) of the specific shock determines the length of the absorption phase and subsequently the start and length of the subsequent phases (i.e. adaptation and transformation). In the case of floods, the absorption phase can be safely assumed to be relatively short, from a few weeks to months, however, in the case of a series of droughts that endure over time, this phase can be assumed to significantly longer, from a few months to one or two years.

Methodological and data related considerations also matter to the appropriate application of the analytical framework. For autocorrelation of behavioural adaptation processes to be quantitatively analysed (as is the case for adaptation and transformation phases), at least two or three years of repeated panel observations would be needed for each farm in the sample. Furthermore, the sequence of data points (i.e. the length of the panel at hand) also determine the duration of resilience phases, as the last year of observations also represents the end of the transformation phase the researcher is able to consider. These constraints explain the choices made in relation to the duration of each phase in the example of droughts in the United Kingdom investigated in this paper (Figure 2.2).

The subsequent empirical analysis applies the analytical steps set out in the section to the case of a series of droughts in the United Kingdom (Sections 3 to 6). Section 7 focuses on explaining some of the non-significant statistical results found in the case of floods in the United Kingdom.

3. Static analysis of the resilience of UK crop farms: Preparedness

Preparedness means being ready for the adverse events (on any nature) that will happen in the future, so that when they happen, the farm is able to absorb and recover, adapting and transforming. In order to be prepared farmers can manage their activity or have invested in assets that make them well prepared. There are individual farm characteristics that may contribute to this resilience. They could also be combined in a composite indicator of resilience preparedness.

3.1. Analysis of *ex ante* resilience preparedness based on selected static farm characteristics

The measurement of *ex ante* preparedness is based on a selection of characteristics that contribute to enhance resilience preparedness. The indicators that reflect these characteristics need to be measurable across time and across farms. The selection of indicators is subject to adequate data availability and access. With respect to the investigation of these indicators over time a sufficiently long timeseries/(un)balanced panel is required. A representative list of ten possible indicators to analyse crop farms' preparedness is summarised in Table 3.1. The analysis covers the data availability for UK crop farms in the Farm Business Survey, that is, for the years 1995 to 2017. Each indicator reflects preparedness with respect to one or more targeted capacities. For instance, off-farm income sources indicate that the farm is better prepared to absorb the income shock of a dramatic fall in production by complementing farm with off-farm income. Unfortunately there are not enough off-farm income data in the UK panel to include this variable in the analysis.

Table 3.1. Selection of characteristics for a resilience preparedness indicator for UK crop farms

Indicator	Targeted Capacity/(ies)	Data
Diversification (on-farm crop-mix diversification, Herfindahl index)	Absorption	Farm accounts (Farm Business Survey, various years)
Off-farm income	Absorption	Farm accounts
Assets (productive assets)	Absorption	Farm accounts
Equity/debt ratio	Absorption	Farm accounts
Scale economies	Absorption / adaptation	OECD performance project phase I
Net investment	Absorption / transformation	farm accounts
Productivity level	Absorption / adaptation / transformation	OECD performance project phase I
Technical change	Adaptation / transformation	OECD performance project phase I
Performance switch	Adaptation / transformation	OECD performance project phase II
Contracts	Transformation	Farm accounts

Note: OECD Performance Projects Phase I and II resulted in two main publications, respectively (Sauer and Moreddu, 2020[5]; Sauer et al., 2021[6]).

Various statistical measures are applied for the distributional moments of these indicators as, for example, mean, minimum/maximum, and standard deviation, and use the boxplot technique to display for each indicator the median, 25th and 75th percentile and upper and lower adjacent value. Some examples of this graphical analysis based on the z-score transformed values are displayed to illustrate distribution of each indicator across farms and its evolution along time.[5] This method also allows to investigate the diversification performance of the three farm productivity classes (low, medium and high) that were identified in Sauer et al. (2021[6]).

Diversification

On-farm diversification may be due to different reasons, but it is a good way of preparing crop farms to absorb negative impacts of external shocks. We measure the agricultural output-based diversification of production (i.e. crop, livestock and other output) through the Herfindahl index by year for the sample of UK crop farms over the time period considered (1995-2017) using the boxplot technique. A closer to unity value for the diversification index translates into a lower level of diversification, hence, we observe an increase in farms' mean preparedness for absorption over time as the level of diversification on UK crop farms increases (by about 15%, i.e. decreasing index values). The variance in diversification per year over the time period considered decreases by about 50% implying a convergence in crop farms' preparedness for absorption capacity due to diversification.

Figure 3.1 shows the Herfindahl diversification index based on z-score transformed values as the relative deviation from the 1995-2017 period mean. The index has a decreasing trend along the sample period showing a general increase in diversification with a minimum in 1996 (z-score index value 0.61) and maximum in 2006 (index value of -0.92). The variance across farms also decreases over time with the highest in 2006 and the lowest in 2004.

[5] The inclusion of only a selected number of figures responds to the need to limit the length of this paper. Additional figures would be made available upon request.

Figure 3.1. UK crop farms - diversification of production: Z-scores (boxplots per year)

Based on Herfindahl index (low value means high diversification)

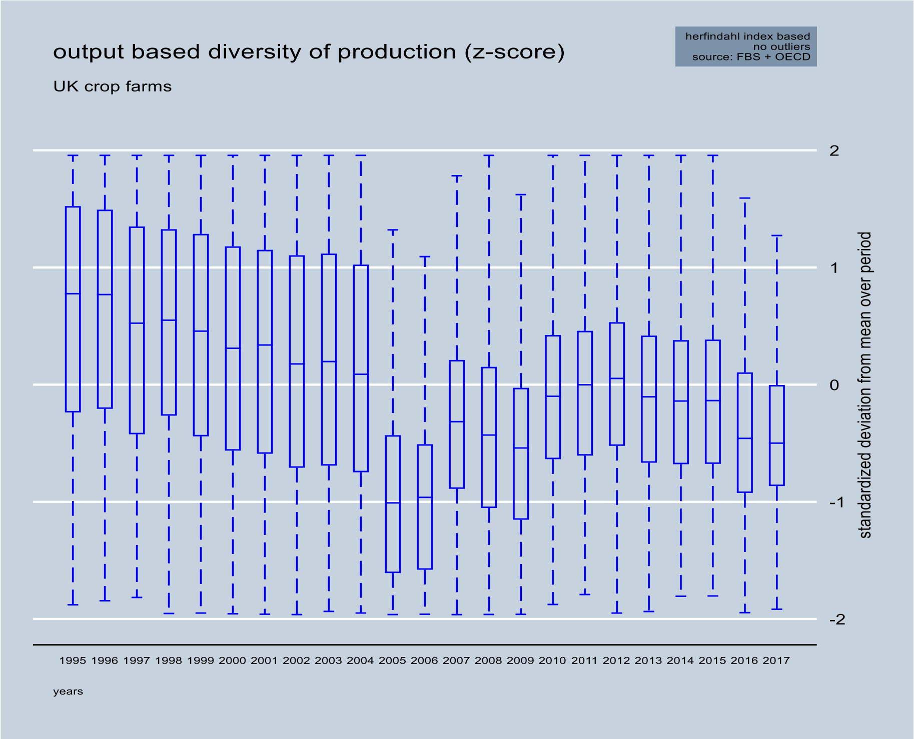
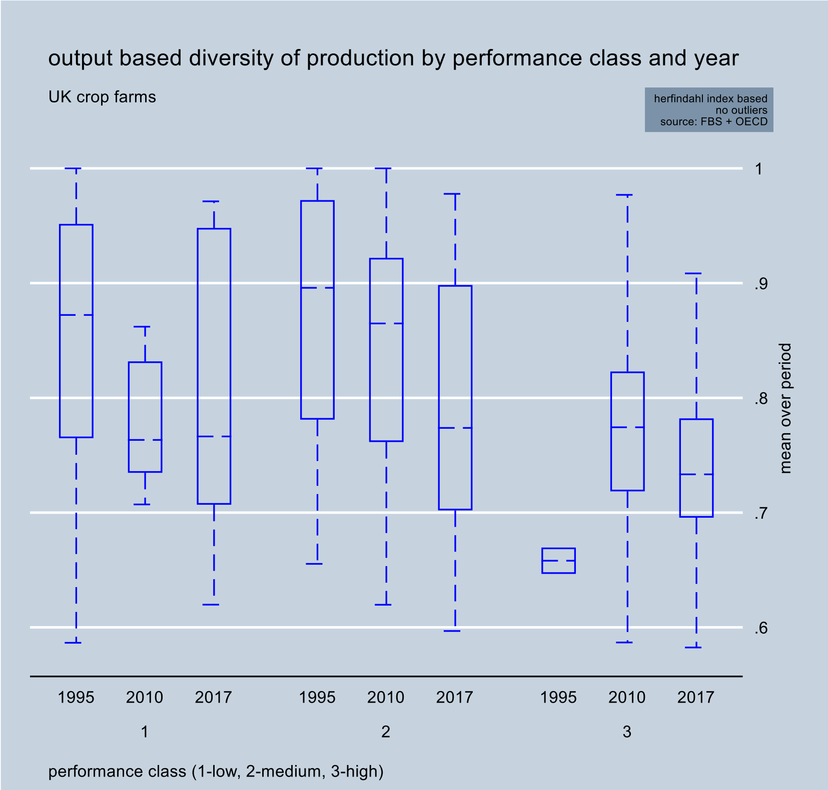


Figure 3.2 plots the distribution of the diversification index for the three productivity classes at three different years (i.e. beginning, mid and end of the time period considered). A decrease of the Herfindahl index is observed for crop farms in low and medium productivity classes 1 and 2, implying an increase in diversification over the full period; whereas a significant increase of the index for the highest productive class 3 over time implies lower diversification and resilience preparedness. The intra-class variance increased over time for all classes in the time period considered, particularly for the highest productive class 3.

However, the most productive farms in the sample (class 3) are still the most diversified at the end of the time period considered (i.e. 2017), whereas medium productive farms (class 2) have most significantly increased their diversity over the full time period considered.

Figure 3.2. UK crop farms – diversification of production by performance class (boxplots per year)

Based on Herfindahl index (low value means high diversification)



Assets

Total assets per hectare and year (i.e. productive assets) is another indicator for UK crop farms preparedness to absorb negative impacts of external shocks. We observe a significant increase in farms' mean absorption capacity due to productive assets over the time period considered (by about 210%). The variance in productive assets per ha over all farms per year also significantly increases over the time period considered (by about 850%) implying a divergence in crop farms' preparedness to absorb capacity associated to productive assets. Figure 3.3 shows the productive assets per hectare based on z-score transformed values as the relative deviation from the mean.

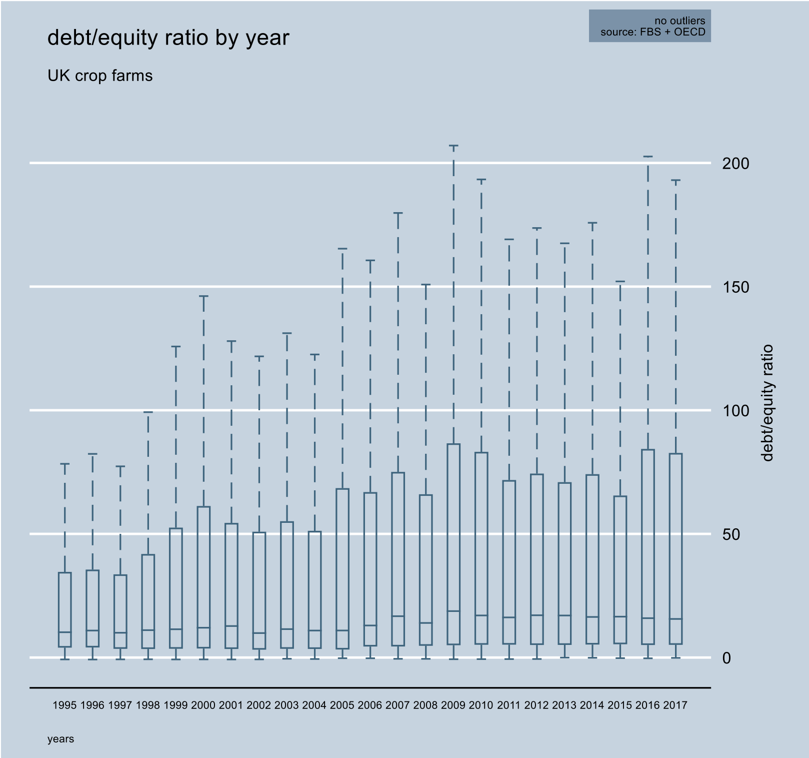
Figure 3.3. UK crop farms – productive assets per ha Z-score (boxplots per year)

The average amount of productive assets per hectare and year significantly vary between performance classes and over time. Medium productive class 2 has the highest level of assets in most years followed by most productive class 3, while the least productive farms in class 1 have the lowest level of assets per hectare. Medium performing crop farms in class 2 show the most significant increase in productive assets over the time period considered, however, also crop farms in other classes experience an increase in productive assets. Divergence across farms in each class has also increased over the period.

Equity/debt ratio

The equity to debt ratio is another major indicator for the crop farm's preparedness to absorb and therefore increase its resilience. For crop farms in the United Kingdom we observe a decrease in the average equity to debt ratio over the period investigated (an increase in the debt to equity) that makes, on average, farms slightly more vulnerable to shocks. More significantly, the variance around the mean ratio significantly increased over all farms indicating a divergence between a reduced number of farms highly indebted farms and the rest (Figure 3.4). Outlier values of high indebtedness occur particularly among most productive farms in class 3.

