Quantifying the resilience of European farms using FADN

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Abstract
Agricultural policymakers call for the operationalisation of farm resilience as a dynamic concept. Therefore, we quantify farm resilience along the dimensions of robustness, adaptation and transformation. Using the rich Farm Accountancy Data Network panel data set, we explore which farm(er) characteristics affect resilience. We employ a control function approach to address the presence of endogeneity in correlated random effects (fractional) probit models. In general, we find that decoupled payments negatively affect robustness, while rural development payments have a positive effect on robustness. Both decoupled and rural development payments have no effect on adaptation and transformation in most European regions.

Keywords: resilience, robustness, adaptation, transformation, correlated random effects (CRE) fractional probit models

JEL classification: Q12, Q18

1. Introduction
The concept of resilience emphasises the importance of successfully dealing with uncertainty and dynamic environments. European farmers have to cope with dynamics and uncertainty by dealing with multiple risks, including droughts (Parsons et al., 2019), climate change (Reidsma, Ewert and Oude Lansink, 2007), changing regulations (Ondersteijn et al., 2002), price volatility (Hardaker et al., 2015) and previously unimaginable crises such as the coronavirus disease 2019 pandemic (Darnhofer, 2020; Meuwissen et al., 2021). Limited resilience renders farmers unable to deal with such risks (Knickel et al., 2018; Meuwissen et al., 2020). The 2020 Common...
Agricultural Policy (CAP) reform underlines the importance of resilient farms (European Commission, 2020a), illustrating that farm resilience has developed into a focal point for policy makers (Darnhofer, 2014; Knippenberg, Jensen and Constan, 2019; Buitenhujs et al., 2020). This has resulted in a call for the operationalisation and quantification of farm resilience to support European agricultural policymakers in developing policies that ensure farm viability.

While most economic theories assume the existence of equilibria or optima, resilience thinking offers additional insights into the importance of creating buffers, being flexible in response to change or exploring future opportunities to adapt or transform (Darnhofer, 2014). We understand resilience as the ability to provide farm functions (i.e. the delivery of public and private goods) while facing economic, social, environmental, and institutional shocks and stresses by exploiting the resilience capacities of robustness, adaptability and transformability (Meuwissen et al., 2019). These three capacities support farmers to deal with uncertainty and are essential for resilient farms. Robustness is related to stability. Robust systems aim to absorb and persist in the face of risk to maintain the current production system (Folke, 2016). In contrast, adaptation and transformation require flexibility. Adaptation represents a farm’s ability to adjust production processes, while transformation reflects a radical change in business focus (Darnhofer, 2014). The relative importance of the three complementary resilience capacities depends on the operational context (Folke, 2016; Meuwissen et al., 2019). For instance, gradual evolution calls for a different mix of robustness, adaptation and transformation compared to a period with radical changes (Walker et al., 2004; Darnhofer, 2014; OECD, 2020).

Despite the complex environment in which farmers operate, the vast majority of agricultural scholars analyse one specific type of risk in isolation (Komarek, De Pinto and Smith, 2020). Several studies also assessed farm resilience to one specific risk across different regions, countries and/or farm types (e.g. Grothmann and Patt, 2005; Di Falco and Chavas, 2006; Peerlings, Polman and Dries, 2014; Béné et al., 2016), providing useful insights into how spatial, institutional and agro-ecological heterogeneity affects farm resilience. However, these studies did not consider responses to multiple risks or uncertainty in general. Neither did these studies assess all three resilience capacities jointly.

Other studies simultaneously assessed robustness, adaptability and transformability using static approaches and cross-sectional data sets. For instance, through surveys on perceived robustness, adaptability and transformability of Ugandan households (Jones and d’Errico, 2019) or Dutch farmers (Slijper et al., 2020). A dynamic study approach requires repetitive measures to account for change over time. While such studies have been conducted, none of them assessed all three resilience capacities simultaneously. For instance, recent work in agricultural and development economics captured the dynamics of resilience by studying household well-being (Barrett and Constan, 2014; Cissé and Barrett, 2018; Knippenberg, Jensen and Constan,
The aim of this paper is to quantify farm resilience in terms of robustness, adaptation and transformation. Our contribution to the existing literature is twofold. First, we explicitly capture dynamics in farm robustness, adaptation and transformation by investigating changes over time. Using the rich Farm Accountancy Data Network (FADN) panel data set from nine European countries, we design an indicator-based framework to measure the resilience capacities. Second, we compare farm resilience across several farm types and European countries and explore which farm(er) characteristics affect robustness, adaptation and transformation. Understanding which characteristics contribute to resilience is important for the design of resilience-enhancing policies. This approach extends existing studies on a European scale, which only focused on adaptability (e.g. Reidsma et al., 2010; Vanschoenwinkel, Moretti and Van Passel, 2019) or studies that considered self-reported resilience without uncovering the actual resilience capacities (Peerlings, Polman and Dries, 2014). Our empirical application uses composite indicators to quantify farm robustness, adaptation and transformation. The econometric approach is based on correlated random effects (CRE) fractional probit models (Wooldridge, 2019). We employ a control function (CF) approach to account for potential endogenous explanatory variables (Papke and Wooldridge, 2008).

As this paper contributes to the call for an operationalisation and quantification of farm resilience (European Commission, 2020a), our findings are especially of interest to European agricultural policymakers. We find that the effectiveness of decoupled payments and rural developments payments to enhance resilience is heterogeneous across regions and farm types. In general, our results reveal that decoupled payments have no significant or a negative effect on farm robustness, while rural development payments enhance farm robustness. Decoupled payments and rural development payments have in most regions no significant effect on both adaptation and transformation, suggesting that alternative policy instruments, such as payments for providing public goods, are needed to support flexibility and the ability to change.

2. Conceptual framework

This section operationalises resilience as a multi-dimensional and dynamic concept. Our conceptual framework develops several indicators along the dimensions of robustness, adaptation and transformation. Most previous studies assessed resilience to a specific risk (e.g. Seo, 2010; OECD, 2020). A limitation of this approach is that the indicators measuring resilience are only applicable to a specific context. Other studies have argued that resilience assessments should address the whole range of risks faced by farms
Table 1. Overview of the resilience capacity indicators. Positive (negative) directions indicate that higher values of an indicator imply higher (lower) levels of a resilience capacity. $+/−$ indicates that either a positive or negative change implies higher levels of a resilience capacity. Application indicates to what farm type a specific indicator applies. ACP = arable, crop, and perennial farms

| Resilience capacity | Resilience capacity indicator (indicator name) | Definition | Direction | Application |
|---------------------|-----------------------------------------------|------------|-----------|-------------|
| Robustness          | Resistance ($resistance$)                      | Percentage decrease in profitability | $+$        | ACP, livestock, mixed |
|                     | Shock ($shock$)                                | Occurs if profitability decreases with at least 30% | $−$        | ACP, livestock, mixed |
|                     | Recovery rate after year 1 ($recovery rate$)   | Degree of recovery after 1 year. Expressed as a percentage of the decrease in profitability | $+$        | ACP, livestock, mixed |
| Adaptation          | Crop diversity ($crop diversity$)              | Change in crop diversity | $+/−$      | ACP, mixed |
|                     | Fertiliser, crop protection and energy costs ($FCE$) | Percentage change in fertiliser, crop protection and energy costs per hectare | $+/−$      | ACP, mixed |
|                     | Irrigation ($irrigation$)                      | Percentage change in irrigated area | $+/−$      | ACP, mixed |
|                     | Labour ($labour$)                              | Percentage change in annual working units (AWU) per hectare | $+/−$      | ACP, livestock, mixed |
|                     | Livestock units per hectare ($LU$)             | Percentage change in livestock units per hectare | $+/−$      | Livestock, mixed |
|                     | Feed ratio ($feed ratio$)                      | Percentage change in the ratio of on-farm produced feed to total feed costs | $+/−$      | Livestock, mixed |
| Transformation      | Organic ($organic$)                           | Conversion from conventional to organic farming or vice versa | $+$        | ACP, livestock, mixed |
|                     | Farm type ($farm type$)                       | Change in farm type (TF8 classification$^a$) | $+$        | ACP, livestock, mixed |
|                     | Farm tourism ($tourism$)                      | Revenue from farm tourism represents at least 30% of total revenue | $+$        | ACP, livestock, mixed |

Notes: $^a$TF8 classifies farm types according to the following types: 1 = fieldcrops, 2 = horticulture, 3 = wine, 4 = other permanent crops, 5 = milk, 6 = other grazing livestock, 7 = granivores, and 8 = mixed.
Quantifying the resilience of European farms (Meuwissen et al., 2019; Perrin et al., 2020). We follow this approach and assess farm resilience to all risks by investigating farm dynamics in terms of yearly changes in farm inputs and outputs. By describing general patterns, we study responses to change and uncertainty without targeting a specific risk. We propose a set of generic indicators that are applicable to several farm types across multiple European countries. Below, we present the robustness, adaptation and transformation indicators (overview in Table 1).

2.1. Robustness

Robustness is the capacity to withstand, absorb and recover from expected and unexpected risks (Meuwissen et al., 2019). To empirically assess robustness, we use three indicators that are based on farm profitability: resistance, severe shocks and recovery rate (Figure 1).

Resistance describes a farm’s ability to absorb the consequences of risks by minimising decreases in farm income or profitability (Urruty, Tailliez-Lefebvre and Huyghe, 2016). More resistant farms are better able to absorb shocks and are hence more robust (Grafton et al., 2019; Dardonville, Bockstaller and Therond, 2021). We define resistance as the decrease in profitability over time (Figure 1), where a lower decrease in profitability implies a more resistant farm. Higher levels of resistance result in more robust farms.

Prior to mathematically defining resistance, it is important to introduce how we benchmark farms based on profitability. The rate of return on assets (ROA) is used as profitability indicator, which is defined as the net farm income before Fig. 1. Illustration of the three robustness indicators: (1) resistance is the percentage decrease in profitability, (2) shock is a severe decrease in profitability and (3) recovery rate is the degree of recovery after a decrease in profitability. The entire box represents the decrease in profitability and the shaded area is the degree of recovery after a year.
taxes divided by the average total assets (Barry and Ellinger, 2011). We benchmark farms to their peers (i.e. farms within the same farm type and country for the same year) by comparing relative profitability (Seo, 2010). This is done by normalising ROA on a scale from 0 to 1, where 0 represents the least profitable farm and 1 is the most profitable farm. All robustness indicators are based on changes in normalised profitability.

Hence, we define resistance as:

\[
resistance_t = \begin{cases} 
0 & \text{if } ROA_t \geq ROA_{t-1} \\
\frac{ROA_t - ROA_{t-1}}{ROA_{t-1}} & \text{if } ROA_t < ROA_{t-1}
\end{cases}
\]  

(1)

where \( resistance_t \) is the resistance at time \( t \), and \( ROA \) is the normalised profitability.

Resistance is a continuous variable in the domain \([-1,0]\), where a value of \(-1\) indicates the lowest possible resistance\(^1\) and values of 0 are assigned to the most resistant farms. Additionally, the maximum value of 0 is assigned if there is no decrease in normalised profitability.

A severe shock in profitability (shock) reflects a farm’s ability to withstand successive risks (Sabatier et al., 2015; Sneessens et al., 2019). Farms that face a severe shock in profitability are less able to withstand risk and are therefore less robust. Following Finger and El Benni (2014), a severe shock is defined as a decrease in normalised profitability of at least 30 per cent. It takes the value 1 if a severe shock occurred and 0 if not. The threshold of a 30 per cent decrease in profitability is based on the OECD (2011), who define a 30 per cent decrease in profitability as a catastrophic risk.

The recovery rate describes the degree of recovery after a set amount of time, given that the normalised profitability has decreased (Urruty, Tailliez-Lefebvre and Huyghe, 2016; Sneessens et al., 2019; Dardonville, Bockstaller and Therond, 2021). It measures the degree to which farms can bounce back to previous levels of normalised profitability. Higher recovery rates indicate a better ability to recover from shocks. Hence, farms with higher recovery rates are more robust. In this study, we use the recovery rate after one year:

\[
recovery\ rate_{t+1} = \begin{cases} 
1 & \text{if } ROA_t \geq ROA_{t-1} \\
\frac{ROA_{t+1} - ROA_t}{ROA_{t-1} - ROA_t} & \text{if } ROA_t < ROA_{t-1}
\end{cases}
\]  

(2)

where \( recovery\ rate_{t+1} \) is the recovery rate after one year. The recovery rate is a continuous variable that is censored in the domain \([0,1]\). It takes the value 0 if there is no recovery and 1 in case of (more than) full recovery.

2.2. Adaptation

Adaptation is reflected by changes in a farm’s input composition, production, marketing and risk management (Meuwissen et al., 2019). These changes can

\(^1\) In the exceptional cases where profitability decreased with more than 100 per cent, we censored the data at \(-1\).
be towards more or less intensive input compositions or production processes (Smit and Skinner, 2002), implying that either an increase or a decrease in the intensity of inputs and production processes is understood as adaptation. To this end, we investigate the absolute value of changes in inputs and production processes. The direction of change is not important for absolute values, indicating that we refrain from making normative claims about the desired direction of adaptation—i.e. if adaptation should be towards more or less intensive production practices. As different farm types use different inputs and production processes, we distinguish between adaptation indicators for arable, crop and perennial (ACP) and livestock farms. For mixed farms that combine cropping and livestock practices, all adaptation indicators for arable and livestock farms apply (Table 1).

2.2.1. Arable, crop and perennial farms
We investigate four ACP adaptation indicators by studying changes in (i) crop diversity, (ii) fertiliser, crop protection and energy costs per hectare, (iii) irrigation and (iv) labour. First, changing a farm’s crop diversity towards more drought-resistant crops helps farms to adapt (Di Falco, Veronesi and Yesuf, 2011). Farmers can either increase or decrease their crop diversity as adaptation strategy, indicating gradual changes towards more diversified or specialised farms. On the one hand, increasing crop diversity reflects an adaptation towards more diversified farms (Reidsma et al., 2010; Cabell and Oelofse, 2012; Bouttes, San Cristobal and Martin, 2018; Paut, Sabatier and Tchamitchian, 2019; Dardonville et al., 2020). On the other hand, under certain circumstances—e.g. favourable market conditions—changing towards more specialised and less diverse farms can also be an effective adaptation strategy (Peerlings, Polman and Dries, 2014; Matsushita, Yamane and Asano, 2016). We measure crop diversity using the Shannon entropy (Shannon, 1948). The Shannon diversity index (SDI) reflects the evenness (the proportion of land covered by a crop) and richness (the number of different crops) of a crop portfolio (Brady et al., 2009):

$$SDI_t = -\sum_{i=1}^{I} p_{i,t} \ln(p_{i,t})$$

(3)

where $SDI_t$ denotes the diversity at time $t$, and $p_{i,t}$ is the share of land covered by crop $i$ ($i =$ cereals, other field crops, vegetables and flowers, vineyards, permanent crops, other permanent crops, forage crops or woodland) at time $t$. The yearly change in SDI reflects the change in crop diversity (Smit and Skinner, 2002; Kremen and Miles, 2012). A bigger absolute value of the change in crop diversity implies a more adaptive farm.