Figure 3.4. UK crop farms – debt to equity ratio (boxplots per year)

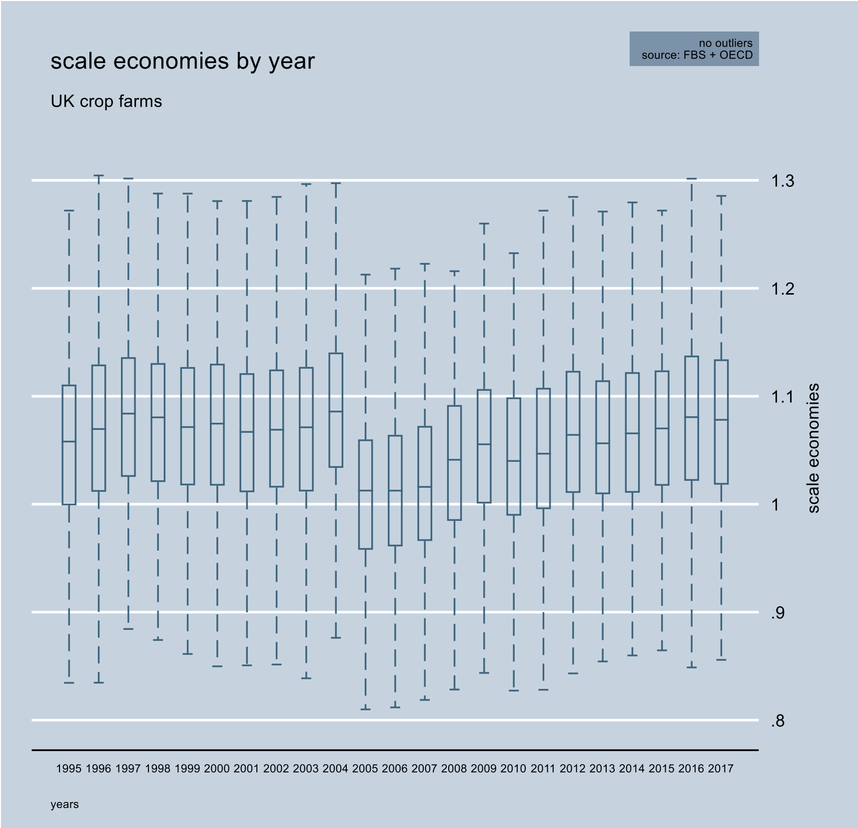


Scale economies

Economies of scale are a core economic performance measure with respect to the scale efficiency of a production unit's operations.[6] A crop farm that produces close to the optimum scale of its operations (i.e. around a scale elasticity of unity) can be regarded as scale efficient, one that produces far below or above this optimum scale can be regarded as scale inefficient. Hence, a crop farm that is more scale efficient can be considered to be better prepared to absorb and adapt. During the sample period the average scale efficiency decreased in 2005 and then increased again up to the end year 2017. The dispersion of farms around the mean has been rather low along the whole period. Differences across productivity classes are smaller than for other indicators.

[6] Economies of scale have been obtained based on the estimation of a (well-defined) second order production function (see OECD, 2020[4]).

Figure 3.5. UK crop farms – scale economies (boxplots per year)



Net investment

The share of net investment out of total investment per farm and year is a primary indicator for a crop farm's preparation to absorb external shocks and to transform to new activities or business models. A decrease is observed in the average crop farm's net investment over the period considered (by about 27%) and an increase in the variance between crop farms' absorption capacity levels over the period considered.

Productivity level

High productivity is an indicator of preparedness to absorb, adapt, and transform after a shock. For the sample of UK crop farms the productivity level increased over the period investigated (by about 6%). However, the variance of UK crop farms' productivity also increased over the period considered.

Technical change

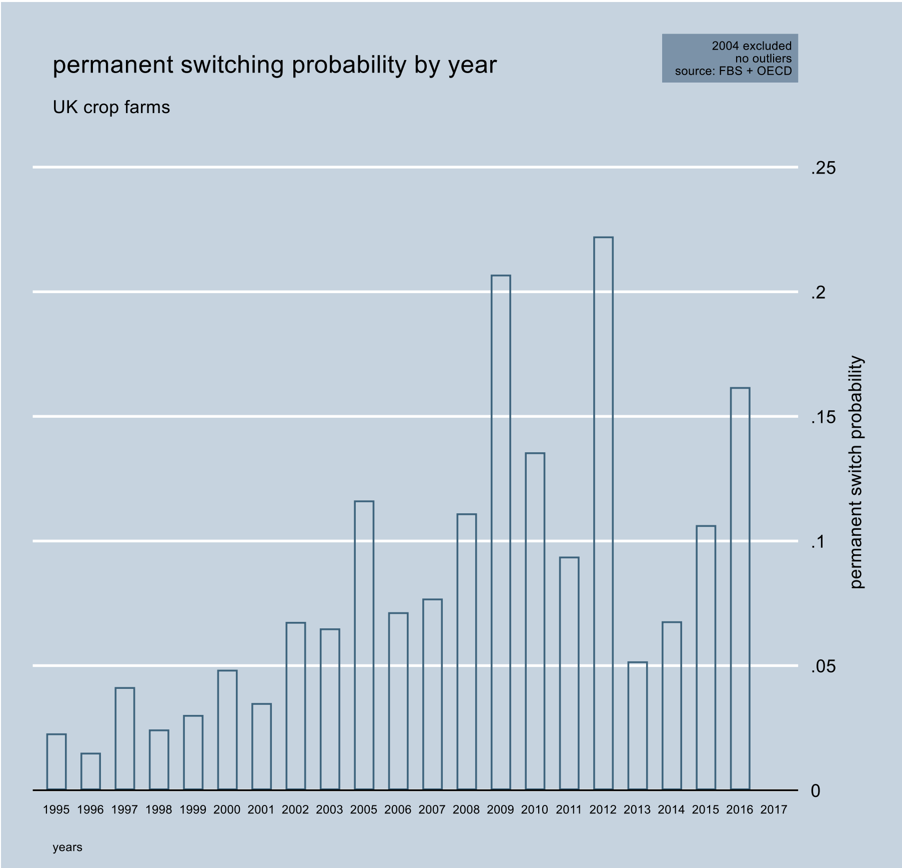
The technical change dynamics of the farm is an indicator of being prepared to adapt and transform whenever needed.[7] For the sample of UK crop farms the level of technical change considerably varied over the period investigated (from about -8% p.a. to about +4.2% p.a.). The most positive change rates are observed during the years 2003 to 2005 with a declining rate of technical change until the end of the period (of about -0.7% p.a. in 2017).

[7] Technical change rates (as the percentage productivity growth per year due to innovation) have been obtained based on the estimation of a (well-defined) second order production function (see Sauer and Moreddu (2020[5])

Performance class switch

Another resilience indicator in Table 3.1 is the estimated probability to switch to a higher performing (i.e. more productive) class. Figure 3.6 shows the average probability for permanently switching to a higher performing class per year over all farms and the total period considered. About 9% of all crop farms in the sample switched permanently to a more productive class per year with a significant increase in the switching probability over the total period considered (to about 16% in 2017). The variance around the average switching probability also significantly increased over the period considered. A similar switching probability is found for low and medium productive crop farms (classes 1 and 2) with a significant increase in the average probability for class 1 (from 2% to about 17% p.a.) and class 2 (from 2% to about 16% p.a.).

Figure 3.6.UK crop farms – probability for productive class switch upwards



Contracting

Contracts are an important means to prepare building up transformation capacity at crop farm level. The amount of contracting at crop farm level (here measured as all contracting related costs) increased over the time period considered by nearly 99% with an average contracting costs of GBP 107 per hectare and year in 2017. However, the variance around the mean contracting costs significantly increased over all crop farms during the time period considered, with an increase in dispersion and lack of convergence on this indicator. The positive as well as negative deviation from the standardised mean of contracting is the greatest for crop farms in the least productive class 1.

How has resilience preparedness of UK crop farms changed in the last two decades?

Table 3.2 summarises the findings on the extent to which resilience preparedness indicators have changed (improved + or deteriorated -) among UK crop farms in the last two decades, on average, for the most productive class 3 and of the trends in convergence or divergence of these indicators among farms. There is mixed evidence on the average crop farm's preparedness dynamics, there is more positive evidence for the preparedness of most productive crop farms, and there is finally clear evidence for an ongoing divergence in preparedness levels of crop farms in the United Kingdom. This means that the difference between the most and the least resilience-prepared farms seems to have grown in the last two decades. The only exception of converging levels across farms is the indicator on production diversification.

Table 3.2. UK crop farms – trends on preparedness indicators 1995-2017

Preparedness indicator (resilience capacity)	Average crop farm	Most productive crop farms	Differences between farms (C convergence / D divergence)
Diversification (absorption)	+	-	C
Productive assets (absorption)	+	+	D
Equity/debt ratio (absorption)	-	-	D
Scale economies (absorption and adaptation)	0	0	0
Net investment (absorption & transformation)	-	+	D
Productivity level (absorption, adaptation, and transformation)	+	-	D
Technical change (adaptation and transformation)	+	-	D
Switching probability (adaptation and transformation)	+	(n.e.)[1]	D
Contracting (transformation)	+	+	D

1. Non-estimated.

In terms of preparedness to absorb shocks, the average resilience preparedness of farms has increased in terms of diversification and assets but has decreased in terms of equity and net investment. For the most productive farms, net investment has also improved and contributed to resilience preparedness. The diversification indicator shows encouraging results in terms of both improved preparedness and convergence among farms towards higher levels of diversification. The gap between the most and the least resilience prepared farms has increased for other indicator such as assets equity and net investment.

In terms of preparedness to adapt and transform their practices and business model, the indicators that show an improvement on average farms are productivity, technical change, switching probability and contracting. However, in all the indicators related to preparedness for adaptation and transformation, there is increasing divergence between the most resilient and the least resilient farms. A key message for policy makers is that this increased divergence seems to reflect a structural adjustment in favour of a group of more resilient and most productive farms.

3.2. Composite resilience preparedness index based on *ex ante* static characteristics

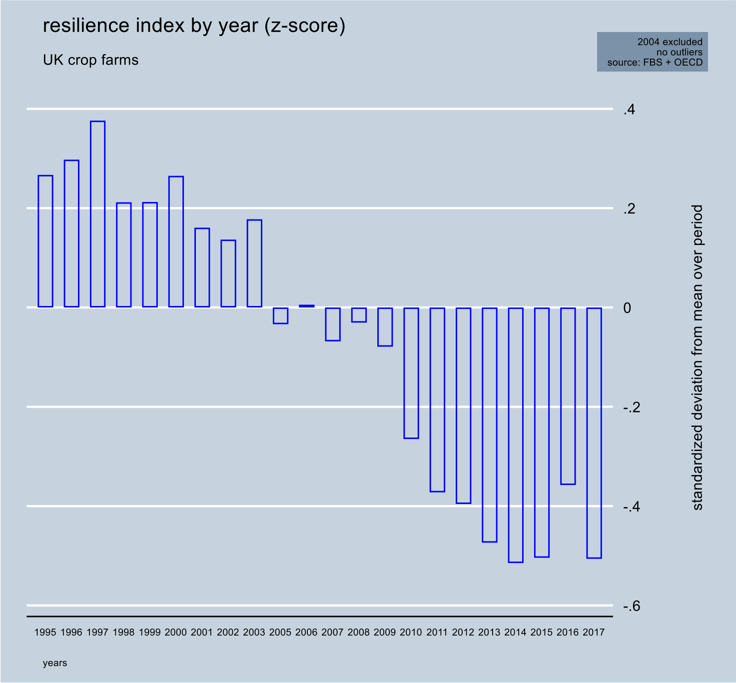
In a next step a composite resilience preparedness index at farm level is estimated based on the static resilience indicators. Data-driven weights using statistical analysis are applied (i.e. principal component analysis, limited-dependent panel regression techniques). Secondly, potential trade-offs or synergies between different previously estimated performance indices (e.g. between resilience and sustainability) are explored by means of marginal effects analysis.

Principal component analysis (PCA) is used to estimate a composite index for resilience preparedness capacity at individual crop farm level (Vidal, Ma and Sastry, 2016[8]). This method has been used to estimate various performance indices at farm level (Sauer and Moreddu, 2020[5])and has proved to generate significant and interpretable scores based on different components. For the resilience preparedness index the different static resilience indicators (in the z-score transformed form) at crop farm level are used that have been analysed in the previous sections: diversification (Herfindahl index), total productive assets per hectare, debt-to-equity ratio, scale economies, net investment share, permanent switching probability and contract costs per hectare. The indicators on off farm income, productivity and technical change have been excluded as not adding additional information or creating statistical bias according to the results of the PCA analysis or simply not sufficient data is available.[8]

The resilience indicator is a weighted combination of all variables whereas the weights are determined by the PCA method. This method is based on the identification of principal components which uses the eigenvalues of these components to maximise the total variance that can be explained by these components and consequently the produced indicator. The principal component with the largest eigenvalues (i.e. contribution to explaining variance) combine in particular net investment, diversity, total assets, and debt-to-equity ratio.

Figures 3.7 and 3.8 show the resilience average index scores by year and by productivity based performance class. As explained in Section 4, this indicator proves to be positively correlated with the *ex post* resilience performance of farms with respect to the reference variable income, but not so much with respect to productivity.

Figure 3.7. UK crop farms – resilience preparedness index by year



[8] The off-farm income data is insufficient to calculate indicators. Productivity is endogenous to switching probability, and technical change based on productivity change.

Figure 3.8. UK crop farms – resilience preparedness index by year and performance class

The yearly resilience preparedness index for UK crop farms significantly decreases over the full time period investigated (see Figure 3.7 that reports the positive/negative deviations from the mean resilience per year). Crop farms in 1997 show the highest positive deviation from the mean index score (mean = 0), whereas crop farms in 2014 show the highest negative deviation. The yearly resilience preparedness index score by performance class (Figure 3.8) decreases in its value during the time period considered for all performance classes (but to a differing extent). Several factors explain this trend. The indicator net investment (with the most significant contribution to the composite resilience index) decreases for the average crop farm in the sample during the period investigated. Furthermore, the equity/debt ratio decreases for the average and most productive farms over the time period considered. Finally, nearly all single preparedness indicators show a significant increase in their variance over the full sample, hence, the probability that extreme values decrease the resilience index value over time is also increasing.

Box 3.1. Multi-dimensional indices

Farms are production units, which differ along multiple characteristics: production structure, environmental impact and environmental sustainability, innovation behaviour, commercialisation focus, openness towards co-operation, input intensity and capital endowment, diversity of production, individual characteristics such as age or education, as well as locational conditions. Multi-dimensional indices combine different variables that measure underlying farm characteristics, selecting those variables that are relevant for the specific dimension of each index.

For subsequent analyses up to nine multi-dimensional indices are defined, subject to data availability, and estimated to identify and measure class membership per farm and year. Table 3.3 provides an overview of the choice of indices' components.