Second, changing the intensity of production processes also facilitates adaptation (Smit and Skinner, 2002; Howden et al., 2007). We use the change in fertiliser, crop protection and energy costs per hectare (FCE) as adaptation indicator representing farm intensity, where higher levels of FCE indicate
more intensive farms (Westbury et al., 2011). The effectiveness of intensification as adaptation strategy could be either high or low, depending on local circumstances, including rainfall, the availability of water, temperature and the current level of production (Reidsma, Oude Lansink and Ewert, 2008; Ge et al., 2016; Dardonville et al., 2020; Dardonville, Bockstaller and Therond, 2021). While increasing temperatures may need adaptation towards drought-resistant crops that need more intensive inputs (Reidsma, Oude Lansink and Ewert, 2008; Mase, Gramig and Prokopy, 2017), farmers facing less extreme weather events may adapt towards less intensive production systems by decreasing FCE (Coomes et al., 2019). Hence, adaptation is the decrease or increase in farm intensity over time, measured by the absolute value of the percentage change in FCE.

Third, irrigation is an adaptation strategy to manage water availability to deal with droughts and adverse weather conditions (Howden et al., 2007). The effectiveness of irrigation depends on the availability of water, national water rights regulations and irrigation costs (Hendricks and Peterson, 2012; Kahil, Connor and Albiac, 2015; Li and Zhao, 2018). On the one hand, farmers could adapt towards more intensive production practices by increasing the irrigated area, potentially resulting in higher farm productivity by improved water management (Reidsma et al., 2009; Foudi and Erdlenbruch, 2012). On the other hand, if water scarcity occurs or irrigation costs increase, farms can adapt by reducing the irrigated area and switching to dryland farming (Deines et al., 2019). Larger absolute values of changes in irrigated areas imply bigger potential changes in water management, indicating higher levels of adaptation.

Finally, changing the amount of labour per hectare is an adaptation strategy reflecting a farm’s flexibility to adjust to peak hours (Meuwissen et al., 2019). Farmers who can easily increase or decrease their labour force are more flexible and more adaptable (Smit and Skinner, 2002; Coomes et al., 2019). For example, they can increase their flexibility by attracting temporal labour to meet seasonal labour demand.

### 2.2.2. Livestock farms

We investigate three adaptation indicators for livestock farms by studying changes in (i) livestock units per hectare, (ii) feed ratio and (iii) labour. First, the stocking rate is an intensity indicator defined as the amount of livestock units per hectare (LU) (Howden et al., 2007; Ruiz-Martinez et al., 2015). Higher stocking rates indicate more intensive farms. Changing towards more intensive or extensive production systems is an adaptation strategy that is reflected by, respectively, increases or decreases in LU (Wreford and Topp, 2020). Livestock farms can either increase or decrease LU as an adaptation measure, which is measured by the absolute value of the change in LU.

Second, livestock farms that are more flexible are better able to adapt to shocks by buying more feed if feed prices are low or producing more feed if feed prices are high (Martin and Magne, 2015; Wreford and Topp, 2020). This adaptation is captured by changes in the ratio self-produced feed to bought
feed (feed ratio), reflecting the self-sufficiency of farms (Havet et al., 2014). Farms that increase their feed ratio are more self-sufficient and increased their feed production relative to the amount of bought feed, while a decrease in feed ratio implies more bought feed. A larger absolute change in feed ratio implies a more adaptable livestock farm.

Finally, labour refers to the flexibility to attract labour. As discussed earlier, an improved ability to change the amount of labour per hectare reflects more flexible farm practices and higher adaptability.

2.3. Transformation

In contrast to adaptation, transformations involve more radical and fundamental changes in the internal farm structure to cope with severe and enduring risks (Meuwissen et al., 2019). To provide a clear distinction between farm adaptation and transformation, we operationalise transformation as a considerable redistribution of the primary production factors (i.e. land, labour and capital) and/or change in output (Vermeulen et al., 2018). We examine three transformation indicators: (i) organic farming, (ii) farm type and (iii) farm tourism. First, the conversion from conventional to organic farming or vice versa (organic) is a transformation that often results in a considerable redistribution of labour practices (Rickards and Howden, 2012). Second, a change in farm type (type) (Neuenfeldt et al., 2019) is characterised by a substantial change in output, as different farm types supply different products. Finally, obtaining a considerable part of revenue from tourism (tourism) implies a shift in business focus from primarily agricultural activities towards a more recreational character (Rickards and Howden, 2012). This transformation occurs if revenue from tourism accounts for at least 30 per cent of the total revenue.2

3. Methods

To move from the complexity of resilience towards a measure that is easy to interpret by policymakers, we aggregate the resilience capacity indicators into composite indicators. We create a separate composite indicator for each resilience capacity and explicitly refrain from aggregating the three resilience capacities into an overall resilience indicator as there is no theoretical foundation that adequately describes the trade-offs between the resilience capacities. Our empirical application uses farm-level data from FADN, which is an unbalanced panel data set that includes detailed farm characteristics and accounting data from nine European countries over the period 2004–2013 (FADN, 2018). Section 3.1 describes our approach to construct composite indicators, Section 3.2 discusses the econometric model, Section 3.3 discusses the data set and Section 3.4 introduces the control variables of the econometric model.

2 To prevent the arbitrary selection of the threshold of 30 per cent, we conducted a sensitivity analysis to compare our findings under different thresholds values (10 per cent, 20 per cent, 40 per cent and 50 per cent). The findings are robust to alternative thresholds, see Tables A40–A51 (Appendix in supplementary data at ERAE online) for more details.
Table 2. Overview of the composite indicators and econometric approach

| Resilience capacity | Composite indicator | Econometric model |
|---------------------|---------------------|-------------------|
| Robustness          | Fractional response variable [0,1] | CRE fractional probit with control function |
| Adaptation          | Fractional response variable [0,1] | CRE fractional probit with control function approach |
| Transformation      | Dummy (1 = transformed, 0 = not transformed) | CRE probit with control function approach |

Notes: CRE = correlated random effects.

3.1. Composite indicators

Each composite indicator reflects a yearly level of robustness, adaptation and transformation. To construct composite indicators for farm robustness and adaptation, we use principal component analysis (PCA) to obtain indicator weights. PCA is a statistical method that reveals how the resilience capacity indicators are associated with each other and converts them into a set of uncorrelated indicators (OECD, 2008). PCA objectively and endogenously assigns weights to each indicator (Reig-Martínez, 2012). To construct the composite indicator for transformation, we aggregate all transformation indicators into a dummy variable that takes the value 1 if at least one of the transformations occurred.3 The procedure below describes how we obtain composite indicators for robustness and adaptation.

Table 1 illustrates that some indicators contribute positively to the composite indicators, while other indicators have a negative effect. In order to make them comparable, we normalise all indicators using the min–max procedure4 (OECD, 2008). After normalisation, we use PCA to assign indicator weights. We compute the composite indicators using the weighted sum of the normalised indicators. The composite indicators are fractional response variables, ranging from 0 to 1, where outcomes at 0 and 1 are allowed. These values represent farms that either score extremely low (0) or high (1) on a resilience capacity. Note that values of 0 or 1 should be treated as normal observations. Therefore, the composite indicators are not truncated or censored. Truncation or censoring would assume that values of 0 or 1 are special observations (e.g. because values below 0 or above 1 could occur but are unobserved). Table 2 presents an overview of the obtained composite indicators and associated econometric approach detailed in the next section.

3 Although it is possible that a farm transforms multiple times per year, this only occurred for a very small proportion of the observations (less than 1 per cent). Therefore, we decided to create a dichotomous variable.

4 Min–max normalisation requires positive values for each indicator score. Therefore, negative values are rescaled to positive values by adding the absolute minimum value to the vector of each resilience capacity indicator.
3.2. Econometric approach

The econometric approach explores which farm(er) characteristics contribute to the resilience capacities. We estimate fractional probit models with CRE for robustness and adaptation (Papke and Wooldridge, 2008). An important advantage of fractional probit models is that values of 0 and 1 can be directly included in the model and are treated as normal observations. CRE fractional probit models use quasi-maximum likelihood (QMLE) to obtain robust estimates. For transformation, we estimate a CRE probit model because this variable is dichotomous. We employ CRE because fixed effects specifications of (fractional) probit models result in biased estimates (Greene, 2004).

3.2.1. Econometric model

The fractional probit model investigates which farm(er) characteristics explain farm robustness or adaptation. Following Papke and Wooldridge (2008), it can be specified as:

\[
E(y_{it1}|y_{it2}, x_{it}, c_i, \varepsilon_{it}) = \phi(y_{it2} \alpha + x_{it} \beta + c_i + \varepsilon_{it})
\]

where \(y_{it1}\) is the robustness or adaptation composite indicator of farm \(i\) at year \(t\), \(\phi(\cdot)\) is the standard normal cumulative distribution function, \(y_{it2}\) is a vector of potentially endogenous explanatory variables, \(x_{it}\) is a vector of exogenous explanatory variables, \(c_i\) is the unobserved heterogeneity of farm \(i\) and \(\varepsilon_{it}\) is a time-varying error term that is potentially correlated with \(y_{it2}\). The selected explanatory variables—ROA, asset turnover (ATO), decoupled payments, rural development payments, farmer age, land, farm type and country—will be detailed in Section 3.4. For transformation, we estimate a CRE probit model. The probit model follows the same specification as the fractional probit model in Equation (4). The only difference is that the dependent variable \(y_{it1}\) is dichotomous instead of a fractional response.

The current model specification likely suffers from two sources of endogeneity: (i) unobserved time-invariant heterogeneity that might affect the resilience capacities and (ii) potential reverse causality between some of the explanatory variables and the dependent variables. Section 3.2.2 explains how CRE deals with unobserved heterogeneity, and Section 3.2.3 explains how we address reverse causality using a CF approach.

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5 We also considered three alternative econometric approaches: (i) beta regressions (Ferrari and Cribari-Neto, 2004), (ii) zero-inflated models (Jansakul and Hinde, 2002) and (iii) double-hurdle models (Jones, 1989). Limitations of these approaches are that beta regressions completely ignore values of 0 or 1, while zero-inflated and double-hurdle models assume that values of 0 and 1 are special observations originating from a different datagenerating process. Double-hurdle and zero-inflated models use two-stage approaches that separately explain values of 0 and/or 1 in the first stage and explain all other values in the second stage. Another limitation is that two of the alternative approaches make strong distributional assumptions about the conditional mean (beta regressions and double-hurdle models).
3.2.2. Correlated random effects

CRE is a flexible extension of the random effect estimator that provides fixed effects estimates by accounting for the time-invariant unobserved heterogeneity (Wooldridge, 2005a). In this way, CRE addresses the unobserved and omitted variable problem. We apply CRE as pure random effects models are likely to be too restrictive due to the assumption that explanatory variables are completely uncorrelated with the unobserved heterogeneity.

Traditional CRE approaches (e.g. Mundlak–Chamberlain) are often only suitable for balanced panel data sets (Wooldridge, 2005b; Giles and Murtazashvili, 2013). However, our data set is an unbalanced panel. Therefore, we follow the approach of Wooldridge (2019) that is also applicable to unbalanced panel data sets. This approach models the unobserved heterogeneity as a function of the number of yearly data entries of a farm and the mean of the time-varying variables interacted with dummy variables for the number of yearly data entries of a farm:

\[ c_i = \sum_{r=1}^{T} \delta_{i,r} \psi_{0r} + \sum_{r=1}^{T} \delta_{i,r} \bar{x}_i \psi_{1r} + a_i \]  

where \( \psi_{0r} \) is a dummy variable that is 1 if a farm is \( r \) years present in the data set, \( \bar{x}_i = \frac{1}{T} \sum_{t=0}^{T} x_{it} \) are the within-unit averages of the time-varying exogenous explanatory variables \( x_i \), \( \psi_{1r} \) is a vector of dummy variables that is 1 if a farm is \( r \) years present in our data set and \( a_i \) is a normally distributed error term: \( a_i | \bar{x}_i \psi_{1r} \sim \text{Normal}(0, \sigma_{ai}^2) \). Including the averages of the time-varying variables in \( c_i \) absorbs correlations with the unobserved heterogeneity and hence relaxes the random effects assumption of strict exogeneity (Wooldridge, 2005b; O’Brien et al., 2010).

3.2.3. Control function

Our model specification potentially suffers from reverse causality between one of the dependent variables (robustness) that is based on changes in profitability and two explanatory variables (ROA and ATO). Additionally, the non-random assignment of decoupled payments and rural development payments and potential reverse causality to all composite indicators may introduce endogeneity. Hence, we investigate if decoupled payments and rural development payments are a source of endogeneity in the models for robustness, adaptation and transformation.

The CF approach addresses endogeneity in non-linear models using a two-stage approach (Papke and Wooldridge, 2008; Wooldridge, 2015). In the first stage, we estimate a reduced form equation for each endogenous variable using pooled ordinary least squares (OLS). In the second stage, we add the residuals of the reduced form equations to the CRE model. We slightly adjust the CF approach of Papke and Wooldridge (2008), based on the CRE specification of Wooldridge (2019):
Estimate the reduced form equation for each endogenous explanatory variable using pooled OLS: \( y_{2it} = z_{it} \eta + x_{it} \beta + c_i + v_{it} \), where \( z_{it} \) is a vector of instrumental variables. Year dummies are included to allow for different time period intercepts. Obtain the estimated residuals of the reduced form equations (\( \hat{v}_{it} \)) for all \((i, t)\) pairs.

Add \( \hat{v}_{it} \) to the second-stage model (Equation 4) and estimate the CRE (fractional) probit model using QMLE. Second lags of the endogenous explanatory variables are used as instrumental variables.\(^6\)

The standard errors of the second-stage model are corrected for adding the first-stage residuals through bootstrapping. Following Wooldridge (2010), we present average partial effects (APE) instead of parameter estimates because of their straightforward interpretation.

### 3.3. Data

Our data set contains FADN data for the period 2004–2013 from nine European countries: Belgium, France, Germany, Italy, the Netherlands, Poland, Spain, Sweden and the United Kingdom. We investigate heterogeneity in the data set across two dimensions. First, we account for differences between Western (Belgium, France, Germany, the Netherlands and the United Kingdom), Southern (Italy and Spain), Northern (Sweden) and Eastern European countries (Poland). Second, we investigate differences between ACP, livestock and mixed farms.\(^7\) We estimate a separate model for each farm type within a region. Since we need one lagged value to compute changes in input and output and a second lag to obtain instrumental variables, as well as data on recovery rate for the year following a shock, our actual analysis is focused on the period 2006–2012.

Given the sensitivity of composite indicators for outliers (OECD, 2008), we trim the upper and lower 1 per cent of the observations from the following variables: (i) ROA (for all farm types), (ii) labour (for all farm types), (iii) FCE (for ACP and mixed farms), (iv) crop diversity (for ACP and mixed farms), (v) LU (for livestock and mixed farms) and (vi) feed ratio (for livestock and mixed farms). Our final sample contains 239,483 observations representing 58,457 farms.

### 3.4. Explanatory variables

Table 3 presents the summary statistics of the explanatory variables.\(^8\) We include the following farm and farmer characteristics as explanatory variables:

6 The dependent variable is based on changes in the resilience capacity indicators (computed as the difference between current and lagged values) and might therefore still be correlated to first lags of the endogenous explanatory variables. To overcome this, we use second lags of the endogenous explanatory variables as instrumental variables.

7 We categorise farm types based on the TF8 classification of FADN. The following categorisation is used: ACP includes fieldcrops, horticulture, wine and other permanent crops farms; livestock includes dairy, other grazing livestock and granivores; and mixed includes all mixed farms.