Table 3.3. Indices for farm classification

Indices Components	Index 1 Structure[1]	Index 2 Environmental sustainability	Index 3 Innovation-coop-comm[2]	Index 4 Technology-Intensity	Index 5 Diversity	Index 6 Individual-hum. cap.[3]	Index 7 Location	Index 8 Household	Index 9 Financial
Agricultural area	X								
Age of operator						X			
Agritourism income			X						
Altitude							X		
Biofuel income			X						
Capital per cow				X					
Capital per labour				X					
Chemicals use per ha		X							
Contract farming			X						
Education						X			
Environmental subsidies per ha		X							
Equity/Debt ratio									X
Experience						X			
Family labour share	X								
Female/Male labour share								X	
Forestry production					X				
Fuel per land		X							
Gender						X			
Herd size	X								
Herfindahl index[1]					X				
Household size								X	
Insurance expenditure			X						
Investment subsidies			X						
Labour per cow				X					
Labour input spouse								X	
Land irrigated share			X						
Land rented share			X						
Less-favoured-area							X		
Material per land				X					
Marital status						X			
Natura 2000							X		
Net investment ratio			X						
Nitrate derogation		X							
Number of holdings	X								
Off-farm income								X	
Organic production		X							
Ownership	X								
Part-time farming								X	
Production diversity					X				
Professional fees			X						
Profit monitoring programme			X						

Rural-Urban classification							X		
Soil classification							X		
Professional fees			X						
Stocking density		X							
Tillage area		X							
Total subsidies									X
Total assets									X
Water charges		X							

Notes: Final choice of indices' components depends on production type and data availability per country case.
1. The structure index includes variables of the physical size of farm operations (area, herd) and reliance on family labour.
2. Innovation-cooperation-commercialisation.
3. Individual and human capital. This index concerns the characteristics of the farm operators, such as age, education, experience and gender.
4. The Herfindahl Index measures the degree of specialisation based on the sum of squared output shares.
Source: Sauer et al. (2021[6]).

In a next step, the resilience preparedness index scores at farm level are regressed on the various performance indices estimated in (Sauer et al., 2021[6]) (Box 3.1). The aim is to identify potential trade-offs or synergies with other performance dimensions of crop farms in the United Kingdom. A fixed-effects panel regression technique is applied (Greene, 2018[9]) to estimate marginal effects between these different indices and performance measures (see Table 3.4 for results).

Table 3.4. UK crop farms – marginal effects on resilience preparedness based on fixed-effects panel regression

Covariate	Estimate (marginal effect, standard error)
Productivity (estimate)	0.1806*** [0.0291]
Technical change (estimate)	0.3489* [0.1869]
Index 1 - structure	-0.0957*** [0.0221]
Index 2 - environmental sustainability	0.0114 [0.0101]
Index 3 - innovation	0.0698*** [0.0083]
Index 4 - technology	0.0663*** [0.0125]
Index 5 - diversity	0.0999*** [0.0086]
Index 6 - individual	0.1083*** [0.0124]
Index 7 - location	-0.3647*** [0.0127]
Index 8 - household	-0.0329** [0.0095]
Index 9 - financial	-0.1307*** [0.0123]

Notes: Estimates based on Fixed-Effects Panel Regressions applied to full sample (n = 14196).
*significant at 10%, **significant at 5%, ***significant at 1%.

The marginal effects estimates in Table 3.43suggest that there are trade-offs between the composite resilience index and different performance indices Sauer and Moredeu (2020[5]), namely farm structure index 1 (measuring small scale family farming), financial index 9 (financial health), and location index 7 (favourable location). The results also suggest synergies between the resilience index and different performance indices and measures, namely economic performance (i.e. productivity and technical change), innovation index 3, technology intensity index 4, and diversity index 5. Furthermore, it can be concluded that there are significant synergies between resilience capacities and economic performance characteristics, diversity characteristics, technological characteristics, and innovation behaviour.

4. Dynamic analysis of resilience of UK farms after drought: Absorption, adaptation, and transformation

Resilience related capacities are built up and maintained to absorb and cushion the potentially disturbing effects by external shocks over time. A robust and state-of-the-art counterfactual approach – needed to derive meaningful estimates for such effects and related farm level adjustments – is missing in the literature. Nevertheless, depending on the target sources for risk (i.e. droughts, floods etc.) the empirical measurement approach might have to be adjusted if large area/whole countries are affected by the event.

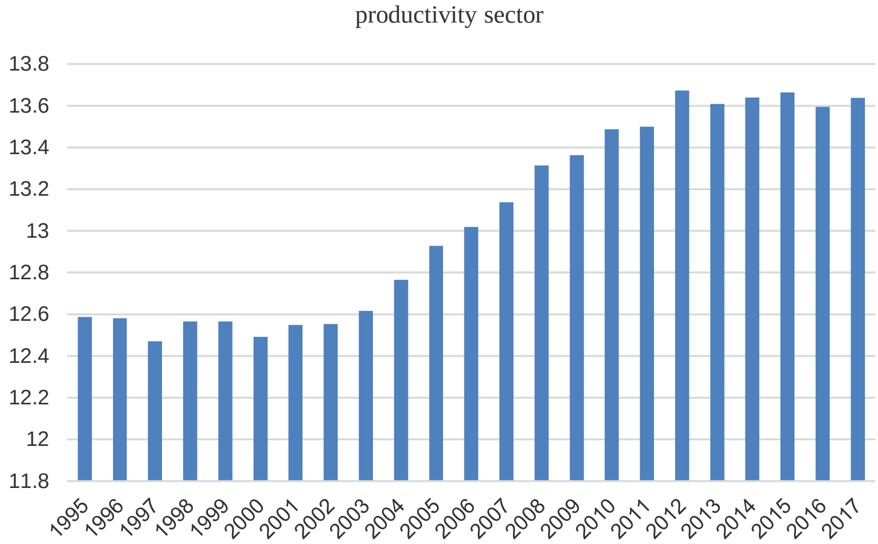
Hence, in the second stage of this comprehensive resilience analysis it is aimed to empirically investigate if and how crop farms in the United Kingdom have been affected by external shocks, e.g. extreme natural events (i.e. droughts) during the time period considered. The type of external shock (i.e. type and duration if adverse event, spatial and temporal effect of adverse event, etc.) determines the selection of method to be used. Hence, a fully fleshed counterfactual approach (i.e. building matched samples and subsequently applying a treatment analysis) is not always feasible and might have to be replaced by a “second-best” type of analysis. Consequently, to robustly analyse the impact of droughts on UK crop farms resilience capacities, a panel fixed effects estimation is used to statistically measure the effect of the adverse event on farms performance. For the latter two reference performance variables were selected, namely productivity and income at farm level per year (please see Annex B for further details).

The panel estimation results are reported and discussed in subsection 4.1 for various performance (i.e. productivity and income) quartiles. The estimation of drivers for resilience capacities are reported and discussed in subsection 4.2.

4.1. Quantifying the impact of a drought shock on income and productivity

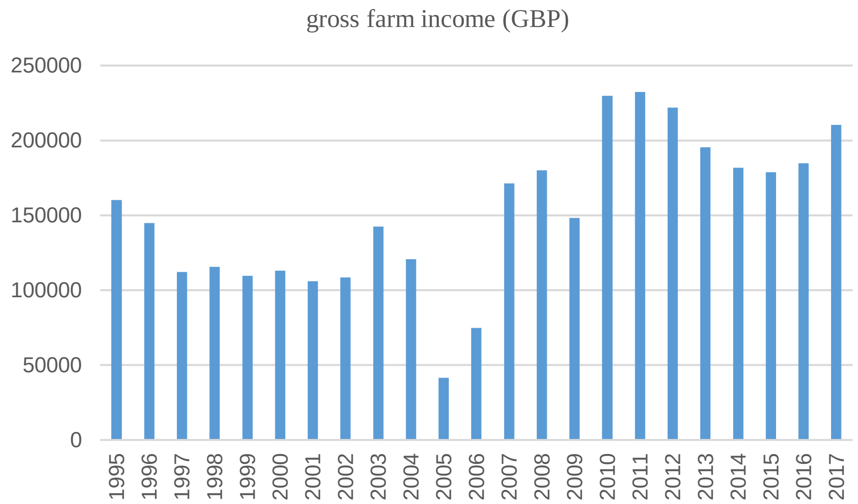
The sector-level development of two of the performance indicators used in the analyses, namely productivity and income, are depicted in Figures 4.1 and 4.2. Productivity growth (Figure 4.1) seems to stagnate in the second drought year 2011, which was characterised by an exceptionally dry spring that had adverse effects on agricultural production. In 2012, a sharp productivity increase can be observed. This increase might be linked to that year’s precipitation pattern, which saw normal rainfall after dry months from January to March, but also to farmers adapting to changing agronomic conditions. Income growth (Figure 4.2) seems to significantly decline in the years following the drought year 2011.

Figure 4.1. UK crop farms – aggregate productivity at sector-level



Note: productivity is the estimated log-value per year.

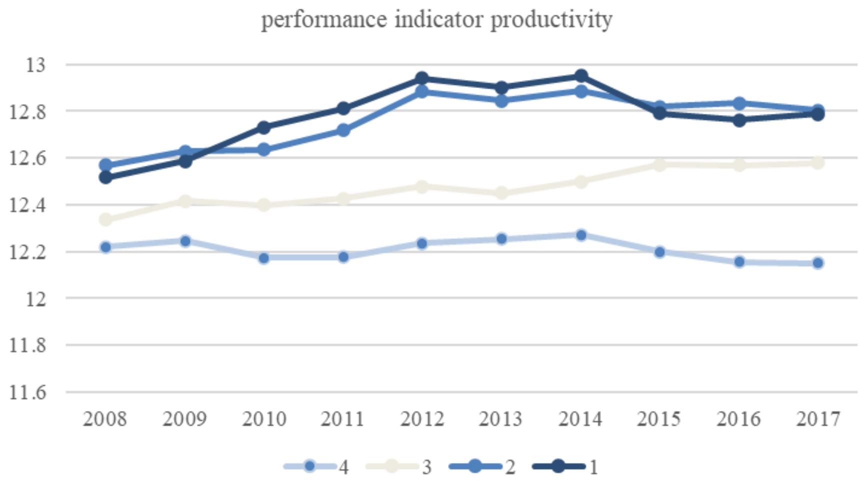
Figure 4.2. UK crop farms – aggregate income at sector-level



Notes: income is the observed value in GBP per year.

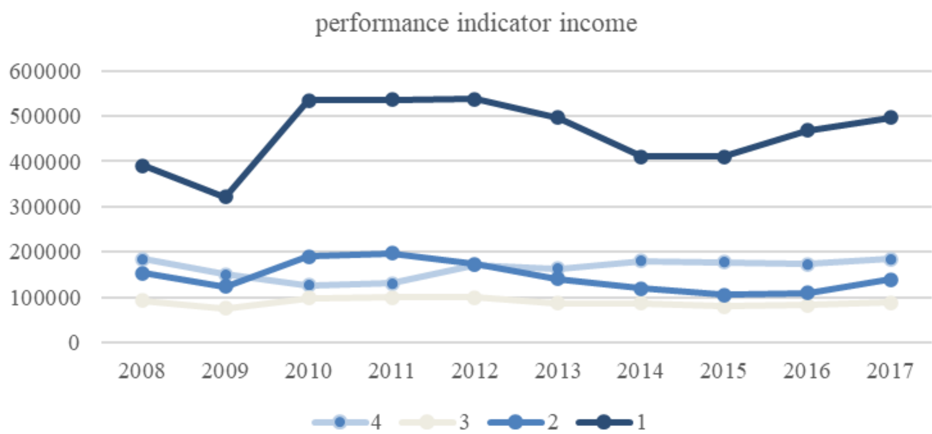
To obtain a more detailed insight in the development of productivity and income over the time period considered the distribution of farms' performances quartile by quartile was analysed. The UK droughts between 2010 and 2012 are events that have affected the whole geographical entity. Figures 4.3 and 4.4 below show the respective dynamics in farms' performances per quartile – a few years before the drought events (pre-shock phase 2008-09), during the absorption phase (i.e. impact of adverse event in 2010-12), and in the adaptation and transformation phases (defined as 2013-15 and 2016-17, respectively, see Figure 2.2). Quartile 1 denotes the best and quartile 4 the worst performers in each case whereas performance is defined as the change in productivity (or income) at farm level from the pre-shock phase to the absorption phase.

Figure 4.3. UK crop farms - aggregate productivity per quartile



Notes: productivity is the estimated log-value per year, 1-4 refer to the quartiles with 1 denoting the 25% best performing farms in the sample. Quartile definition is based on productivity change between pre-shock and absorption phase.

Figure 4.4. UK crop farms – aggregate income per quartile



Notes: income is the observed value in Euro per year, 1-4 refer to the quartiles with 1 denoting the 25% best performing farms in the sample. Quartile definition is based on productivity change between pre-shock and absorption phase.

Despite an apparent small aggregate impact of the drought on the performance reference variables, the development of the relative performance of crop farms in the United Kingdom significantly varies between performance quartiles with the below average performers are more significantly affected (i.e. quartiles 3 and 4). This suggests that the drought events might indeed have had a significant impact on the relative performance of many crop farms in the time period investigated. This is explored further statistically by estimating the productivity change and income change effect by these adverse events in 2010 to 2012 (structural change in these years) by also controlling for a host of other possible factors. Tables A.1 and A.2 in Annex A present the findings of the various fixed effects regressions for each performance quartile. It was found that the change in productivity and income has been significantly affected by the droughts for most of the crop farms. The worst and second worst performing farms (quartiles 3 and 4) have been negatively affected most dramatically. For the worst performers (quartile 4) a statistically significant effect for the decrease in the performance indicator productivity change is found.

Table 4.1 summarises the performance development for the two performance reference variables (productivity and income), and for all quartiles of UK crop farms in the sample by resilience capacity: pre-shock phase (2008, 2009), absorption phase (2010-2012), adaptation phase (2013-2015), and transformation phase (2016, 2017). The quartiles are defined by their performance during the absorption phase.

Table 4.1. UK crop farms – performance development by phase: Changes in productivity and income

Changes on productivity level by phases and quartiles (productivity index)				
	Best performers	Second best performers	Second worst performers	Worst performers
Pre-shock level	12.54	12.59	12.37	12.23
Absorption	0.23	0.09	0.03	-0.06
Adaptation	0.15	0.19	0.08	0.08
Transformation	-0.15	-0.05	0.06	-0.1
Changes on income level by phases and quartiles (monetary income)				
	Best performers	Second best performers	Second worst performers	Worst performers
Pre-shock level	356 677	134 931	76 894	162 670
Absorption	50%	39%	25%	-18%
Adaptation	-10%	-26%	-7%	21%
Transformation	-6%	-18%	-14%	3%

Notes: Quartile definition is based on productivity or income change between pre-shock and absorption phase. Changes shown in each phase are calculated with respect to the previous phase (i.e. absorption with respect to pre-shock, adaptation respect to absorption, and transformation respect to adaptation.