8 Supplementary Appendix 1 (Tables A1–A5 (Appendix in supplementary data at ERAE online)) provides summary statistics on the major farm characteristics for the initial and final sample.
Table 3. Descriptive statistics of the composite indicators and farm(er) characteristics (standard deviations are presented in parentheses)

|                        | Western Europe |               | Southern Europe |               | Northern Europe |               | Eastern Europe |               |
|------------------------|----------------|---------------|-----------------|---------------|-----------------|---------------|----------------|---------------|
|                        | ACP | Livestock | Mixed | ACP | Livestock | Mixed | ACP | Livestock | Mixed | ACP | Livestock | Mixed | ACP | Livestock | Mixed |
| Robustness             | 0.858 | 0.841 | 0.842 | 0.833 | 0.801 | 0.832 | 0.814 | 0.834 | 0.819 | 0.791 | 0.770 | 0.802 |
| (0.224) | (0.234) | (0.240) | (0.259) | (0.270) | (0.267) | (0.261) | (0.236) | (0.257) | (0.291) | (0.299) | (0.281) |
| Adaptation             | 0.098 | 0.108 | 0.126 | 0.089 | 0.070 | 0.100 | 0.162 | 0.127 | 0.181 | 0.134 | 0.136 | 0.147 |
| (0.078) | (0.107) | (0.079) | (0.084) | (0.075) | (0.080) | (0.117) | (0.107) | (0.113) | (0.090) | (0.107) | (0.084) |
| Transformation\(^a\)   | 0.051 | 0.058 | 0.127 | 0.079 | 0.071 | 0.294 | 0.079 | 0.091 | 0.304 | 0.118 | 0.104 | 0.114 |
| (0.138) | (0.067) | (0.075) | (0.139) | (0.088) | (0.084) | (0.076) | (0.061) | (0.058) | (0.090) | (0.062) | (0.060) |
| ROA                    | 0.112 | 0.061 | 0.064 | 0.111 | 0.105 | 0.090 | 0.038 | 0.040 | 0.022 | 0.105 | 0.098 | 0.084 |
| (0.138) | (0.067) | (0.075) | (0.139) | (0.088) | (0.084) | (0.076) | (0.061) | (0.058) | (0.090) | (0.062) | (0.060) |
| ATO                    | 0.515 | 0.308 | 0.366 | 0.216 | 0.240 | 0.184 | 0.241 | 0.269 | 0.225 | 0.246 | 0.258 | 0.219 |
| (0.497) | (0.243) | (0.237) | (0.269) | (0.178) | (0.146) | (0.316) | (0.141) | (0.167) | (0.173) | (0.145) | (0.108) |
| Log(land)              | 3.521 | 4.284 | 4.677 | 2.699 | 3.400 | 3.582 | 4.277 | 4.383 | 4.656 | 3.210 | 3.196 | 3.061 |
| (1.746) | (0.925) | (1.034) | (1.441) | (1.181) | (1.270) | (1.249) | (0.801) | (0.789) | (1.298) | (0.680) | (0.780) |
| Age                    | 50.291 | 49.573 | 49.750 | 55.696 | 51.503 | 54.135 | 56.092 | 52.700 | 53.474 | 44.673 | 43.789 | 44.433 |
| (9.377) | (9.509) | (9.359) | (12.892) | (11.824) | (12.730) | (9.306) | (9.234) | (9.110) | (9.018) | (8.726) | (9.002) |
| Decoupled payments     | 0.095 | 0.141 | 0.146 | 0.117 | 0.105 | 0.142 | 0.186 | 0.125 | 0.152 | 0.108 | 0.079 | 0.100 |
| (0.100) | (0.099) | (0.074) | (0.155) | (0.101) | (0.112) | (0.115) | (0.072) | (0.079) | (0.087) | (0.058) | (0.054) |
| Rural development payments | 0.010 | 0.055 | 0.025 | 0.022 | 0.034 | 0.026 | 0.042 | 0.105 | 0.070 | 0.045 | 0.046 | 0.055 |
| (0.034) | (0.219) | (0.051) | (0.062) | (0.069) | (0.052) | (0.079) | (0.099) | (0.073) | (0.094) | (0.074) | (0.077) |

Sample size (%) by country

|                  | Belgium | 5.076 | 7.750 | 8.339 |
|------------------|---------|-------|-------|-------|
|                  | France  | 44.970 | 29.749 | 31.118 |
|                  | Germany | 33.144 | 36.382 | 51.038 |
|                  | The Netherlands | 9.342 | 7.936 | 2.330 |
|                  | United Kingdom | 7.468 | 18.183 | 7.174 |
| Spain            | 45.055 | 53.276 | 46.429 |
| Italy            | 54.945 | 46.724 | 53.571 |
| Sweden           | 100.000 | 100.000 | 100.000 |
| Poland           | 100.000 | 100.000 | 100.000 |

|                  | N        | 38,888 | 42,969 | 14,162 |
|------------------|----------|-------|-------|-------|

Notes: ACP = arable, crop and perennial farms; ROA = rate of return on assets; ATO = asset turnover.
\(^a\)Transformation is a dummy variable. Therefore, no standard deviation is presented.
profitability, asset turnover, decoupled payments, rural development payments, farmer age, land, the TF8 farm typology of FADN and country. We use ROA as profitability indicator. To measure farm operational efficiency, we use the asset turnover (ATO). ATO is defined as total revenue divided by total assets. Land is the total agricultural area expressed in hectares. We take the logarithm of the total agricultural area to decrease the range in order to minimise heteroscedasticity. Age is the age of the farm operator which represents the farmer’s experience with risk and uncertainty (Peerlings, Polman and Dries, 2014). Decoupled payments are the share of decoupled payments that a farm receives relative to their total revenue including subsidies (Wauters and de Mey, 2019). Decoupled payments are a form of government support aiming to provide a more stable income (de Mey et al., 2016). While decoupled payments primarily function as income support, rural development support aims to enhance rural development and sustainable production. We define rural development payments as the share of rural development payments that farmers receive relative to their total revenue including subsidies. Furthermore, we control for heterogeneity across the TF8 typology of FADN (farm type), which classifies farms according to eight typologies: fieldcrops, horticulture, wine, other permanent crops, milk, other grazing livestock, granivores and mixed farms. The farm type dummies capture differences in agro-ecological context that are heterogeneous across farm types. Finally, country is a dummy variable that accounts for differences in the socio-economic and institutional context across countries.

4. Results

Section 4.1 presents how we computed the composite indicators; Section 4.2 presents the results of our econometric model.

4.1. Composite indicators

We construct composite indicators for the resilience capacities for each farm type within a region. The procedure below applies to the composite indicators of robustness and adaptation. To investigate if PCA is an appropriate method to assign indicator weights, we run the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (Kaiser, 1974) and Bartlett’s test of sphericity (Hair et al., 2014). We conclude that PCA is an appropriate method to obtain indicator weights because all KMO values exceed 0.5, and the Bartlett test rejects the hypothesis of no intercorrelations between indicators (all p-values <0.01). Supplementary Appendix 1 provides more details on the KMO and Bartlett test (Tables A6–A14; Appendix in supplementary data at ERAE online). Tables A15–A20 (Appendix in supplementary data at ERAE online) present the weights of the resilience capacity indicators obtained

9 Rural development support consists of environmental subsidies, subsidies for less favourite areas and other rural development payments (European Commission, 2020b).
Fig. 2. Average scores of the resilience capacities by NUTS-2 region (Nomenclature of Territorial Units for Statistics regions). NUTS-2 regions are units at which regional policies apply. NUTS-2 regions with less than 10 observations are left blank. ACP = arable, crop and perennial farms.
from our PCA analysis. The composite indicator scores are calculated by the weighted sum of all resilience capacity indicators (Table 3).

Figure 2a–i present the spatial distribution of the composite indicators for all resilience capacities. The obtained composite indicators are heterogeneous over space and farm type. A few notable patterns arise. First, farms in countries with relatively low scores for robustness in all farm types (Sweden and Poland) are better able to adapt and transform compared to most other countries. Second, mixed farms have more often transformed than ACP and livestock farms.