Overall, there is sufficient empirical evidence that the performance of crop farms in the United Kingdom has been significantly affected by the drought event in 2010 to 2012. This external shock impact has led to a negative development of productivity and income in the absorption period for the worst performing crop farms over these years, and on income of most quartiles in the adaptation and transformation periods. The first policy relevant question is then, how those farms dynamically absorbed, adapted, and transformed in the subsequent years after such an external shock impact.

Looking at productivity, the farms that are best performing in absorption are the worst performing in transformation. The second best performing in absorption are the best performing in adaptation and the best performing across the three phases. The second worst performing in absorption are the best performing in transformation. These results indicate some practical trade-offs between the different resilience capacities. It is rare that the same farms are most resilient in all phases of absorption, adaptation, and transformation.

The results on income show a very clear distinction between the farms that perform well on absorption and those performing well in adaptation and transformation. The best performing three quartiles in absorption are the same that perform worst perform in adaptation and transformation. The farms with weaker income absorption resilience are those that have stronger adaptation and transformation capacities.

Hence, a second high policy relevant issue is to investigate possible drivers for a positive probability of being among the best performing of those crop farms on absorption, adaptation and transformation of those crop farms. This will be investigated by empirically robust methods in the next two sections.

4.2. Drivers of absorption, adaptation, and transformation resilience: Productivity

This section looks at what drives the probability for a crop farm in the United Kingdom to be among the best performing farms in the respective resilience capacities associated with the different phases of dynamic adjustment, i.e. pre-shock, absorption, adaptation, and transformation phases. Estimates for each phase are made using a multinomial regression analysis defining as the reference outcome the probability of being a member of the best performing group or quartile.[9]

Table 4.2 summarises the findings over all analyses for the performance reference variable "productivity". It is found that the capacity to absorb an adverse shock as e.g. a drought (i.e. absorption phase) is positively correlated with innovation (index "innovation") and the technical change realised on the farm (indicator technical change) as well as the inputs capital (indicator depreciation per ha) and materials (indicator material costs per ha). A positive correlation is noted with the sustainability of production (index "sustainability") and the size of the farm (negative sign of the index "structure" of family-farm orientation), however, also a negative correlation with the amount of subsidies received (indicator subsidies per ha).

With respect to the resilience capacity to adapt after the experience of an adverse shock (i.e. adaptation phase) it is found that crop farms with a higher land endowment as well as labour and capital use are more likely to successfully adapt. A positive correlation is noted of the capacity to adapt with the efficiency of production management (indicator scale elasticity), the degree of innovation (index "innovation") and the level of technical change on the farm (indicator technical change).

Finally, with respect to the resilience capacity to transform after an adverse shock (i.e. transformation phase) the results suggest that crop farms with a higher use of contracts (indicator contract costs per ha) are more likely to successfully transform. Farms with a higher degree of innovation (index "innovation") are more likely to successfully transform to more resilient agricultural operations. However, the results also suggest that smaller crop farms with less land endowment and labour use might be more prone to a successful transformation.

Overall it can be concluded that crop farms' ability to successfully absorb, and adapt is highly correlated with their readiness to plan and implement innovation reflected in the positive signs of index "innovation" and indicator technical change in Table 4.2. Furthermore, efficient farm management is highly correlated with the farms ability to successfully adapt after an adverse event (indicator scale elasticity). Not surprisingly, the level of productivity and the index of innovation are the only drivers that contribute to improve all resilience capacities: preparedness, absorption, adaptation and transformation. On the other hand, age is a negative driver of all three productivity resilience capacities.

Finally and more surprisingly, whereas larger and less family-oriented crop farms seem more prepared to successfully absorb and adapt productivity, smaller farms seem more prepared to successfully transform to more resilient agricultural operations as they might be less specialised (index "structure" of family orientation, and land and labour indicators).

[9] Details on the estimate results and on the descriptive statistics can be obtained from the authors upon request.

Table 4.2. UK crop farms – drivers for resilience capacities: Productivity

Contribution of each driver to increase the probability of the farms in the worst (first sign in each cell) and second worst quartile (second sign in each cell) to get into the best performing (more resilient) quartiles

Driver	Absorption	Adaptation	Transformation
Land (number of hectares)	-+	**++**	**--**
Labour (annual full time equivalent)	**++**	**++**	**--**
Total output per ha (GBP)	--+	++	**--**
Depreciation per ha	**++**	**++**	-+
Costs for pesticides per ha	+-	**--**	++
Energy costs per ha	+-	**--**	**++**
Material costs per ha	**++**	++	-+
Contract costs per ha	--	--	**++**
Total assets per ha	--	--	--
Net investment (GBP)	**--**	**--**	--
Net investment share on total	+-	++	++
Environmental subsidies per ha	++	+-	+-
Subsidies per ha	**--**	++	-+
Hired-family labour ratio	**--**	--	-+
Age (years)	**--**	**--**	--
Debt-equity ratio	++	--	--
Scale elasticity (efficiency)	--	**++**	+-
Index “structure” (family orientation)	**--**	**+-**	**++**
Index “sustainability”	**++**	**--**	++
Index “innovation”	**++**	**++**	**++**
Index “technology”	**--**	**--**	+-
Index “diversity”	--	--	++
Index “individual”	+-	++	++
Index “location”	-+	--	+-
Index “household”	+-	**++**	+-
Index “financial”	++	+-	--
Index “resilience preparedness”	-+	+-	--
Productivity	**++**	**++**	**++**
Technical change	**++**	**++**	**--**

Notes: Quartile definition is based on productivity change between pre-shock and absorption, adaptation and transformation phases. Hence, potential endogeneity related to the inclusion of productivity levels as an explanatory variable is largely avoided as the dependent variable is based on productivity changes (measured as probability of quartile membership). Bold: statistically significant.

4.3. Drivers of absorption, adaptation, and transformation resilience: Income

Table 4.3 summarises the findings of all analyses for the second resilience performance variable: income. The capacity to absorb the adverse shock of the drought (absorption phase) is positively correlated with the size of the farm (index “structure” and indicator total output per ha), the labour, capital and materials input use (indicator labour, indicator depreciation per ha and indicator material costs per ha) as well as the realised technical change on the farm (indicator technical change). In addition, a higher share of net investment (indicator net investment share) but also subsidies (indicator subsidies per ha) seem positively correlated with the probability to successfully absorb the impact of an adverse event. A positive correlation is noted with the sustainability of production (index "sustainability").

With respect to the resilience capacity to adapt after the experience of an adverse shock (adaptation phase) crop farms with a higher output per ha and capital input per ha seem more successfully adapting the resilience of their agricultural operations (indicator total output per ha and indicator depreciation per ha). Furthermore, crop farms successful adaption is positively correlated with the efficiency of management (indicator scale elasticity), their financial resources (index "financial"), and finally also the degree of diversity of operations (index "diversity") and their level of pre-shock resilience preparedness (index "resilience").

Crop farms' capacity to successfully transform after an adverse event is positively correlated with the share of net investment (indicator net investment share) and level of productivity (indicator productivity) as well as the sustainability of operations (index "sustainability").

Income resilience ability to successfully absorb, adapt and transform is highly correlated with the size of their operations as measured by indicators on total output per ha, depreciation per ha and structure, and by the availability of financial resources (index "financial"). The efficiency of farm management (indicator scale elasticity) as well as the sustainability of operations (index "sustainability") contribute to a successful absorption, adaptation and transformation towards more resilient agricultural operations. Diversification is found to be good for absorption and adaptation, but not for transformation.

Government subsidies also have an impact on the probability of being among the most resilient farms. In particular, the amount of subsidies per hectare has a negative incidence on productivity absorption capacity (Table 4.2), but a positive impact on income absorption capacity (Table 4.3). These results mean that the subsidies help to smooth income but do not help to smooth productivity. Furthermore, the government subsidies do not seem to have a positive impact on longer term adaptation and transformation capacities.

The *ex ante* resilience preparedness index is a positive driver of the three income resilience capacities: absorption, adaptation, and transformation (Table 4.3). This is not the case for the productivity resilience capacities (Table 4.2). This means that the *ex ante* indicator designed in Section 3 is a good indicator of resilience preparedness with respect to the reference variable income, but not to reference variable productivity.

Finally the only single variable that has a positive impact on all resilience capacities for both productivity and income, is the productivity of the farm.

Table 4.3. UK crop farms – drivers for resilience capacities: Income

Contribution of each driver to increase the probability of the farms in the worst (first sign in each cell) and second worst quartile (second sign in each cell) to get into the best performing (more resilient) quartiles

Driver	Absorption	Adaptation	Transformation
Land (number of hectares)	++	--	--
Labour (annual full time equivalent)	++	--	--
Total output per ha (GBP)	++	++	++
Depreciation per ha	++	++	++
Costs for pesticides per ha	--	--	--
Energy costs per ha	--	--	++
Material costs per ha	++	-+	++
Contract costs per ha	--	--	--
Total assets per ha	--	--	--
Net investment (GBP)	--	--	--
Net investment share on total	++	--	++

Driver	Absorption	Adaptation	Transformation
Environmental subsidies per ha	**--**	++	--
Subsidies per ha	**++**	--	++
Hired-family labour ratio	-+	+-	++
Age (years)	++	--	--
Debt-equity ratio	--	--	**-+**
Scale elasticity (efficiency)	+-	**++**	++
Index "structure" (family orientation)	**--**	+-	--
Index "sustainability"	**++**	+-	**++**
Index "innovation"	**--**	-+	-+
Index "technology"	**--**	**--**	**--**
Index "diversity"	++	**++**	**--**
Index "individual"	-+	**--**	-+
Index "location"	++	**--**	+-
Index "household"	**++**	-+	--
Index "financial"	++	**++**	++
Index "resilience preparedness"	++	**++**	++
Productivity	**++**	**++**	**++**
Technical change	**++**	**--**	--

Notes: Quartile definition is based on productivity change between pre-shock and absorption, adaptation and transformation phases. Bold: statistically significant.

5. Measuring UK crop sector level resilience after drought

Two different methodologies are proposed to analyse sector resilience. The first is based on a descriptive statistical analysis of the distribution of the best and worst performing farms of the sector throughout the three phases of absorption, adaptation, and transformation. The second is based on the Markov chain analysis as was applied in Sauer et al. (2021[6]) with a focus on the transformation capacity of the sector after the shock.

5.1. Descriptive statistics of the three dynamic resilience capacities at sector level

This section provides a more detailed analysis of the distribution of the three dynamic resilience capacities at sector level. On the absence of information on other sectors to make comparisons, the statistical moments of the distribution of worst and best performers in the three phases is analysed. Using again the performance indicators productivity and income, the distribution of higher than average performers is formed (i.e. first and second best quartiles) and the distribution of lower than average performers (i.e. two worst quartiles). This is completed for each resilience capacity as measured in the respective phase: absorption, adaptation, and transformation whereas the quartiles' definition is based on the change in performance indicator from the pre-shock phase to the absorption, adaptation and transformation subphase, respectively. For each distribution in each phase the core distributional moments are described (i.e. mean, median, variance, skewness, and kurtosis) in Table 5.1.

The main indicator of more resilience for each phase would be the increase in the mean and median of both top performers together with a convergence in the mean and median between top and worst performers. Other indicators of resilience that could be developed based on higher moments of the distribution, in particular the variance, the skewedness and the kurtosis, are also discussed.

Table 5.1. UK crop farms - distributional moments of top and worst performers on productivity and income

	Pre-shock			
Performance reference variable	**Productivity**		**Income**	
Two top or worst quartiles	Top	Worst	Top	Worst
Median	12.83	11.78	179146.50	45914.50
Mean	13.03	11.69	280951.70	51280.49
Variance	0.434	0.219	9.40e+10	1.41e+09
Skewness	1.419	-1.181	2.934126	.6806103
Kurtosis	5.042	4.435	12.90728	3.480713
Observations	251	251	251	251
Resilience phase	**Absorption**			
Performance reference variable	Productivity		Income	
Two top or worst quartiles	Top	Worst	Top	Worst
Median	12.58	12.25	220696.00	70234.50
Mean	12.69	12.27	357935.60	110032.90
Variance	0.801	0.684	95798.627	62775.428
Skewness	0.654	0.481	2.970	5.077
Kurtosis	3.588	3.967	12.662	36.533
Observations	168	168	168	168
Resilience phase	**Adaptation**			
Performance reference variable	Productivity		Income	
Two top or worst quartiles	Top	Worst	Top	Worst
Median	12.73	12.23	178919.00	72873.00
Mean	12.93	12.30	366595.00	109611.40
Variance	0.794	0.626	159265.217	39427.374
Skewness	0.843	0.411	3.282	3.125
Kurtosis	3.680	3.917	15.381	17.758
Observations	135	136	135	136
Resilience phase	**Transformation**			
Performance reference variable	Productivity		Income	
Two top or worst quartiles	Top	Worst	Top	Worst
Median	12.83	12.182	143818.50	64243.00
Mean	13.02	12.23	266383.70	118958.10
Variance	0.818	0.610	107174.714	78414.218
Skewness	0.850	0.258	3.452	3.516
Kurtosis	4.082	3.199	15.017	16.904
Observations	106	107	106	107

The *mean productivity* of the top performing crop farms increased from the absorption phase to the adaptation phase by about 2% and then from the adaptation phase to the transformation phase by about 1%. The *median productivity* of the top performing crop farms increased by about 1.2% and then by about 0.8%, respectively (Table 5.1). Hence, crop farms in the higher than average part of the productivity distribution managed to increase their mean and median productivity in the overall time period after the impact of the drought event (2010 to 2012). Lower than average performing crop farms, on the other hand, mostly experienced a stagnating or slightly decreasing productivity performance during those years. In terms of sector productivity resilience across the three capacities two results are relevant: an increasing productivity across best and worst performers from the absorption to the adaptation and transformation phases; but an increasing divergence in productivity between the best and worst performing in the phases of absorption, adaptation, and transformation.

With respect to the top performers it is found that the *variance in productivity* slightly decreased from the absorption to the adaptation phase (by about 0.2%) and then increased again from the adaptation to the transformation phase (by about 3%). However, for the worst performers the variance in productivity significantly decreased. Hence, it can be concluded that predominantly the higher than average performing crop farms in the United Kingdom have increased the diversity of performance at sector level whereas the lower than average performing crop farms have decreased this diversity in the time period considered. Furthermore, the difference between the two distributions grows over time.

The *skewness* of the *productivity* distribution refers to the asymmetry in a distribution compared to the reference normal (bell shaped) distribution with a skew of zero. Negative skew refers to a longer or fatter tail on the left side of the distribution, while positive skew refers to a longer or fatter tail on the right and the sign. The kurtosis of the productivity distribution finally refers to the thickness of the tail of the distribution and therefore the probability of the occurrence of extreme values.

The skewness of the productivity distribution for top performing crop farms shows a low but positive value in all resilience subphases and increased by nearly 29% from the absorption to the adaptation phase. The kurtosis of the top performing farms' productivity distribution has also increased by 2.5% (absorption to adaptation phase) and nearly 11% (adaptation to transformation phase), respectively.

The skewness of the productivity distribution for the worst performing crop farms is also positive in all resilience subphases but decreased. It is, however, significantly lower than the corresponding measure for the best performing crop farms. Finally, the kurtosis of the worst performing farms' productivity distribution has decreased along the resilience subphases. The kurtosis is higher than the corresponding measure for the best performing farms during the absorption and adaptation phases but lower in the transformation phase. This implies a very light positively skewed productivity distribution for worst performing crop farms with high but decreasing chances of positive performance outliers.

The *mean income* of the top performing crop farms increased from the absorption phase to the adaptation phase by about 2.5% but then decreased from the adaptation phase to the transformation phase by about 27%. The mean income of the worst performing crop farms stagnated from the absorption phase to the adaptation phase and then increased from the adaptation phase to the transformation phase (Table 5.1). The *median income* of the top performing crop farms decreased by about 19% and then again by about 20%, respectively. The median income of the worst performing crop farms, however, slightly increased by about 0.4% and then also decreased by about 12%, respectively. For both performance groups of crop farms the median income decreased over the full time period investigated. In terms of the income resilience capacities of the sector, these results show some absorption resilience capacity of the best performing but no adaptation and transformation resilience of the worst performing.

With respect to the top performers the *variance in income* significantly increased from the absorption to the adaptation phase (by about 66%) and then decreased from the adaptation to the transformation phase (by about 23%). For the worst performers the variance in income first decreased from the absorption to the adaptation phase (by about 27%) and then significantly increased from the adaptation to the transformation phase (by nearly 100%).

The *skewness* of the *income* distribution for top performing crop farms shows a high positive value (i.e. extremely skewed) in all resilience subphases and it increased further by 10% from the absorption to the adaptation phase and by about 5% from the adaptation to the transformation phase. The *kurtosis* of the top performing farms' *income* distribution has been also highly positive in all subphases (i.e. excess kurtosis) and increased further by about 21% (absorption to adaptation phase) before it slightly decreased by about 4% (adaptation to transformation phase). This implies a highly positive skewed income distribution for top performing crop farms with high and increasing chances of positive performance outliers.

The *skewness* of the *income* distribution for the worst performing crop farms is also positive in all resilience subphases but decreased from the absorption to the adaptation phase and increased from the adaptation to the transformation phase, respectively. It is significantly higher than the corresponding measure for the best performing crop farms in the absorption phase but then shows about the same value for the subsequent phases. Finally, the *kurtosis* of the worst performing farms' *income* distribution has been highly positive but significantly decreased. This implies again a heavily positive skewed income distribution for worst performing crop farms with high but decreasing chances of positive performance outliers.

Table 5.2 finally summarises the dynamics of sector level resilience throughout the different subphases measured as relative changes from pre-shock to absorption, from absorption to adaptation, and from adaptation to transformation for both performance indicators productivity and income. We refer to the core distributional moments outlined before (i.e. mean, median, variance, skewness, and kurtosis) and measured for each phase (see Table 5.1). We consider how these moments have been developed through the specific phase for both top and worst performing crop farms whereas a positive sign implies to an increase in resilience and a negative sign refers to a decrease in resilience (see also note for Table 5.2).

The top performing crop farms in the United Kingdom increased their resilience mainly from the pre-shock to absorption phase (here especially for income). For those farms the difference between productivity mean and median decreased between the two phases as well as the skewness and kurtosis of the productivity distribution. With respect to the income distribution we find that income mean and median increased between the two phases (pre-shock to absorption), whereas the income variance and income kurtosis significantly decreased.

Worst performing crop farms in the United Kingdom, however, increased their resilience from pre-shock to absorption (for productivity) and more significantly from the absorption to the adaptation phase (for productivity and income). For worst performers resilience significantly increased between these two phases due to an increase in mean and median both for productivity and income. Furthermore, the difference between these two measures significantly reduced with respect to productivity whereas the variance in income reduced and finally the productivity kurtosis significantly lowered between the pre-shock and absorption phases.

Table 5.2. UK crop farms - evolution of sector level resilience

Performance indicator	Sector-level resilience			
Preshock to absorption phase	Productivity		Income	
	Top performers	Worst performers	Top performers	Worst performers
Mean & Median	- / -	+ / +	+ / +	+ / +
Difference Mean | Median	-	-	+	+
Variance	-	-	+	+
Skewness	-	+	+	+
Kurtosis	+	+	+	-
Absorption to adaptation phase	Productivity		Income	
	Top performers	Worst performers	Top performers	Worst performers
Mean & Median	+ / +	- / +	-/+	+/-
Difference Mean | Median	+	+	+	-
Variance	+	+	-	+
Skewness	+	-	+	-
Kurtosis	-	+	-	+
Adaptation to transformation phase	Productivity		Income	
	Top performers	Worst performers	Top performers	Worst performers
Mean & Median	+/+	-/-	-/-	-/+
Difference Mean | Median	+	+	+	-
Variance	-	+	+	-
Skewness	+	-	+	+
Kurtosis	-	+	+	+

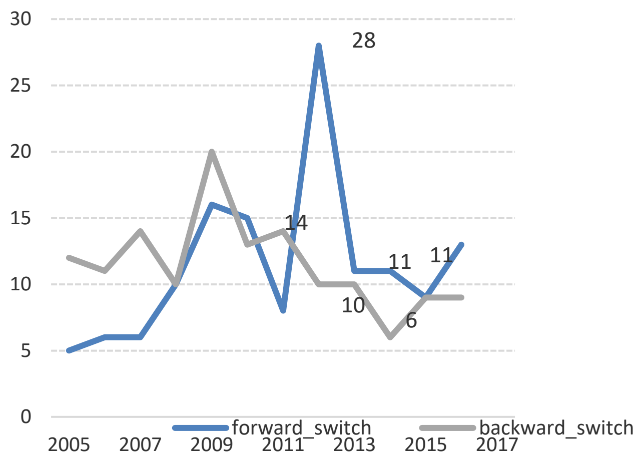
Note: Resilience performance (relative change from phase to phase) have to be interpreted as follows: "+" means resilience increase; "-" means resilience decrease. Higher mean/higher median: +/+; higher difference mean-median: +; lower variance: +; higher skewness: +; lower kurtosis: +.

5.2. Analysis of how the structural change (transformation) of the sector is affected by the shock (Markov)

Section 5.1 describes the performance of the sector in terms of the distribution of farms that are best and worst performing in absorbing, adapting and transforming. Part of the sector resilience is also the change that the shock may generate on the dynamics of productivity classes. After the drought, does the sector increase its capacity of structural transformation, improving the dynamics of farms that switch forward to more productive farm classes and reducing the backwards swifts to less productive classes? This will be an indicator of the transformation resilience capacity of the sector. Figure 5.1 seems to confirm a change of behaviour in the series of forward (moving to a higher productivity class) and backward (moving to a lower productivity class) movements after the drought. The drought was followed by a temporary fall in the forward switches in 2011, but an increase in 2012 while the backwards changes initiated a falling trend. In the period 2005-10 backward movements were more frequent than forward ones. But in the period 2012-17 the forward movements exceeded the backward switches.

Figure 5.1. Switching behaviour across productivity farm classes

Number of farms switching to higher or lower performing class per year



Source: Sauer et al. (2021[6]).

This change in dynamics is reflected in the Markov chain dynamics as analysed in Table 5.3 following the same methodology as in Sauer et al. (2021[6]).[10] The most productive class is the most numerous among UK crop farms with 92.5% of farms in 2005 and 87.2% in 2011. In the period prior to the drought, the crop sector in United Kingdom experienced a significant switch of farms from the most productive class that lost 4.6 percentage points in the share, in favour of the medium and least productive classes. On the contrary, in the period that follows the drought, the most productive farm class gained 3.8 percentage points that come from the medium productive class while the least productive class share hardly changes. The six years after the drought are enough to almost revert the deterioration of the productivity performance across UK crop farms that took place in the previous years since 2005.

[10] The analysis is based on the probability of farms changing productivity class from one year to next. For each period 2005-10 and 2011-17, a full 3X3 matrix of probabilities of changes from one of the three productivity classes to another is calculated. Then, this transition matrix is used to simulate the time productivity dynamics applying Markov chain analysis in each of the two period.

Table 5.3. UK crop farms: Observed and implied dynamics of class shares before and after the drought

Shares applying Markov Chain analysis

	Performance class 3 Most productive	Performance class 2 Medium productive	Performance class 1 Least productive
Before the drought: 2005-10			
Initial shares 2005	92.52%	6.96%	0.52%
Observed changes in shares during the period	-4.63%	3.51%	1.12%
Implied shares In t+3	90.15%	8.72%	1.13%
Implied shares In t+9 (convergence to steady state)	87.92%	10.44%	1.65%
After the drought: 2011-17			
Initial shares 2011	87.25%	11.75%	1.00%
Observed changes in shares during the period	3.82%	-3.98%	0.17%
Implied shares In t+3	89.34%	9.46%	1.20%
Implied shares In t+8 (convergence to steady state)	91.28%	7.46%	1.26%

Note: Markov chain analysis is applied to annual time series starting from the initial shares in each period and using as probability transition matrixes those calculated from farm data 2005-10 and 2011-17. Technically, the implied shares at convergence represents the eigenvector of the matrix corresponding to Eigen value equal to 1.

The probability transition matrixes are quite different in the two sub-periods. Meanwhile the Markov simulations in 2005-10 reflect the trend of the share of most productive farms to fall over time from 92.5% to 90.1% in three years and to 87.9% in nine years, after which the shares of different productivity classes would remain almost stable in a steady state. The Markov simulations of 2011-17 reflect the opposite trend of a reduction in the number of the least productive farms (classes 1 and 2): their share would decrease from 12.5% in 2011 to 10.7% in three years and 8.7% after the eight years that would be required to get almost stable class shares.

This analysis does not allow testing for a causal relationship between the drought that significantly touched UK crop farms in 2010-11 and the change in the productivity dynamics of the sector. Other factors, including policy changes in the application of the more decoupled payments under the CAP, may have also contributed to this change in productivity transformation dynamics. However, there is evidence that the sector showed a quite resilient long-term transformation capacity. Despite the short-term impact of drought on reducing farm productivity, the crop sector in the United Kingdom showed a significant improvement in the productivity of their farms, revealing an *ex post* capacity to transform the structure of the sector towards a more productive profile. This productivity transformative resilience is in line with the results in Section 5.1 for the best performing farms. Somehow, the time of the drought represents an important turning point to revert a negative trend on productivity classes and reveals a resilience transformation capacity of the sector.

6. Exploring composite indicators of all resilience capacities of UK crop farms

6.1. A combined resilience score for each farm and the sector

The construction of a combined index for the resilience capacities at farm and sector level for crop farming in the United Kingdom is explored in this section. This combined resilience index is based on four dimensions corresponding to the different resilience capacities: preparedness, absorption, adaptation, and transformation.

For the preparedness capacity at farm level the composite resilience preparedness indicator is used based on the various static indicators discussed in Section 3 (see in detail Section 3.2 and Figures 3.7 and 3.8). The distribution of this preparedness indicator was analysed, and each observation assigned to a quartile with quartile 1 as very low resilient to quartile 4 as highly resilient. For the remaining resilience capacities; absorption, adaptation and transformation, the distribution for the performance indicators was analysed again (productivity or income) and each observation assigned to a quartile with quartile 1 as very low resilient in the specific phase, to quartile 4 as highly resilient in the specific phase (see also Section 4.2).

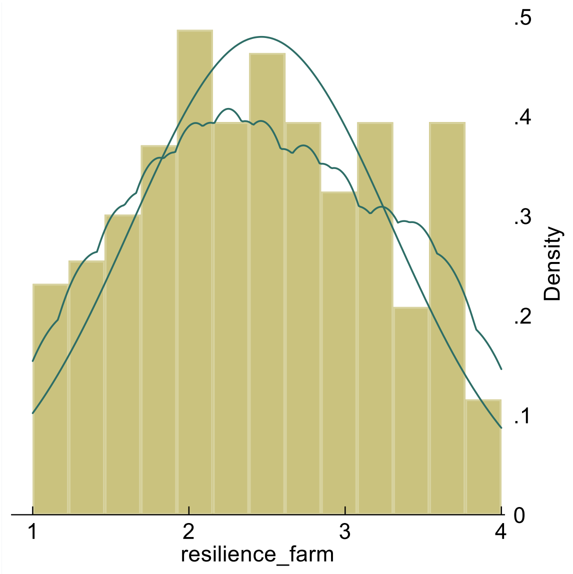
This allows one score for each farm (from 1 low resilient to 4 high resilient) for each of the four resilience capacities: preparedness, absorption, adaptation, and transformation. Combining these four indicators in one overall resilience index for each farm, using equal weights for each resilience capacity results in the combined resilience indices for the performance indicator productivity and income. The distribution of these indicators across the 336 farms in the sample is summarised in Table 6.1 and depicted in Figure 6.1.

Table 6.1. UK crop farms - combined resilience indices

	Sector-level resilience	
Performance indicator	Productivity	Income
Distributional measure		
Mean	2.4747	2.4639
Standard deviation	0.8254	0.8298
Minimum	1	1
Maximum	4	4

Both indices on productivity and resilience show very similar values regarding their mean and standard deviation. Figure 6.1 illustrates the distribution of the combined resilience index for the performance measure productivity throughout the various resilience phases (i.e. over the full time period investigated). this overall resilience indicator shows that the crop farming sector in the United Kingdom roughly follows a normal distribution with a slightly stronger right tail.

Figure 6.1. UK crop farms – distribution of combined resilience index (productivity)



Notes: Combined resilience index for performance indicator productivity based on four resilience capacities; 1 = least resilient, 4 = most resilient. The smooth line refers to a representative normal distribution, the jagged line refers to the estimated Kernel density.