4.2. Regression results

Prior to interpreting the results, we discuss the validity of the instrumental variables. We use second lags of the endogenous variables as instruments, indicating that the equation is exactly identified. We conclude that our instrumental variables are valid based on the following criteria: (i) the significance of the proposed instruments in the first-stage regression, (ii) the Kleibergen–Paap F-statistics\(^{10}\) that are larger than 10 and exceed the critical values of Stock and Yogo (2002) and (iii) the significance of the Kleibergen–Paap rk LM statistics. Tables A21–A31 (Appendix in supplementary data at ERAE online) of the Appendix provide more details on the instrument validity tests. Furthermore, we test which of the potential endogenous variables should be treated as endogenous using a Hausman test (Papke and Wooldridge, 2008). This test inspects if the residuals of the reduced form equations are significantly different from zero in the second-stage model. If the residuals have a significant effect on the dependent variable, we reject exogeneity and conclude that the variable is endogenous. A non-significant effect implies that we cannot reject exogeneity.

Tables 4–6 present the APE of the CRE (fractional) probit models. Additionally, we investigate the robustness of our findings to alternative model specifications by estimating the following models: (i) models based on other weighting methods (equal weights) to compute composite indicators for robustness and adaptation, (ii) models based on other threshold values for farm tourism as transformation indicator, (iii) models including age squared and land squared as additional explanatory variables and (iv) models including additional economic and environmental explanatory variables. The results of the robustness checks can be found in the Supplementary Appendix (Tables A32–A100; Appendix in supplementary data at ERAE online). In general, we find that the reported results are statistically robust to alternative model specifications. Additionally, we test if the estimated parameters are significantly different across regions using seemingly unrelated estimation (Zellner, 1962). Tables A101–109 (Appendix in supplementary data at ERAE online) of the

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\(^{10}\) The reduced form regression is based on pooled OLS, which uses clustered standard errors at the farm level. Therefore, we use the Kleibergen–Paap F-statistics instead of Cragg–Donald's F-statistics.
Table 4. Average partial effects of models with farm robustness as dependent variable across different regions and farm types

| Region          | Western Europe | Southern Europe | Northern Europe | Eastern Europe |
|-----------------|----------------|-----------------|-----------------|----------------|
|                 | ACP            | Livestock       | Mixed           | ACP            | Livestock       | Mixed           | ACP            | Livestock       | Mixed           | ACP            | Livestock       | Mixed           |
| ROA             | −0.056**       | 0.066           | 0.164**         | −0.385***      | −0.620***      | −0.804***       | 1.979***       | 0.263***        | 2.936***        | −1.259***      | −1.292***       | −1.380***       |
|                 | (0.024)        | (0.041)         | (0.069)         | (0.049)        | (0.064)        | (0.243)         | (0.159)        | (0.135)         | (0.350)         | (0.173)        | (0.201)         | (0.176)         |
| ATO             | 0.193***       | −0.077***       | −0.096***       | 0.018          | 0.000          | 1.075***        | −0.358***      | −0.365***       | 0.488***        | 1.726***       | 1.699***        | 2.041***        |
|                 | (0.028)        | (0.009)         | (0.015)         | (0.026)        | (0.028)        | (0.175)         | (0.118)        | (0.049)         | (0.132)         | (0.115)        | (0.120)         | (0.110)         |
| Log(land)       | 0.028***       | 0.001           | 0.018***        | 0.015**        | 0.010**        | 0.019**         | 0.056**        | 0.028           | 0.000           | 0.018**        | −0.083          | 0.067***        |
|                 | (0.004)        | (0.006)         | (0.010)         | (0.003)        | (0.005)        | (0.012)         | (0.025)        | (0.019)         | (0.052)         | (0.016)        | (0.019)         | (0.015)         |
| Age             | 0.001**        | 0.000           | 0.000           | 0.001          | 0.000          | 0.000           | 0.005**        | 0.001           | −0.005          | 0.000          | 0.004***        | 0.002**         |
|                 | (0.000)        | (0.000)         | (0.001)         | (0.000)        | (0.000)        | (0.001)         | (0.003)        | (0.002)         | (0.004)         | (0.001)        | (0.001)         | (0.001)         |
| Decoupled payments | −0.250***     | 0.108***        | −0.281***       | 0.078**        | −0.193**       | 0.117           | −0.473***      | −0.800***       | 0.454           | 0.950***       | 0.020           | 0.310***        |
|                 | (0.044)        | (0.031)         | (0.057)         | (0.030)        | (0.109)        | (0.092)         | (0.135)        | (0.234)         | (0.382)         | (0.098)        | (0.102)         | (0.083)         |
| Rural development payments | 0.153*** | −0.023         | −0.225***       | −0.124***      | 0.171***       | 0.389***        | 0.510***       | 0.061           | −0.404          | −0.263***      | 0.806***        | 0.892***        |
|                 | (0.085)        | (0.093)         | (0.104)         | (0.030)        | (0.061)        | (0.128)         | (0.162)        | (0.078)         | (0.483)         | (0.074)        | (0.079)         | (0.054)         |
| Country a       | Yes            | Yes             | Yes             | Yes            | Yes            | Yes             | No             | No              | No              | No             | No              | No              |
| Farm type b     | Yes            | Yes             | No              | Yes            | Yes            | No              | Yes            | Yes             | No              | Yes            | Yes             | No              |
| Year c          | Yes            | Yes             | Yes             | Yes            | Yes            | Yes             | Yes            | Yes             | Yes             | Yes            | Yes             | Yes             |
| CRE parameters d | Yes            | Yes             | Yes             | Yes            | Yes            | Yes             | Yes            | Yes             | Yes             | Yes            | Yes             | Yes             |
| Endogenous variables e | ROA, DP | ROA, ROA, ATO | ROA, ATO, ROA, ATO, DP | None | ROA, ATO, DP | None | ROA, DP, ROA, DP | None |
| N              | 38,888         | 42,969          | 14,162          | 54,105         | 23,369         | 3,920           | 1,132          | 3,601           | 437             | 15,898         | 19,543          | 21,459          |

Notes: ACP = arable, crop and perennial farms; ROA = rate of return on assets; ATO = asset turnover; DP = decoupled payments; RDP = rural development payments.

a Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)).

b Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8 farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms).

c Year indicates if year dummies are included in the model (Yes) or not (No).

d CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No).

e Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. If endogenous variables are present, the presented standard errors are obtained by 1,000 bootstrap replications and are fully robust.

* p < 0.10, ** p < 0.05, *** p < 0.01.
Table 5. Average partial effects of models with farm adaptation as dependent variable across different regions and farm types