For the moment, we cannot compare the aggregate number with other sectors or other countries, but we can already investigate the distribution of scores for different capacities across the farms in the sample. For instance, Figure 6.2 suggests that most of the farms are highly resilient only on 2 or maximum 3 of their capacities, while only a very small minority of 5 farms out of the 336 in the sample are highly resilient in the four capacities. This reveals that, in practice, there are trade-offs between the different resilience capacities. The correlation between the scores in the different capacities across the farms in the sample provides more insights on the nature of these trade-offs (Table 6.2). Correlations across capacities are higher for income than for productivity and the highest correlation occurs between the adaptation and transformation capacities.

Table 6.2. Correlation between the four resilience capacities

a) Income reference variable

	Preparedness	Absorption	Adaptation	Transformation
Preparedness	1.0000			
Absorption	0.8634	1.0000		
Adaptation	0.8654	0.8467	1.0000	
Transformation	0.8095	0.7984	0.9279	1.0000

b) Productivity reference variable

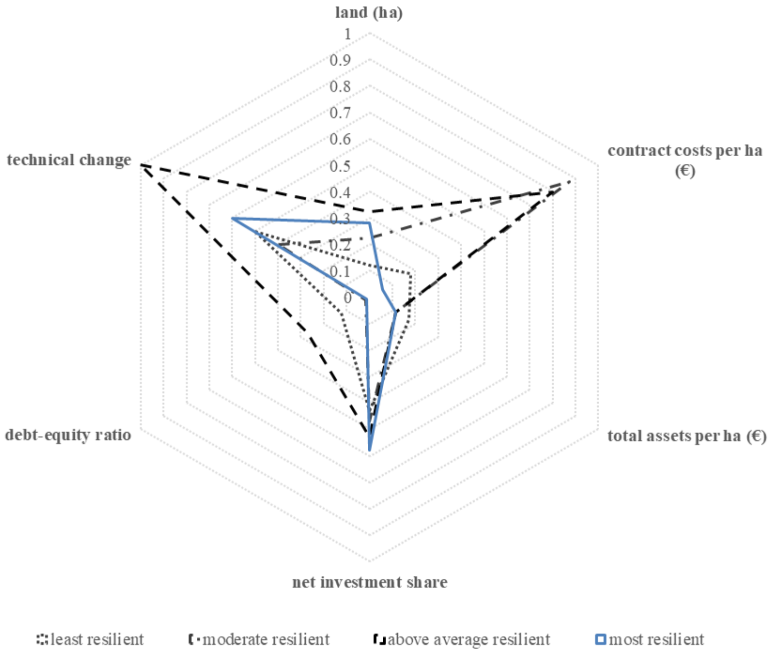
	Preparedness	Absorption	Adaptation	Transformation
Preparedness	1.0000			
Absorption	0.3263	1.0000		
Adaptation	0.4630	0.6242	1.0000	
Transformation	0.5417	0.5990	0.7318	1.0000

6.2. Brief analysis of farms' combined resilience performance

In this section, selected characteristics of sample farms showing a certain overall resilience performance (i.e. resilience index score) are analysed. Which characteristics are correlated with a high or low overall resilience level based on the value for the combined resilience index (Table 6.1 and Figure 6.1)? Tables A.3 and A.4 in Annex A summarise the means of selected characteristics and measures per overall resilience index score.

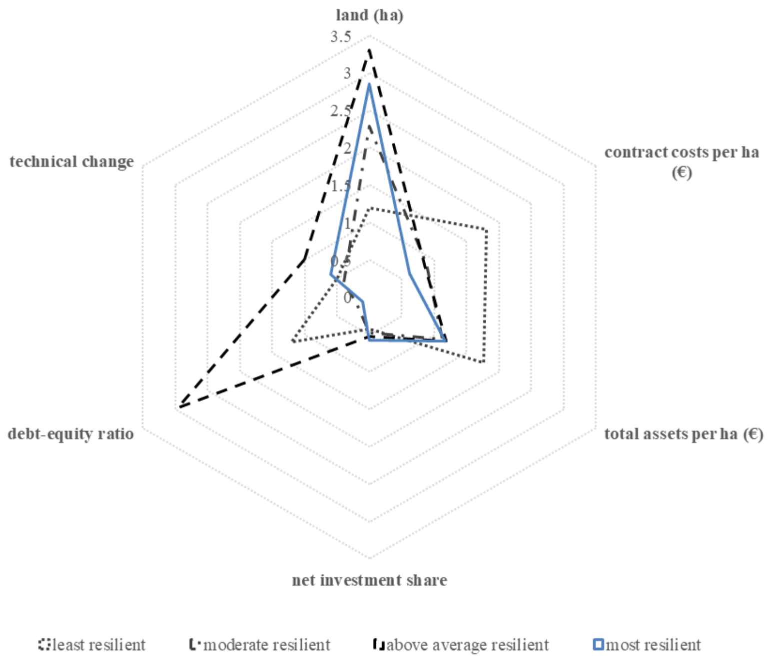
For this in-depth analysis the focus is on the following crop farm characteristics: land endowment, contract costs, total assets, net investment share, debt-equity ratio, and rate of technical change. Figures 6.2 and 6.3 illustrate the different characteristics per resilience index type (i.e. productivity or income based) and resilience index score (i.e. values of 1 'least resilient', 2 'moderate resilient', 3 'above average resilient', or 4 'most resilient').

Figure 6.2. UK crop farms – characteristics of resilient sample farms (productivity)



What is the profile of the most resilient crop farms in the United Kingdom, those that have a score of 4 and therefore are in the best performing quartile of the four resilience capacities? Their share of net investment is among the highest, but they have the lowest debt per equity. Most resilient crop farms in the United Kingdom show also a relatively high total land endowment as well as total assets per ha. The rate of technical change (i.e. change in annual productivity growth) is relatively high, however, the use of contracts is the lowest among their peers. In absolute terms, most income resilient farms have high land and total assets, but most productivity resilient farms have high values of technical change and net investment.

Figure 6.3. UK crop farms – characteristics of resilient sample farms (income)



What is the profile of the least resilient crop farms in the United Kingdom, those that have a score of 1 and therefore are in the worst performing quartile of the four resilience capacities? Least resilient crop farms in the United Kingdom show the lowest total land endowment of all crop farms and the lowest share of net investment for all crop farms. The debt to equity rate is relatively high whereas the rate of technical change (i.e. change in annual productivity growth) is of medium to low size. Those crop farms have the highest total assets per ha and finally show a medium to high use of contracts (depending on the performance indicator used).

7. Dynamic analysis of resilience of UK farms after floods

Beside the previously analysed drought events in the United Kingdom, similar methods have been used to empirically analyse the resilience impacts by floodings, focusing on UK regional flood events in the years 2007, 2009 and 2012 and measure their impact on farm and sector performance using resilience indicators as reported in the preceding section. The nature of an event like floods is more sudden and localised than droughts and requires an adapted statistical approach, by applying Propensity Score Matching (PSM) in combination with Difference-in-Difference (DID) techniques (see Annex B for further details). The estimation results are briefly reported and discussed for productivity and income performance indicators.

While crop farmers in the United Kingdom seem to change their production performance as a response to droughts (see in detail Section 4), the same cannot be observed after flood events in 2007, 2009 and 2012 in the United Kingdom. None of the PSM-DID models that were applied for the floodings in the years 2007, 2009 and 2012 showed significant differences in the performance indicators between affected and unaffected farms (apart from a changing equity/debt ratio for affected farms after the 2007 flood).

Several potential resilience reference variables have been investigated, including productivity and income. As all models estimated for the flood events in 2007, 2009 and 2012 show similar results, we only present the 2007 model results in more detail in Annex A (Tables A.5 and A.6). Table A.5 presents the estimates for the logit model on which the propensity score calculation and test results with regard to matching quality are based. Table A.7 in Annex A gives exemplary DID estimation results for the outcome variable ‘productivity’. The DID coefficient shows a negative sign, but is not statistically significant, indicating that flood affected and flood unaffected farms do not perform differently in terms of productivity growth.

Table 7.1 below summarises the PSM-DID estimation results for individual years and the pooled effect for all three flood events. Column E (impact) shows the direction of farm responses after a flood event and column S (significance) indicates whether the estimated effect was statistically significant. No impact on performance of crop farms is significant at a satisfactory statistical level with respect to major flood events in the United Kingdom during the period investigated. Therefore, no further statistical analysis of resilience seems reasonable for this event given the dataset at hand.

Table 7.1. UK crop farms – DID estimation results for various resilience indicators and flood events

Flood event	2007		2009		2012		Pooled	
Indicator	E	S	E	S	E	S	E	S
Productivity	-	n.s.	+	n.s.	+	n.s.	+	n.s.
Income	0	n.s.	+	n.s.	0	n.s.	0	n.s.
Technical Change	0	n.s.	0	n.s.	0	n.s.	0	n.s.
Scale Elasticity	-	n.s.	-	n.s.	0	n.s.	-	n.s.
Sustainability	0	n.s.	0	n.s.	+	n.s.	0	n.s.
Equity/Debt Ratio	+	**	0	n.s.	0	n.s.	0	n.s.
Assets	0	n.s.	0	n.s.	0	n.s.	0	n.s.
Technology	0	n.s.	0	n.s.	0	n.s.	0	n.s.
Diversity	0	n.s.	-	n.s.	+	n.s.	0	n.s.
Innovation	0	n.s.	0	n.s.	+	n.s.	0	n.s.

Note: E = sign of the estimated impact; S = significance; n.s = not significant

8. Concluding remarks and policy implications

Policy makers are increasingly embracing a broad resilience approach to risk management in a world of increasing uncertainty about external shocks linked to climate change and other forces (OECD, 2020[2]). Traditional risk management policies like insurance or countercyclical payments focused on the income absorption capacity of farms. These results suggest that a more holistic approach to enhance other capacities (such as *ex ante* preparedness and *ex post* adaptation and transformation) may be warranted. For that purpose, policies should prioritise knowledge and technical assistance to enhance the capacity of the farmer to plan and adjust beyond the absorption phase of the shock. Being able to measure these capacities is the first step to understanding that policies may enhance some resilience capacities at the expense of others, and incorporate this knowledge both in farming decision making and in policy design.

This paper develops a statistical method to estimate the resilience performance of farms using farm level data. Building on previous work the framework of analysis distinguishes between four different resilience capacities: preparedness, absorption, adaptation, and transformation. These capacities differ conceptually and each deserves a separate measurement in a dynamic context in which recovery takes place after the shock. The *ex post* dynamics of two refence variables is analysed: productivity and income. The methods are based on several statistical steps that can be applied with adapted statistical methods to different adverse events and to different farm level databases. A sample of crop farms in the United Kingdom is used to measure these capacities in the context of droughts. The results and conclusions in this paper are specific to this case study. More generalisable results and policy implications would require the application of this method to other countries and sectors.

The first step is based on *static analysis of preparedness*. This is an *ex ante* estimation based on variables that can be presumed to indicate better preparedness for any potential adverse event that may come. This includes many variables such as the diversification of economic activities, the capitalisation of the farm and other structural and behavioural variables. The estimated preparedness index is applicable as an ex *ante* measurement before any event – such as drought or flood – takes place.

The yearly resilience preparedness index for UK crop farms significantly decreases in the last three decades driven by reductions in investment and in the equity/debt ratio. This preparedness indicator is positively correlated with the *ex post* resilience performance of farms with respect to the reference variable income, but less the case with respect to productivity.

There is also evidence for an ongoing divergence in preparedness levels of crop farms in the United Kingdom. This means that the difference between the most and the least resilience-prepared farms seems to have grown in the last two decades. Increased diversification of activity and larger asset holdings have helped UK farms to be better prepared for shocks. The observed decreases in equity holdings and net investments negatively affect average resilience preparedness. Diversification is the indicator that shows more encouraging results in terms of both improved preparedness and convergence among farms towards higher levels of diversification. In terms of preparedness to adapt and transform their practices and business model, the only indicators that show an improvement on average farms are switching probability and contracting. However in all the indicators related to preparedness for adaptation and transformation, there is increasing divergence between the most resilient and the least resilient farms.

In order to undertake a *dynamic analysis* of the *ex post* resilience performance of farms, a second step is required to identify the existence and to estimate the size of the shock. Using external sources the existence of an adverse events (drought or floods) is identified before estimating its impact on the reference variable of performance. Two reference variables are considered in this paper: productivity and income. Given the different natures of drought and flood events, two different statistical methods are applied to estimate the existence of significant impacts on farm performance after the 2010-12 drought and the 2007, 2009 and 2012 floods in the United Kingdom. Statistically significant impacts are found for droughts but not for floods, which is consistent with other OECD work (OECD, 2016[10]). Therefore the dynamic analysis of resilience is focused on droughts only.

Among the farms in this sample, it is rare that the same farms are most resilient in all phases of absorption, adaptation, and transformation. The productivity dynamics results indicate some practical trade-offs between these different capacities. The farms that are best performing in absorption are badly performing in transformation, while the second worst performing in absorption are the best performing in transformation. The results on income dynamics show an even clearer distinction between the farms that perform well on absorption and those performing well in adaptation and transformation. The best performing three quartiles in absorption are the same that performed worst in adaptation and transformation, while farms with weak income absorption have stronger adaptation and transformation capacities.

To complete this dynamic analysis, *the main drivers of the different resilience capacities* are statistically estimated for both productivity and income impacts. Among the UK crop farms. the overall ability to keep *productivity* resilience by successfully absorb and adapt is highly correlated with farms' readiness to plan and implement innovation and efficient management. The level of productivity and the index of innovation are the only drivers that contribute to improve all resilience capacities: preparedness, absorption, adaptation, and transformation. On the other hand, age is a negative driver of all three productivity resilience capacities. Larger crop farms seem more able to successfully absorb and adapt productivity, but smaller family farms seem more prepared to successfully transform to more resilient agricultural operations.

Resilience ability to successfully absorb, adapt and transform aftershocks impacting on *income* is highly correlated with the size of their operations and the availability of financial resources. Both scale efficiency and sustainability contribute to a successful absorption, adaptation, and transformation. Diversification is found to be good for income absorption and adaptation, but not for transformation.