|                      | Western Europe |          | Southern Europe |          | Northern Europe |          | Eastern Europe |          |
|----------------------|----------------|----------|-----------------|----------|-----------------|----------|----------------|----------|
|                      | ACP | Livestock | Mixed | ACP | Livestock | Mixed | ACP | Livestock | Mixed | ACP | Livestock | Mixed |
| ROA                  | -0.024*** | -0.046*** | -0.024 | -0.030*** | 0.002 | -0.051* | -0.036 | -0.145*** | -0.230** | -0.080*** | 0.039 | -0.005 |
| (0.005)              | (0.014) | (0.017)  |        | (0.006) | (0.011) | (0.030) | (0.067) | (0.056) | (0.111) | (0.020) | (0.028) | (0.021) |
| ATO                  | 0.003 | 0.008 | -0.008 | 0.017*** | 0.011 | 0.048*** | -0.038 | -0.020 | 0.013 | 0.059**  | 0.000 | -0.002 |
| (0.002)              | (0.007) | (0.009) |        | (0.004) | (0.017) | (0.018) | (0.040) | (0.036) | (0.123) | (0.015) | (0.017) | (0.017) |
| Log(land)            | 0.000 | 0.010*** | 0.001 | 0.002 | 0.000 | -0.000 | -0.039*** | 0.003 | 0.017 | 0.004 | 0.007 | 0.007** |
| (0.001)              | (0.003) | (0.004) |        | (0.001) | (0.002) | (0.004) | (0.015) | (0.011) | (0.021) | (0.003) | (0.006) | (0.003) |
| Age                  | -0.000*** | -0.001*** | -0.001*** | -0.000 | -0.000 | -0.000 | -0.005*** | -0.000 | -0.003* | -0.001*** | -0.001*** | -0.001*** |
| (0.000)              | (0.000) | (0.000) |        | (0.000) | (0.000) | (0.000) | (0.002) | (0.001) | (0.002) | (0.000) | (0.000) | (0.000) |
| Decoupled payments   | -0.014 | 0.019 | 0.004 | -0.002 | 0.012 | 0.172** | 0.066 | 0.328*** | 0.259 | 0.007 | 0.165*** | 0.056** |
| (0.018)              | (0.016) | (0.025) |        | (0.005) | (0.008) | (0.029) | (0.066) | (0.136) | (0.203) | (0.023) | (0.044) | (0.028) |
| Rural development    | 0.094*** | -0.000 | 0.029 | 0.011 | 0.001 | -0.016 | -0.053 | 0.153*** | 0.124 | 0.025 | -0.126** | 0.020 |
| payments             | (0.022) | (0.001) | (0.037) | (0.008) | (0.012) | (0.038) | (0.092) | (0.074) | (0.308) | (0.016) | (0.046) | (0.013) |
| Countrya              | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No | No | Yes | Yes |
| Farm typeb            | Yes | Yes | No | Yes | Yes | No | Yes | No | Yes | Yes | Yes | Yes |
| Yearc                | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| CRE parameterd       | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Endogenous variablesf | DP, RDP | None | DP | None | None | DP | None | None | DP | None | RDP | DP |
| N                    | 38,888 | 42,969 | 14,162 | 54,105 | 23,369 | 3,920 | 1,132 | 3,601 | 437 | 15,898 | 19,543 | 21,459 |

Notes: ACP = arable, crop and perennial farms; ROA = rate of return on assets; ATO = asset turnover; DP = decoupled payments; RDP = rural development payments.

a Country indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)).
b Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8 farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms).
c Year indicates if year dummies are included in the model (Yes) or not (No).
d CRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No).
e Endogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. If endogenous variables are present, the presented standard errors are obtained by 1,000 bootstrap replications and are fully robust.

*p < 0.10, **p < 0.05, ***p < 0.01.
Table 6. Average partial effects of models with farm transformation as dependent variable across different regions and farm types

|                     | Western Europe |         | Southern Europe |         | Northern Europe |         | Eastern Europe |         |
|---------------------|---------------|---------|-----------------|---------|-----------------|---------|----------------|---------|
|                     | ACP           | Livestock | Mixed           | ACP     | Livestock       | Mixed   | ACP            | Livestock | Mixed   | ACP     | Livestock | Mixed   |
| ROA                 | 0.006***      | 0.051    | −0.127          | 0.020   | 0.025           | −0.090  | 0.031          | −0.049    | −0.388  | 0.099***| 0.044    | −0.068  |
|                     | (0.001)       | (0.032)  | (0.079)         | (0.018) | (0.039)         | (0.171) | (0.194)        | (0.143)   | (0.608) | (0.034) | (0.069)  | (0.084) |
| ATO                 | −0.006***     | −0.010   | −0.015          | −0.008  | −0.019          | −0.156  | −0.060         | −0.244*** | −0.002  | 0.099***| −0.136***| 0.054   |
|                     | (0.001)       | (0.017)  | (0.037)         | (0.011) | (0.027)         | (0.111) | (0.105)        | (0.107)   | (0.361) | (0.027) | (0.051)  | (0.065) |
| Log(land)           | 0.001***      | −0.000   | 0.004           | 0.018***| 0.002           | −0.007  | −0.032         | −0.030    | 0.026   | 0.005   | −0.015   | 0.025** |
|                     | (0.000)       | (0.007)  | (0.017)         | (0.003) | (0.004)         | (0.021) | (0.027)        | (0.028)   | (0.105) | (0.005) | (0.014)  | (0.012) |
| Age                 | −0.000***     | −0.000   | −0.000          | −0.001***| 0.000           | 0.000   | −0.003         | −0.004    | 0.003   | 0.001   | −0.000   | −0.001  |
|                     | (0.000)       | (0.000)  | (0.001)         | (0.000) | (0.000)         | (0.002) | (0.004)        | (0.002)   | (0.004) | (0.000) | (0.001)  | (0.001) |
| Decoupled payments  | −0.039***     | 0.026    | −0.032          | −0.005  | −0.004          | 0.134   | 0.060          | 0.393***  | 1.248   | −0.877***| 0.110    | −0.033  |
|                     | (0.004)       | (0.036)  | (0.140)         | (0.013) | (0.024)         | (0.107) | (0.207)        | (0.211)   | (0.734) | (0.085) | (0.086)  | (0.114) |
| Rural development payments | 0.181*** | 0.049***  | 0.103            | 0.065***| 0.067**         | 0.002   | −0.090         | −0.138    | 0.113   | 0.626***| −0.059   | 0.010   |
|                     | (0.006)      | (0.017)  | (0.183)         | (0.025) | (0.033)         | (0.208) | (0.226)        | (0.194)   | (0.975) | (0.057) | (0.050)  | (0.054) |
| Country a           | Yes           | Yes      | Yes             | Yes     | Yes             | Yes     | Yes            | No        | No      | No      | Yes      | No      |
| Farm type b         | Yes           | Yes      | No              | Yes     | Yes             | No      | Yes            | Yes       | No      | Yes     | No       | No      |
| Year c              | Yes           | Yes      | Yes             | Yes     | Yes             | Yes     | Yes            | Yes       | Yes     | Yes     | Yes      | Yes     |
| CRE parameters d    | Yes           | Yes      | Yes             | Yes     | Yes             | Yes     | Yes            | Yes       | Yes     | Yes     | Yes      | Yes     |
| Endogenous variables e | DP, RDP None | None      | None            | None    | None            | None    | None           | None      | None    | None    | None      | None    |
| N                   | 38,888        | 42,969   | 14,162          | 54,105  | 23,669          | 3,920   | 1,132          | 3,601     | 437     | 15,898  | 19,543   | 21,459  |

Notes: ACP = arable, crop and perennial farms; ROA = rate of return on assets; ATO = asset turnover; DP = decoupled payments; RDP = rural development payments.

dCountry indicates if country dummies are included in the model (Yes) or not (No). No indicates that only one country represents a region (i.e. Northern Europe (Sweden) and Eastern Europe (Poland)).

Farm type indicates if farm types dummies are included in the model (Yes) or not (No). No indicates that only one TF8 farm typology is included in the model (i.e. the mixed farm models only contain data from mixed farms).

cYear indicates if year dummies are included in the model (Yes) or not (No).

dCRE parameters indicate if the correlated random effects parameters are included in the model (Yes) or not (No).

eEndogenous variables indicate which explanatory variables are treated as endogenous based on a Hausman test. If endogenous variables are present, the presented standard errors are obtained by 1,000 bootstrap replications and are fully robust.

*p < 0.10, **p < 0.05, ***p < 0.01.
Appendix show that the estimated parameters are in general significantly different across regions, supporting the estimation of regional models instead of one common European model.

Our results reveal that the effect of ROA on farm robustness is mixed and differs across regions. For all Northern European farms and Western European mixed farms, profitability positively affects robustness. This positive effect suggests that more profitable farms are better able to absorb, withstand and recover from adverse events. These findings are consistent with Cabell and Oelofse (2012), who describe that being reasonably profitable improves the capacity to recover and contributes to creating buffers. However, we find evidence that ROA negatively affects robustness for all Southern and Eastern European and Western ACP farms. A possible explanation for this relationship is that more profitable years compared to the average farm profitability do not necessarily help to obtain a more stable profitability, which could lead to less robust farms. In most regions, we find no significant effect or a negative effect of profitability on adaptation and transformation.