Age is generally found a negative driver of the three resilience capacities with respect to both productivity and income impacts. Government subsidies available to UK farmers also have an impact on the probability of being among the most resilient farms. In particular, the amount of subsidies per hectare has a negative incidence on productivity absorption capacity, but a positive impact on income absorption capacity. This means that the subsidies, as stable sources of revenue, help to smooth income but do not help to smooth productivity. Furthermore, the government subsidies do not seem to have any positive impact on longer term adaptation and transformation capacities. The only single variable that has a positive impact on all resilience capacities for both productivity and income, is the productivity of the farm. This high correlation between productivity and resilience is an important finding when analysing potential trade-off between policy objectives.

The third step consists of exploring possible *aggregate crop sector resilience* indicators, first through the analysis of the distribution of productivity and income performance across farms. There is an increase in productivity across best and worst performers from the absorption to the adaptation and transformation phases; but an increasing divergence in productivity between the best and worst performing. There is strong income absorption capacity of the best performing farms but no adaptation and transformation resilience of the worst performing. This divergence contributes to lower overall resilience of the sector in the adaptation and transformation phases compared to the absorption phase.

An additional method to analyse aggregate sector performance is through the dynamics among productivity performance classes along the phases of absorption, adaptation and transformation. The dynamics among productivity classes of UK crop farm sector experiences a significant change after the period of drought 2010-12, even if no causal relationship can be stablished. According to the Markov chains analysis, the declining trend in the share of most productive farms since 2005 was reverted after 2011. Despite the short-term impact of drought on reducing farm productivity, the crop sector in the United Kingdom showed a significant improvement in the productivity of their farms, revealing an *ex post* capacity to transform the structure of the sector towards a more productive profile.

The final fourth step focuses on exploring possible *composite indicators of the four resilience capacities* at farm level. Based on quartiles, scores for each of the resilience capacity are calculated for each farm. This allows to calculate a resilience score encompassing *ex ante* preparedness and the three *ex post* capacities of each farm. Using this information for an aggregate composite indicator for the crop sector is not particularly useful without a benchmark. This would require calculating the same composite indicator for other sectors or other countries to be able to compare and could be a useful next step of this work.

However, the analysis of composite scores across crop farms in the United Kingdom already provides useful insights. Most of the farms are highly resilient only on two or maximum three of their capacities and very rarely to all. This means that, in practice, there are trade-offs between the different resilience capacities amongst UK crop farms.

The profile of the most resilient crop farms in the United Kingdom, those few farms that are in the best performing quartile of the four resilience capacities, is characterised by a high share of net investment and low debt equity ratios. In absolute terms, the structural characteristic of most resilient crop farms differs for the reference variable income or productivity: most income resilient farms have high land and total assets, but most productivity resilient farms have high values of technical change and net investment.

This work provides a *robust method* to analyse the resilience of farming activities using farm level data, and quantifying four different capacities associated to resilience: *ex ante* preparedness, and *ex post* absorption, adaptation and transformation. The method is based on the dynamic analysis of farm productivity and income, and is applied to a sample of UK crop farms with respect to two different shocks: droughts and floods. The significance of the results depends on the specificities of the shock and the quality and quantity of the data available. This has proved to be a potential limitation of the method that provides reasonable results for droughts, but non-significant results for floods. Applying the same methodology to different samples of farms with different characteristics and in different countries will allow to better benchmark resilience capacities at farm and sector level.

A major implication of this analysis in the sample of UK farms is that resilience is not a monolithic concept and that distinguishing between different resilience capacities makes sense because most often farms that have a strong capacity of absorb shocks, are weaker in adapting and transforming. Furthermore, once the farm has absorbed the shock, there may be less incentive to transform. There are practical trade-offs that are relevant for farm managers decisions and for policy makers' strategies. When seeking the enhancement of farm resilience, both farmers and policy makers would gain if they referred to one or other of the resilience capacities and are able to measure them empirically.

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Annex A. Detailed statistical results

Table A A.1. UK crop farms – fixed effects regression productivity changes in 2010-12, estimates by quartile

Productivity	Top performers	2nd Best performers	2nd Worst performers	Worst performers
Covariate	Estimate (std error)	Estimate (std error)	Estimate (std error)	Estimate (std error)
Drought event	0.006** (0.003)	-0.002 (0.002)	-7.44e-04 (0.003)	-0.005** (0.002)
Age farmer	3.34 e-04* (1.75e-04)	-2.83e05 (1.56e-04)	1.97* (1.13e-04)	2.07e-05 (1.74e-04)
Gender farmer	0.002 (0.004)	0.011*** (0.004)	-0.015*** (0.004)	-1.07e-04 (0.005)
Subsidies per ha	2.31e-05 (1.81e-04)	1.27e-04*** (2.19e-05)	-2.59* (1.41e-04)	2.12e-04 (2.18e-04)
Env subsidies per ha	9.90e-06 (1.79e-04)	-9.08e-05*** (2.86e-05)	3.04e-04** (1.43e-04)	-2.36 (2.19e-04)
Total output per ha	-1.54e-06 (2.29e-06)	2.18e-06 (1.84e-06)	-5.62e-07 (4.17e-07)	1.06e-05*** (2.21e-06)
Assets per ha	3.57e-07 (4.47e-07)	-7.70e-07** (3.72e-07)	-0.002 (0.002)	-3.34e-06*** (5.62e-07)
Debt/equity ratio	1.80e-08 (5.59e-08)	5.64e-08 (7.52e-08)	-5.26e-07 (4.17e-07)	-7.76e-09 (2.40e-08)
Net investment share	0.004 (0.003)	9.55e-05 (0.002)	-0.002 (0.002)	5.56e-04 (0.002)
Index 1 structure (estimate)	-0.031*** (0.005)	-0.012*** (0.002)	-0.011*** (0.002)	-0.018** (0.009)
Index 2 sustainability (est.)	-0.006*** (0.001)	-0.003** (0.001)	-0.008*** (0.001)	-0.007*** 0.001)
Index 3 innovation (est.)	0.001 (0.008)	0.002*** 5.26e-04)	0.004*** (0.001)	-9.39e-04 (0.001)
Index 4 technology (est.)	0.008*** (0.001)	0.004*** (0.001)	0.003 (0.002)	0.011*** (0.001)
Index 5 diversity (est.)	-0.004* (0.001)	-0.003** (0.001)	-0.002 (0.001)	-0.002 (0.001)
Index 6 individual (est.)	5.22e-04 (0.003)	-0.009*** (0.003)	0.011*** (0.003)	-0.003 (0.004)
Index 8 household (est.)	.0.003 (0.004)	-1.48e-04 (0.004)	0.006 (0.005)	-0.003 (0.004)
Index 9 financial (est.)	0.002 (0.003)	0.005** (0.002)	0.009*** (0.003)	0.015*** (0.004)
Off-farm	-6.46e-06*** (2.30e-06)	-6.78e-06 (4.53e-06)	-8.61e-06*** (2.20e-06)	-6.94e-07 (2.59e-06)
Constant	2.51*** (0.011)	2.54*** (0.011)	2.526*** 0.007	2.528*** (0.012)
Sigma_u	0.043	0.049	0.048	0.047
Sigma_e	0.008	0.007	0.007	0.009
Rho	0.962	0.982	0.979	0.964
R-sq (within/between/overall)	0.509/0.606/0.569	0.381/0.657/0.684	0.496/0.683/0.681	0.448/0.528/0.524
Corr(u_i, Xb)	-0.169	0.481	0.588	0.228
Obs per group (min/avg/max)	1/4.8/10	2/4.3/8	1/4.3/10	2/4.4/10
F-test	(18, 207) 11.95***	(18, 215) 7.36***	(18, 219) 11.96***	(18, 201) 9.06***
F-test u_i=0	(59, 207) 73.60***	(69, 215) 78.62***	(71, 219) 89.15***	(64, 201) 55.34***

Notes: Estimates based on Fixed-Effects (Within) Panel Regressions applied to quartiles; *significant at 10%, **significant at 5%, ***significant at 1%; dependent variable: change in productivity, quartile definition is based on productivity change between pre-shock and absorption phase.

Table A A.2. UK crop farms – fixed effects regression income changes in 2010-12, estimates by quartile

Income	Top performers	2nd Best performers	2nd Worst performers	Worst performers
Covariate	Estimate (std error)	Estimate (std error)	Estimate (std error)	Estimate (std error)
Drought event	-5687.115 (52041.7)	25319.291* (10721.91)	-5939.068 (8993.44)	-1221.676 (22646.56)
Age farmer	103.324 (2025.89)	-939.451** (479.19)	262.929 (562.21)	-96.005 (1451.21)
Gender farmer	19610.46 (55420.81)	93436.14*** (22910.33)	-8545.088 (14468.76)	17224.84 (1451.21)
Subsidies per ha	4066.867*** (519.61)	307.007 (626.68)	252.655 (779.95)	638.626** (330.71)
Env subsidies per ha	-4749.058*** (591.04)	-476.279 (632.51)	-386.733 (779.95)	-501.074 (361.22)
Total output per ha	320.764*** (32.57)	111.534*** (8.21)	64.123*** (6.81)	96.065*** (16.38)
Assets per ha	-15.669** (7.04)	-2.651** (1.49)	-2.923** (1.29)	-7.016** (3.16)
Debt/equity ratio	-9.821 (110.61)	-0.023 (0.14)	0.048 (1.96)	2.012e-04 (0.21)
Net investment share	8951.72 (41430.84)	16208.98** (7538.71)	4124.806 (6737.83)	14032.35 (20557.33)
Index 1 structure (estimate)	-82599.13** (38461.37)	25964.68 (39145.16)	-34405 (23338.68)	58324.52 (42500.7)
Index 2 sustainability (est.)	42973.21** (22482.17)	37437.45*** (5031.59)	5652.378 (3851.85)	-2385.045 (10828.03)
Index 3 innovation (est.)	5570.527 (8265.13)	-12513.42*** (4403.31)	2200.849 (5030.34)	-31681.64*** (8675.04)
Index 4 technology (est.)	-22994.92 (29661.52)	-3168.333 (5228.74)	-9637.193* (5653.38)	19021.59 (15423.4)
Index 5 diversity (est.)	-49543.18** (20367.54)	-17248.87*** (5512.66)	-8485.938** (4258.72)	-17064.02 (11322)
Index 6 individual (est.)	474.761 (37242.19)	-64141.96*** (17063.96)	7629.381 (10001.94)	-18914.24 (34519.14
Index 8 household (est.)	-50848.44 (98289.68)	-23767.74** (9743.88)	-1213.265 (13945.51)	-11608.2 (49689)
Index 9 financial (est.)	113273.7*** (42002.74)	33368.63** (16201.52)	2776.782 (14384.08)	13029.17 (24050.69)
Off-farm	6.876 (52.228)	-39.323*** (11.26)	-1.157 (7.12)	5.463 (19.77)
Constant	-160763.3 (167729.6)	47664.89 (34628.61)	26278.5 (40511.05)	105927.6 (86322.57)
Sigma_u	229295.12	188558.47	60447.09	431110.6
Sigma_e	120219.94	26082.95	23891.86	77481.56
Rho	0.784	0.981	0.865	0.969
R-sq (within/between/overall)	0.581/0.821/0.822	0.562/0.001/0.007	0.359/0.283/0.288	0.264/0.466/0.436
Corr(u_i, Xb)	-0.037	-0.606	-0.205	-0.853
Obs per group (min/avg/max)	1/4.4/9	1/4.4/10	1/4.4/10	1/4.4/10
F-test	(18, 212) 16.29	(18, 229) 16.33	(18, 195) 6.07	(18, 206) 4.10
F-test u_i=0	(66, 212) 7.17***	(71, 229) 42.01***	(62, 195) 7.50***	(64, 206) 4.52***

Notes: Estimates based on Fixed-Effects (Within) Panel Regressions applied to quartiles; *significant at 10%, **significant at 5%, ***significant at 1%; dependent variable: change in income, quartile definition is based on productivity change between pre-shock and absorption phase.

Table A A.3. UK crop farms – characteristics of resilient sample farms, productivity

	Resilience Index Score												
	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3	3.25	3.5	3.75	4
Characteristics / Measures													
Land (ha)	120.56	91.04	182.21	210.30	225.29	178.88	301.80	259.48	325.29	317.95	297.95	652.38	280.98
Labour (awu)	0.91	1.35	1.68	2.26	2.63	1.83	5.92	2.24	2.37	3.17	3.87	10.68	5.64
Total output per ha (€)	1398.90	1713.07	1431.60	1481.14	1503.34	1458.19	2139.93	1534.61	1421.73	1593.83	1680.78	1969.91	2301.50
Depreciation p.ha. (€)	147.51	141.73	130.53	173.69	149.77	148.04	228.65	181.91	140.25	223.33	214.77	235.03	259.71
Costs for pesticides p.ha.	250.54	302.08	320.75	296.17	253.16	304.87	330.67	317.18	266.52	304.29	316.91	339.04	372.60
Energy costs p.ha. (€)	58.11	70.28	69.65	85.00	85.10	77.04	105.90	76.32	70.28	77.54	126.11	114.82	103.20
Material costs p.ha. (€)	1.44	8.18	4.97	3.34	13.10	11.52	8.04	7.75	12.40	12.47	26.96	14.66	38.77
Contract costs p.ha. (€)	178.94	106.71	124.81	62.06	87.40	97.09	91.04	47.60	79.72	96.32	32.92	73.24	57.90
Total assets p.ha. (€)	17285.21	14971.46	9832.51	12903.63	11284.53	10970.58	14333.02	10518.56	11381.09	13054.21	8813.37	9927.28	11522.20
Net investment (€)	21112.44	18745.44	35719.68	64619.28	68460.90	48499.76	166840.20	108399.90	86910.76	200987.10	144136.90	281943.70	138428.70
Net investment share	0.43	0.41	0.41	0.48	0.47	0.48	0.54	0.53	0.53	0.56	0.54	0.58	0.58
Environmental subs. p.ha. (€)	25.24	40.28	32.51	35.64	36.50	31.57	27.67	36.05	57.43	36.31	25.73	30.54	16.49
Subsidies p.ha. (€)	26.86	42.65	34.47	37.26	37.67	33.09	28.29	38.02	61.88	38.11	26.81	33.44	16.63
Hired-family labour ratio	0.31	1.17	0.89	8.30	2.98	1.62	60.49	0.62	15.08	0.94	1.58	7.09	4.22
Age (years)	58.70	62.86	56.89	58.53	55.63	57.69	59.58	59.58	58.86	57.55	58.83	54.99	54.76
Debt-equity ratio	1232.30	666.68	110.57	78.69	181.71	177.08	647.98	739.81	2714.67	139.63	97.85	26.52	112.68
Productivity (ln estimate)	11.74	11.59	12.32	12.40	12.21	12.25	12.89	12.64	12.60	12.86	12.86	13.41	13.15
Technical change (% p.a.)	0.005	0.004	0.005	0.003	0.004	0.003	0.006	0.006	0.010	0.010	0.002	0.010	0.006
Observations (n)	100	110	130	160	210	170	200	170	140	170	90	170	50

Notes: p.ha. - per ha, resilience index score: 1 - least resilient, 4 - most resilient, time period: 2008-2017.

Table A A.4. UK crop farms – characteristics of resilient sample farms, income

	Resilience Index Score												
	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3	3.25	3.5	3.75	4
Characteristics / Measures													
Land (ha)	119.12	93.45	180.50	205.20	228.77	175.93	308.76	253.85	330.88	315.59	294.56	663.94	284.92
Labour (awu)	0.90	1.35	1.70	2.24	2.65	1.80	5.57	2.29	2.47	3.15	3.84	10.72	5.68
Total output per ha (€)	1417.81	1745.02	1477.88	1452.85	1527.43	1452.09	2147.93	1502.30	1415.72	1692.28	1660.40	1988.30	2322.49
Depreciation p.ha. (€)	145.22	142.80	135.14	174.70	152.33	146.47	232.61	185.93	142.25	225.32	210.78	238.07	262.73
Costs for pesticides p.ha.	267.14	315.79	321.28	301.15	255.97	300.60	346.57	317.10	286.50	306.37	318.00	347.88	377.70
Energy costs p.ha. (€)	59.87	72.39	70.63	87.21	88.20	75.63	109.92	78.33	72.29	87.42	127.47	115.74	107.07
Material costs p.ha. (€)	1.78	10.20	7.89	4.53	13.10	13.08	14.23	6.57	13.55	14.40	28.92	17.64	39.02
Contract costs p.ha. (€)	181.36	106.71	125.90	62.06	87.40	97.09	94.03	48.31	85.41	96.30	35.93	75.49	62.74
Total assets p.ha. (€)	17596.22	14873.50	10042.81	13232.73	11284.53	10820.84	17307.28	11019.52	11789.76	13346.34	10134.49	9994.08	11701.20
Net investment (€)	20029.98	19133.47	36934.96	64057.11	68460.90	46985.36	169620.21	109952.00	87780.13	202679.70	147691.46	282905.73	142709.20
Net investment share	0.42	0.41	0.40	0.47	0.47	0.47	0.55	0.53	0.53	0.57	0.54	0.58	0.58
Environmental subs. p.ha. (€)	24.77	38.30	33.21	38.46	36.50	31.80	26.03	34.75	59.80	35.89	23.37	30.50	16.50
Subsidies p.ha. (€)	26.80	43.71	34.40	40.17	42.62	35.54	28.20	39.89	67.82	39.21	26.50	34.02	16.66
Hired-family labour ratio	0.31	1.10	0.88	6.22	3.21	1.60	50.43	1.63	18.65	0.99	2.45	7.68	4.67
Age (years)	58.68	63.80	57.01	58.50	55.68	57.55	58.09	59.50	58.80	57.52	58.63	54.55	54.72
Debt-equity ratio	1202.11	691.35	113.73	73.15	185.52	175.22	655.47	740.87	2958.22	549.37	100.07	36.82	110.62
Productivity (ln estimate)	11.72	11.60	12.31	12.41	12.25	12.24	12.91	12.63	12.61	12.86	12.87	13.42	13.16
Technical change (% p.a.)	0.005	0.004	0.005	0.003	0.004	0.003	0.006	0.006	0.010	0.010	0.002	0.010	0.006
Observations (n)	90	120	130	170	200	170	200	160	150	160	100	170	50

Notes: p.ha. - per ha, resilience index score: 1 - least resilient, 4 - most resilient, time period: 2008-2017.

Table A A.5. UK crop farms – matching estimates (2006 for flood in 2007)

Variable	Estimate	Z-value
Land	0.113***	3.89
Labour	-0.324*	-1.41
Assets per ha	0.003**	6.99
Fertilisers and crop protection costs per ha	0.009***	2.34
Depreciation per ha	-0.019***	-5.42
Total output per ha	0.003***	-4.81
Energy costs per ha	0.051***	7.56
Other material costs per ha	-0.001	-0.20
Contract work costs per ha	0.003**	2.02
Environmental subsidies per ha	0.009	1.07
Intercept	-3.218***	-3.03
Regression statistics		
Number of observations	254	
LR chi2(10)	742.33***	

Notes: Estimates based on Logit Regression for Propensity Score Matching. *significant at 10%, **significant at 5%, ***significant at 1%.

Table A A.6. UK crop farms – matched samples (2007 flood)

Variable	(1) Potential affected farms	(2) Potential unaffected farms	(3) Selected affected	(4) Selected unaffected
Labour	3.10	2.79***	3.00	2.97
Land	249.64	278.58***	254.21	258.70
Energy per ha	113.47	107.90***	110.42	109.34
Total assets per ha	6225.08	6841.87***	6521.12	6684.30
Depreciation per ha	115.84	118.04*	116.03	116.90
Fertiliser and pesticides costs per ha	213.21	217.85**	215.18	215.74
Total output per ha	1276.52	1100.34***	1201.32	1143.21*
Number of observations	130	124	41	41
	MeanBias	MedBias		
Unmatched	38.7	36.2		
Matched	6.0	5.9		

Notes: Balance after 1:1 nearest neighbour matching, caliper (0.1), common support *significant at 10%, **significant at 5%, ***significant at 1%.

Table A A.7. UK crop farms – DID estimation results for resilience indicator productivity

Variable	Estimate	T-value
Dummy affected	-0.016 (0.051)	-1.01
Interaction term	-0.114 (0.043)	1.02
Year 2006	-0.233*** (0.057)	-3.12
Year 2007	-0.237*** (0.055)	-5.44
Year 2008	-0.144** (0.061)	-2.11
Year 2009	-0.031 (0.044)	-1.25
Year 2010	-0.089 (0.042)	-1.44
Total output	0.064*** (0.030)	8.22
Capital depreciation	0.003*** (0.001)	4.47
Labour	0.229*** (0.022)	8.14
Land	0.002*** (0.000)	10.71
Intercept	12.211*** (0.046)	108.95
Regression statistics		
Number of observations	492	
R-Squared	0.66	
Prob>F	0.000	

Notes: Estimates based on DID Fixed-Effects Regression. *significant at 10%, **significant at 5%, ***significant at 1%. Standard errors in brackets.

Annex B. Methodologies used in this paper

B.1. Methodology for dynamic analysis (Section 4)

The method subsequently outlined is applied to analyse the UK droughts between 2010 and 2012, which are events that have affected the whole geographical entity. They affected all crop farms almost equally. For this reason, panel regressions are applied to study potential drought impacts at farm level. As such methods are unable to demonstrate causality between extreme events and resilience performance reference variables, structural breaks were analysed before applying an autoregressive distributed lagged model (ARDL) and a panel fixed effects model. Following Andrews and Fair (1988[11]) and Hansen (1997[12]),a “Wald test” was used to examine whether there are structural breaks in the farm performance and resilience indicators at the time when the droughts examined occurred between 2010 and 2012. This was done by analysing coefficients of T in a time-series regression of the performance and resilience indicators:

$$IND_t = \alpha + \rho T(t > \tau) + \gamma Z_t(l) + \varepsilon_z.$$

In this equation, IND_t denotes the performance reference value at time t, T is the time trend, τ refers to drought years and $Z_t(l)$ denotes a group of control variables.

Aggregate (sector level) values at period t are defined as a weighted sum of farm-level values:

$$\Pi_t = \sum_{i \epsilon \Omega_t} s_{it} \pi_{it}$$

where s_{it} denotes the share of farm i in the industry at time period t (i.e. revenue or cost shares) and π_{it} denotes the farm level indicator value. Ω_t represents the set of all farms in the same period. The multi-pronged hypotheses underlying the above structural break test are that if a structural break in an indicator series is detected, then the droughts had a significant effect on the respective indicator. This test was not only applied for sector level time series, but also for an unbalanced panel following the work of Bai and Perron (1998[13]) and Bai (2010[14]). After completing the structural break tests, the ARDL and panel fixed effects models were applied to measure the impact of droughts given the farms’ relative performance:

$$IND_t = \beta_0 + \beta_1 DROU_t + \gamma Z_t(l) + v_t$$

$$IND_{it} = \beta_0^t + \beta_1^t DROU_{it} + \gamma^t Z_{it}(l) + u_i + \varepsilon_{it}$$

where IND_t and IND_{it} are aggregate and farm level indicator values, $DROU_t$ and $DROU_{it}$ are the dummy variables for drought years. They take a value of 0 before 2010 and 1 otherwise, while $Z_t(l)$ and $Z_{it}(l)$ are control variables previously defined and u_i captures farm-specific effects. The estimated coefficients for the drought variables provide insights into how the droughts affected the resilience performance reference variable.

In a final step it is aimed to identify farms that prove to be most resilient with respect to drought or flood related shock events. Different resilience phases are distinguished based on the specific shock event investigated and a multinomial regression type estimation is employed (Greene, 2018[9]) to measure the marginal impact of various farm and farmer characteristics on the farms’ resilience relative performance in terms of the reference variables: productivity or income. Hence, let $IND_{i\Delta t}$ denote the change in a farm-level productivity or income between two different resilience phases (e.g. pre-shock phase and absorption phase) and X_{it} denotes a group of explanatory variables (i.e. farm and farmer related characteristics) and PI_{it} denotes different pre-estimated performance indices at farm level measured for a specific resilience phase (e.g. pre-shock phase):

$$IND_{i\Delta t} = \beta_0 + \beta_1 X_{it} + \gamma PI_{it} + \varepsilon_{it}$$

The estimated coefficients for the farm and farmer related characteristics as well as performance indices provide finally insights into potentially effective drivers for successful resilience behaviour at farm level.

The panel estimation results are reported and discussed in subsection 4.2 for various performance (i.e. productivity and income) quartiles. The estimation of drivers for resilience capacities are reported and discussed in Section 5.

B.2. Methodology for shock identification (Section 7)

Beside the previously analysed drought events in the United Kingdom, similar methods have been used to empirically analyse the resilience impacts by floodings, focusing on UK regional flood events in the years 2007, 2009 and 2012 and measure their impact on farm and sector performance using resilience indicators as reported in the preceding section. The nature of an event like floods is more sudden and localised than droughts and requires an adapted statistical approach, by applying Propensity Score Matching (PSM) in combination with Difference-in-Difference (DID) techniques.

The combination of PSM and DID is well-suited to quantitatively investigate the impact of external disturbances/shocks on key resilience indicators in cases where disturbances occur unevenly across space, but evenly across time. Such a situation was to be observed for floods in the United Kingdom in 2007, 2009 and 2012. The 2007 UK floods for example affected especially parts of central and northern England, northern Scotland and large parts of Northern Ireland in summer 2007. The basic idea behind the DID matching approach is to compare two groups that are 'treated' differently, by e.g. a policy measure or an external shock, in terms of outcome changes over time relative to the outcomes observed for a pre-disturbance baseline. It is advantageous when treatment (in our case an external disturbance) is exogenous, covariates can be balanced across affected and non-affected groups and baseline outcomes controlled for. Using the DID method with a matching procedure such as Propensity Score Matching for the baseline data makes certain that the comparison group is similar to the group that is affected before applying double differences to the matched sample. Compared to a pure DID application its additional benefit is to account for observable heterogeneity in the initial conditions. Consequently, possible bias arising from both observable and unobservable variables can, under certain assumptions (e.g. DID common trend assumption), be ruled out (Heckman, Ichimura and Todd, 1997[15]). Further refinements of the DID methodology like (Callaway and Sant'Anna, 2021[16]) do not solve the underlying problem of data availability and requires the assumption of "irreversibility" of treatment which does not hold in the case of a drought.

Given a two-period setting where $t = 0$ refers to the period before a disturbance occurred and $t = 1$ to the period after the shock, letting Y_t^T and Y_t^C be the respective outcomes for an individual affected (T) and unaffected units (C) in time t, the DID method will estimate the average impact of the disturbance as follows:

$$DID = E(Y_1^T - Y_0^T \middle| T_1 = 1) - E\left(Y_1^C - Y_0^C \middle| T_1 = 0\right)$$

where $T_1 = 1$ denotes the presence of the disturbance at $t = 1$, whereas $T_1 = 0$ denotes unaffected areas. With baseline data one can thus estimate impacts by assuming that unobserved heterogeneity is time invariant and uncorrelated with the treatment over time. Within a regression framework the DID estimator can be expressed in its simplest form by the following equation:

$$Y_{it} = \alpha + \beta T_{i1} t + \rho T_{i1} + \gamma t + \varepsilon_{it}$$

where the coefficient β on the interaction between the post-disturbance variable T_{i1} and time $t = 1, \dots, T$ gives the average DID effect. This two-period model can be generalised with multiple time periods to a panel fixed-effects model including a range of time-varying covariates X_{it}. Assuring that affected and non-affected units (in our case farms) share similar characteristics, i.e. avoiding to compare the uncomparable, via PSM leads to more robust results. For this purpose, affected and unaffected farms are matched based on the propensity score with a chosen matching algorithm. The propensity score itself is estimated using a logistic regression:

$$P(T = 1 | X_1, \dots, X_n) = \frac{\exp\,(\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n)}{1 + \exp\,(\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n)}$$

where T defines being affected or not and X are observed covariates.

If multiple shocks occur over a certain time period (in our case flood events in 2007, 2009 and 2012), impacts on farm and sector resilience from multiple waves can be aggregated into a single set by weighting the estimates from the individual waves by their relative sample size:

$$\delta_W = \sum_{t=2}^{T} \frac{N_t}{N} \hat{\delta}_t$$

where t is the index for the respective panel wave, T is the total number of waves, N_t is the number of subjects at wave t, N is the total number of observations in all waves, and $\hat{\delta}_t$ is the estimate of the average impact at wave t. The variance for the weighted average impact may be estimated as:

$$\hat{\sigma}^2_{\delta_W} = \sum_{t=2}^{T} \frac{N_t^2}{N^2} \hat{\sigma}^2_{\hat{\delta}_t} + 2 \sum_{2 \le g < h \le T} \frac{N_g N_h}{N^2} Cov(\hat{\delta}_g, \hat{\delta}_h)$$

where g and h refer to individual waves.

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Comments are welcome and can be sent to tad.contact@oecd.org.