We find that ATO decreases robustness for livestock farms in Western and Eastern Europe, while having a positive effect on the robustness of mixed farms. There are mixed results for ACP farms. For most livestock farms, higher operational efficiency is related to lower buffer capacities and reserves, which comes at the cost of farm robustness (Darnhofer, 2014). A possible explanation for this could be that farms with higher ATO use their assets more efficiently, keeping their asset buffers low. An explanation for the positive effect of ATO on mixed farm robustness in most regions is that these farms are already diverse as they combine livestock and arable farming practices, giving them sufficient redundancy and buffers (Altieri et al., 2015). Hence, an increased operational efficiency would make them more robust. We find no effect of ATO on adaptation or transformation in most models. Only for Southern European mixed and ACP farms and Eastern European ACP farms, we find only a positive effect of ATO on adaptation. This effect reveals that a higher operational efficiency facilitates small adaptations that do not require investments in new assets.

Furthermore, we find that land has mixed effects on robustness, while land has no significant effect on adaptation and transformation in most models. Age has a positive effect on robustness for ACP in most regions and livestock and mixed farms from Eastern Europe. An explanation for this is that older farmers are more experienced in dealing with risk and more willing to remain the status quo, which makes them more robust (Peerlings, Polman and Dries, 2014). Age negatively affects adaptation for all Western and Eastern European farms and ACP and mixed farms in Northern Europe. This implies that younger farmers are more open to change, resulting in more adaptable farms. We find that age has no significant effect on farm transformation, except for ACP farms in Western and Southern Europe.

Despite for Eastern Europe farms, we find in general negative or non-significant effects of decoupled payments on robustness. For most Western and Northern European farms, the results indicate a negative effect of decoupled payments on robustness occurred. A possible explanation for this could be that
income support offered by decoupled payments does not prevent exposure to risk (Kleinhanß et al., 2007; Zheng and Gohin, 2020) and potentially creates a dependency on subsidies (de Mey et al., 2016). This suggests that farms receiving more decoupled payments have a reduced ability to adequately respond to risk, resulting in less robust farms. Furthermore, we find that decoupled payments have no effect on adaptation and transformation in most regions. Only for Southern European mixed farms and Eastern European livestock and mixed farms, we find that decoupled payments increase farm adaptation. An explanation for this could be that livestock and mixed farm adaptation requires more capital (e.g. purchasing a new breed of dairy cows) compared to adaptation of arable farms in Southern and Eastern European countries (Peerlings, Polman and Dries, 2014). Furthermore, decoupled payments constrain farm adaptation of livestock farms in Northern Europe. Farm transformation is only supported by decoupled payments for livestock and mixed farms in Northern Europe. A possible explanation for this positive effect could be that decoupled payments are used to invest (Moro and Sckokai, 2013) and that these investments could be used to stimulate farm transformation. For ACP farms from Western and Eastern Europe, we found a negative effect of decoupled payments on transformation.

One of the aims of the rural development policy is to promote a resilient agricultural sector (European Commission, 2020b). In general, our results reveal that rural development payments contribute to robustness in most regions, while these payments have no effect on adaptation and transformation. On the one hand, the positive effect of rural development payments on robustness indicates that payments aiming to support innovation and environmental friendly practices help farms to absorb shocks and maintain current production practices. On the other hand, the mostly non-significant effect of rural development payments on adaptation and transformation suggests that alternative policy instruments, such as payments for providing public goods, may be more effective to enhance adaptation and transformation. Only for some regions and farm types—i.e. Western European ACP and livestock farms, Southern European ACP and livestock farms, and Eastern European ACP farms—rural development payments successfully promote innovations that stimulate farm transformation (Dwyer, 2013).

5. Discussion and conclusions

This paper quantified European farm resilience in terms of robustness, adaptation and transformation. We investigated general patterns that reflect how farms deal with change, risk and uncertainty. This approach allows for a comparison of farms from different regions and farm types. We developed a novel indicator framework that captures dynamics by investigating changes in inputs and outputs over time. Composite indicators were used to aggregate the resilience capacity indicators into a measure that is easy to interpret for policymakers. Our empirical application used FADN data from nine European
countries to explore which farm and farmer characteristics affect the resilience capacities.

The characteristics that have a positive effect on the resilience capacities help agricultural policymakers to create future pathways towards more resilient farms. Importantly, we found that our results are heterogeneous across regions and farm types. Furthermore, the direction of effects often differs between resilience capacities, implying that there were trade-offs between robustness, adaptation and transformation. This calls for a holistic view on resilience, invariably considering all three resilience capacities. We found that decoupled payments have no significant effect or a negative effect on farm robustness in most regions and farm types. This suggests that decoupled payments do not stimulate farmers to obtain a more stable farm income. In most regions, decoupled payments had no effect on adaptation and transformation. Finally, our results revealed that the rural development measures of the CAP in general support farm robustness but are less effective in facilitating adaptation and transformation.

As we contribute to the call for empirical resilience assessments, our results are of interest to European agricultural policymakers (European Commission, 2020a). However, the proposed method has two limitations: (i) the underrepresentation of environmental and social dimensions and (ii) limitations related to the design of the FADN data set. Below, we discuss these limitations.

First, the environmental and social dimensions of farm resilience are somewhat underrepresented. Additional insights into environmental aspects (e.g. by collecting data on nitrogen and phosphorus balances or biodiversity indicators) would improve resilience assessments by an increased understanding of a farm’s natural capital (Reidsma et al., 2020). In line with Dardonville, Bockstaller and Therond (2021), we find that capturing dynamics in social dimensions are constrained by what can be quantified and are hence hard to include in econometric models. Additional insights into social aspects could increase our understanding on how farms respond and deal with change (Cinner and Barnes, 2019). To better capture the social dimension, researchers could investigate a farmer’s network and ability to learn (Urquhart et al., 2019), self-assessed resilience capacities (Jones and d’Errico, 2019; Slijper et al., 2020) and future literacy—i.e. the ability to anticipate to future risk (Miller, 2015; Mathijs and Wauters, 2020). These examples illustrate that future resilience assessments benefit from interdisciplinary research using sequential mixed methods, in which qualitative and quantitative research data are combined from researchers with different scientific backgrounds.

Second, we illustrate that quantifying farm resilience is data-demanding, ideally involving repetitive measures over time. The FADN data set has some limitations for quantifying farm resilience. For instance, FADN does not report the reason why farms dropped out. Some farmers might not be willing to cooperate to data collection anymore, while others may have stopped farming. Another explanation could be the rotating panel schemes applied in several countries. Knowing which farms dropped out due to farm exit helps researchers to investigate if less resilient farms are more likely to quit...
farming. Additionally, FADN is limited to yearly observations and does not capture monthly or quarterly changes. Adaptation processes such as changes in the timing of sowing or harvesting activities cannot be observed. Collecting data at a higher frequency (e.g. via precision agricultural equipment) will allow researchers to capture more detailed dynamics, resulting in more accurate resilience assessments. However, this would surely bring additional data collection costs.

The findings have important implications for European policymakers who aim to enhance farm resilience. We show that some of the most important policy instruments from the CAP Pillar I (decoupled payments) and Pillar II (rural development payments) only affect robustness but have, in general, no effect on adaptation and transformation. This implies that stimulating farm adaptation and transformation requires alternative policy instruments. For instance, those that support business models that incorporate payments for public good provision (e.g. landscape and biodiversity services). While our resilience assessment helps designing optimal resilience-enhancing policies in future CAP reforms, it also calls for a broadening of FADN data collection to be fully able to strengthen agricultural resilience in the face of a broadening risk landscape.

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Supplementary data

Supplementary data are available at ERAE online.

Competing financial interests

The authors declare no competing financial interests.

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